Kidney Abnormality Detection and Segmentation

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Abstract— As kidney disease is one of the deadliest cancers at present times, its detection and segmentation is one of the most important operations. The kidney disease can be identified by various methods which include CT scan, MRI and ultrasound. Among these techniques, US imaging in mostly preferred because of its low cost and non-invasive. However, the ultrasound images have low contrast and mainly contain speckle noise which creates a challenging task in kidney abnormalities detection. In this paper, an effective approach is developed that can eliminate the speckle noise from images and increase the accuracy of the system. For this, different images are taken from the available dataset or can be captured form the real world through camera. The images are pre-processed by using the Kuwahara filter so that any noise present in the image can be removed and enhanced image is obtained. In addition to this, the kuwahara filter preserves the edges of the image. Once the refined images are obtained, feature extraction process starts in which seven GLCM features i.e. contrast, correlation, energy, homogeneity, pixel value, min pixels value and max pixel value are extracted. The implementation of the CFA algorithm in the model reduces the overall complexity of the model by selecting only those features which are important and contain necessary information for segmenting and classification process. The selected features are then given to the PNN network for training and testing. The performance of the proposed model is evaluated in the MATLAB software. The simulation outcomes obtained proved that the proposed model is more precise, efficient and effective in identifying various kidney diseases.

Keywords: PV Systems, Fault Detection, Deep Learning Methods

I. INTRODUCTION

Kidney cancer is among the deadliest, and unfortunately, it is difficult to detect early on by normal clinical. Kidney stone problem (nephrolithiasis) is a common type of urological disease with a high recurrence rate of 10 % after one year, 50 % over a period of 5-10 years and 75 % over 20 years period [1]. Kidney function and activity is highly dependent on kidney volume in a variety of diseