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# AN EFFICIENT SYSTEMATIZED APPROACH FOR THE DETECTION OF CANCER IN KIDNEY

**Ahmed J. Obaid**

Department of Computer Science, Faculty of Computer Science and Mathematics, University of Kufa, Iraq.
E-mail: ahmedj.aljanaby@uokufa.edu.iq

**Abstract-** In the monitoring and control of chronic kidney tumor disease, early detection and analysis are considered to be significant. Several detection techniques exist but defining the disease is still crucial since it provides various indications which facilitate the aim of desired intervention and treatments. In this paper an efficient kidney tumor detection is proposed in which the input image is preprocessed by median filter making it noise-free. Subsequently, the image is segmented by adopting K means clustering for segmenting data and partitioning it into homogeneous subgroups considering its similarity. Further, the features are extracted by Principal Component Analysis which reduces the huge group of variables to optimal group. Finally the image undergoes classification through Probabilistic Neural Networks in which a training data set is employed to generate a classified output image detecting the presence of tumor. The dataset utilized in this approach is kidney tumor dataset with tumor diameter of 7 pixel to 90 pixel. With PNN, the accuracy obtained is 96.8% and the presence of tumor is efficiently detected in kidney.

**Keywords:** Speckle noise, K means, Principal Component Analysis, Probabilistic Neural Networks.

## 1 INTRODUCTION

Kidney cancer is one of the deadliest diseases, and it's hard to diagnose earlier with traditional clinical approaches. Renal cancer is among the top ten cancers that kill people, but study into it is currently incomplete. Renal cancer patients have few care options for ages, and lifespan is usually measured in months rather than years. As a result, automatic diagnostic software will assist a doctor in rapidly identifying the illness and assisting patients in surviving [1]. Generally, image analysis concepts are utilized for the automatic diagnosis depending on the pre-defined groups as well as annotated imaging data. Even, image strength and texture variations occur, reducing the contrast between background as well as artefacts and further blurring image boundaries. As a consequence, a single object can be identified as fragments. Furthermore, images are often arranged in overlapping or touching clusters, which has stratified features that take up vast space, making them more confluent [2].

In order to tackle this, images have to undergo four phases namely: preprocessing, segmentation, feature extraction and classification. Initially, preprocessing involves the elimination of speckle noise preventing the loss of edge information as well as critical features. A variety of experiments on eliminating speckle noise were performed over the past few decades. Linear filters are considered to be one of the efficient approaches for preprocessing of images. In linear filters, the filter's transfer function modifies a portion of the signal frequency spectrum. But the noise and image characteristics that are scattered across the image are ignored by linear filters which blurs the contrast and the edge region of the image [3]. Another filter called Lee filter was designed on the linear minimum mean squared error (LMMSE) estimator specifically for single polarization Synthetic Aperture Radar (SAR) image despeckling. The problem with these approaches is that they necessitate selecting identical pixels to guarantee scene stationarity [4]. Preprocessing is also done by using an effective hashing algorithm to select a collection of pre-learned locally adaptive filters to be applied to image patches. These filters are trained from pairs of LR and HR training image patches, as well as hashing is accomplished by evaluating the statistics of local gradients. Yet, their efficiency can be improved through regularizing the training adopting efficient procedures [5]. Discrete Cosine Transform (DCT) predefined filters are another type of filters to obtain input attributes with reduced reconstruction time and is widely utilized in real-time applications. Still, these filters require further improvement in performance and quality [6]. Concentrating the above mentioned drawbacks, median filter is utilized in this approach for efficient preprocessing of images by removing noise with the preservation of edges.

Subsequently, the preprocessed images has to be segmented and it forms an important phase for both medical research as well as clinical practice. Since manually segmenting three-dimensional images takes a long time and is subject to inter-and intraobserver variation, automatic segmentation is essential. Automatic Optic Disc (OD) and Optic Cup (OC) segmentation methods have been the focus of study in recent decades. Early attempts for OC and OD segmentation depends on hand-craft features like color, contrast thresholding, level set approach and clustering dependent techniques. Manually built features, on the other hand, lack adequate discriminative capacity, so imaging situations and the complexity of pathological regions have a significant impact on efficiency [7]. Segmentation is also performed by U-net algorithm which addressed the problem of minimal quality segmentations from minimal quality image data, but may result in loss of features [8]. The supervised techniques like thresholding and histogram based image segmentation also face deterioration in performance due to variations between training and test data [9]. Hence, in this approach, K-means clustering algorithm is adopted which is an unsupervised algorithm used to identify different classes or clusters in the given data based on the similarity of data.

After the segmentation of images, feature extraction is performed which is a dimensionality reduction process. Local Binary Pattern (LBP) is an efficient feature extraction method in which a texture feature is extracted on a pixel level with a local neighborhood. Using binary thresholding with the center pixel value pattern, the operator marks the pixels of a local area. It can be improved further to extract more sophisticated features [10]. Independent Component Analysis (ICA) has also attained huge attention in discriminating independent blind sources from observed mixture prominent approaches. Anyway, an increasing factor that ICA approach may possess prospective restrictions if functional networks possess large spatial overlaps [11]. Linear Discriminant Analysis (LDA) is another feature extraction approach which targets to improve the distance between the mean of each class as well as decrease the spreading in the class. Yet, it required further capacity enhancement offering minimal side information, with rigidity towards rotation as well as content loss attacks [12]. Another unsupervised algorithm like Locally Linear Embedding (LLE) is a dimensionality reduction approach depending on Manifold Learning. Though it is simple, the discrimination of extracted features do not occur, resulting in depleted performance [13]. Therefore, Principal Component Analysis (PCA) is adopted for the extraction of features avoiding redundant information.

Feature extraction of images is followed by the classification involving categorization of all pixels in a digital image into one of several classes. The rapid accessibility of remote sensing images has put traditional supervised classification algorithms like Support Vector Machines (SVM) to the test. Although gathering an adequate number of training samples is essential for achieving satisfactory classification accuracy, it is also labor-intensive and time-consuming, and it is often impossible [14]. Artificial Neural Networks (ANN) are also used in medical image processing for a number of feature extraction as well as pattern recognition problems but they did not consider the losses [15]. Another classification approach is decision tree (DT) to determine the efficient attribute variable of classification capability. By the best attribute variables, the data will be partitioned into various subsets. Specifically, decision trees are classification approaches described by their increased nature of interpretability as well as robustness. On the other hand, since the precision of integrated classifiers as well as sub-classifiers is highly correlated, it is important to improve classifiers with greater classification accuracy [16]. Considering these factors, Probabilistic Neural Networks (PNN) are deployed for image classification offering quick training process with no local minima issues[17-30].

In this paper, efficient detection of cancer in kidney is performed adopting image processing concepts. The preprocessing of images is done by median filter and is segmented by K means clustering. The features of the images are extracted by PCA and finally PNN is adopted for classification.

## 2 PROPOSED METHODOLOGY

The basic block diagram depicting the processing of input images and its retrieval is given below figure 1.

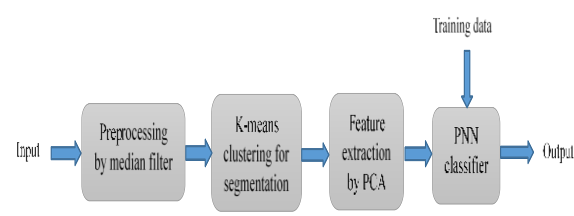



**Figure 1** Block diagram of proposed approach

The kidney tumor image is initially fed to the median filter for preprocessing during which the images are subjected to noise removal. The filter utilized extracts the speckle noise without affecting the sharpness of the image. The noise free image is then segmented by K means clustering in which the data is segmented and a mean value is generated for each clusters. Consequently, feature extraction is performed by PCA to reduce the complexity, time consumption and memory wastage. Finally the image is classified using PNN and the tumor detection in kidney is performed.

### 2.1 Preprocessing of Input Image

Raw images are subjected to image pre-processing in order to minimize image noise. Pre-processing is used to mitigate the severity of speckle noise, reflection, and other related factors in images. Filtering is one of the pre-processing techniques that aids in image enhancement by eliminating image noise. The efficiency of a filter is associated with the reduction of unwanted signals while maintaining the optimum signal. Before object detection, image enhancement as well as filtering methods are performed in the image to minimize the deteriorating interference of the impulse noise in the image. The type of filter that should be added to an image for optimum efficiency is determined by the amount of noise and the strength of the noise.

In this approach, median filter is utilized which comes under the category of non-linear filters. This is used to hide the unwanted noise of the grayscale image. This filter relies on the pixel mean and conserves the edges as well as boundaries. Initially, an input image of size M*N is considered and the image is further divided into n number of windows each having a center value. This value has to be replaced with median value evaluations for eliminating the noise. The median is estimated by initially maintaining the pixel values in numerical order and displacing the regarded pixel with center pixel value. It eliminates the speckle noise of the image without degrading its sharpness. Figure 2 shows Median value calculation of a pixel. The median value is calculated as follows,

| | | |
|---|---|---|
| 7 | 1 | 8 |
| 6 | 4 | 5 |
| 9 | 2 | 3 |

Actual image

| | | |
|---|---|---|
| | | |
| | 5 | |
| | | |

Median value

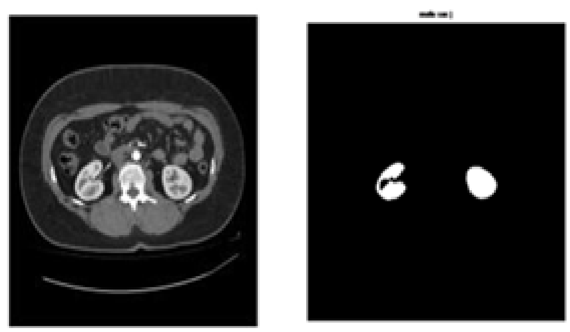
**Figure 2** Median value calculation of a pixel

### 2.2 Image Segmentation

After the pre-processing step, a clustering analysis tool named K-means clustering is adopted, which is a multivariate statistical technique utilized to segment data considering its similarity and partitions into homogeneous subgroups. The major concept of K-means is to introduce a centroid for every cluster which is the mean of cluster points. The steps followed by K-means algorithm are given below,

1) Initially choose the centers of K clusters and perform steps 2 and 3 till the stabilization of cluster membership occurs.
2) Create a new partition by providing each data to nearest cluster centers.
3) Estimate the cluster centroid by considering a new cluster center.

The segmentation approach also involves preprocessing, analysis of clusters and post processing. By calculating the centroid, the midpoint of the spinal cord is obtained and hence the image is partitioned into two parts in which the left and right kidneys are attained distinctly. Thus the segmentation of kidney images is performed using K-means clustering which is followed by feature extraction. Figure 3 shows Segmentation of image.



a) Actual image B) Segmented image

**Figure 3** Segmentation of image

### 2.3 Feature Extraction Of Images

The features present in the images are responsible for the generation of improved accuracy but huge count of features maximize the complexity of process, time consumption, memory wastage etc. this may lead to overfitting issue. In order to tackle this, Principal Component Analysis is adopted for the extraction of features from images. PCA minimizes huge group of correlated variables to optimal group of uncorrelated variables which are termed as principal components. The impacts of PCA on the input data are given below,

1) It orthogonalizes actual vector, thus resulting vectors remain uncorrelated to one another.
2) The component with high variance is considered initially and eradicates vectors with minimal variations.

The process of PCA is given below,

Consider $y_1, y_2, \ldots y_m$ as M*1 vectors

Step 1: $\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i$

Step 2: Subtract the mean $\emptyset_i = y_i - y$

Step 3: Generate matrix A= $[\phi_1\ \phi_2 \ldots \phi_N]$(M*N),

$$C = \frac{1}{N}\sum_{n=1}^{N} \emptyset_n \emptyset_n^T$$

$$= \frac{1}{N} AA^T$$

Step 4: Estimate eigen values of C: $\lambda_1 > \lambda_2 > \ldots \lambda_N$

Step 5: Estimate eigen vectors of C: $v_1, v_2, \ldots v_N$

$y - \bar{y} = a_1 v_1 + a_2 v_2 + \cdots + a_N v_N$ (linear eigen vector combination)

$$= \sum_{i=1}^{N} a_i\, v_i \quad \text{where } a_i = \frac{(y-\bar{y}).v_i}{(v_i.v_i)}$$

Step 6: Maintain the terms of K maximum eigen values.

$$\hat{y} - y = \sum_{i=1}^{k} a_i\, v_i \text{ where K<<N}$$

The linear transformation performing feature extraction is given by

$$\begin{bmatrix} a_1 \\ a_2 \\ \cdot \\ \cdot \\ a_K \end{bmatrix} = \begin{bmatrix} u_1^T \\ u_2^T \\ \cdot \\ \cdot \\ u_K^T \end{bmatrix} (y - \bar{y}) = U^T (y - \bar{y})$$

### 2.4 Image classification

After the extraction of features, image classification is performed which is a significant arena in which deep neural networks is considered to be an important factor for the analysis of medical images. The image classification recognizes input images and generates classified output image to determine the presence of disease. In this approach, PNN is deployed which a multilayered feed forward neural network obtained from Bayesian network. It has four layers,

1) Input layer
2) Hidden layer
3) Pattern layer
4) Output layer

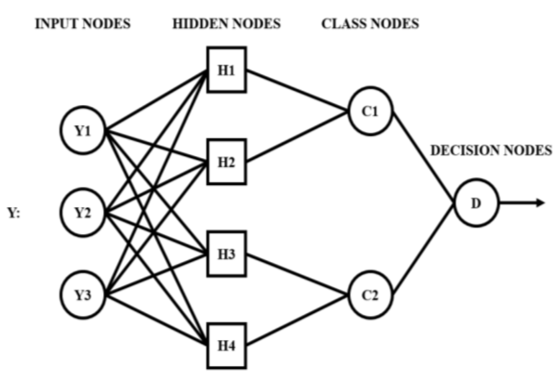



**Figure 4** Architecture of PNN

The architecture of PNN is depicted in figure 4. Every neuron in input layer denotes a predictor value and it inputs the values to hidden layer. When the number of input variables are N, the number of neurons required in the input layer are N-1.The hidden layer has single neuron corresponding to every condition in training data set. The values of predictor variables are stored with target value. Corresponding to each target variable, there exists a pattern neuron which sum the values of class they denote. The output layer compares the weighted value calculated for every target class thereby generates the maximum value to the predicted class. Thus the proposed approach effectively performs detection of tumor in kidney images.

## 3 RESULTS AND DISCUSSION

The input images are obtained from kidney tumor dataset and the resolution of the image is 510*510 of 1*1 $mm^2$ /pixel and the spacing value is 1 mm. The dataset is divided into three subsets which include training, validation and testing. The segmented kidney tumor image using K means clustering is given below figure 5.

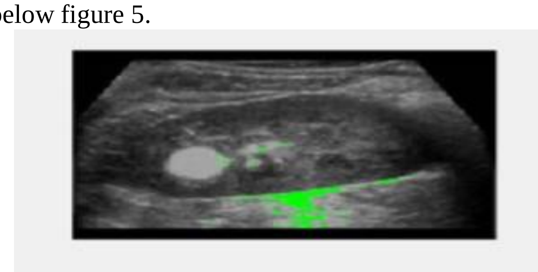


**Figure 5** Segmented kidney tumor image using K means clustering

### 3.1 Performance Evaluation

The performance of the tumor diagnosis is estimated by the attributes depending on confusion matrix. It is defined as the table which estimates the classification model performance on a set of test data for which the true values are determined.

**Table 1:** Confusion matrix

| | | Actual value | |
|---|---|---|---|
| | | Positive | Negative |
| Obtained value | Positive | TP | FP |
| | Negative | FN | TN |

TP (True Positive) → Count of accurate predictions of positive instance

TN (True Negative) → Count of accurate predictions of negative instance
FP (False Positive) → Count of inaccurate predictions of positive instance
FN (False Negative) → Count of inaccurate predictions of negative instance

**Performance metrics**

The performance analysis for the below mentioned metrics are done in this approach.

**a) Accuracy**

It denotes the percentage of appropriately classified instances and is given by,

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

**b) Sensitivity**

It denotes the proportion of positives that are accurately detected and is given by,

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

**c) Specificity**

It denotes the proportion of negatives which are accurately detected and is given by,

$$\text{Sensitivity} = \frac{TN}{TN+FP}$$

**d) Precision**

It denotes the fraction of relevant instances among the retrieved instances and is given by,

$$\text{Precision} = \frac{TP}{TP+FP}$$

**e) Recall**

It denotes the fraction of relevant instances that were retrieved and is given by,

$$\text{Recall} = \frac{TP}{TP+FN}$$

**f) F-measure**

It denotes the measure of accuracy of tests performed and is given by,

$$\text{F-measure} = \frac{(2*Precision*Recall)}{(Precision+Recall)}$$

Table 1 provides Confusion matrix. The table 2 below shows the comparison of PNN classifier with existing classifiers like SVM (Support Vector Machine), RBF (Radial Base Function) and MLP (Multi-Layer Perceptron). From the table it is clear that PNN exhibited efficient results in terms of accuracy, sensitivity, specificity, precision, recall and F-measure.

**Table 2:** Comparison of PNN with existing classifiers

| Algorithm | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) | Recall (%) | F-measure (%) |
|---|---|---|---|---|---|---|
| PNN | 96.8 | 100 | 100 | 100 | 100 | 1 |
| SVM | 60.8 | 98.74 | 99.64 | 98.72 | 98.72 | 0.9938 |
| RBF | 86 | 96.3 | 99.64 | 98.6 | 96.3 | 0.7809 |
| MLP | 51.6 | 0 | 99.28 | 0 | 0 | 0 |

The corresponding graph for the comparison of PNN with existing classifiers is given below figure 6.

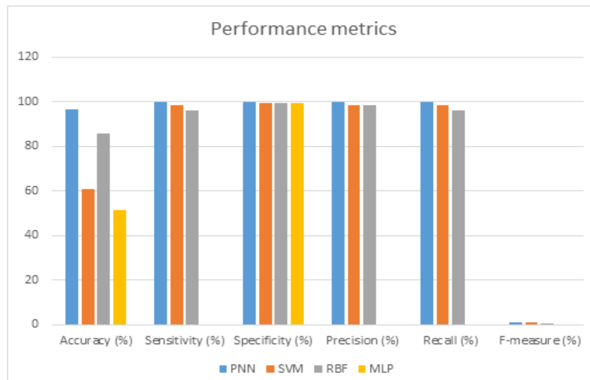



**Figure 6** Comparison of PNN with existing classifiers

Thus the efficient detection of tumor in kidney is performed through preprocessing, segmentation, feature extraction and classification of images.

## 4 CONCLUSION

In this paper, an efficient kidney tumor detection approach is proposed which identifies the tumor in input images of kidney through various processing phases of images. Median filter along with K means is adopted for the preprocessing and segmentation of images respectively. The features are extracted by PCA and the classification of images is performed through PNN approach. The performance metrics including accuracy, sensitivity, specificity, precision, recall and F-measure are analyzed. Future works may concentrate on the detection of kidney tumor adopting various algorithms.

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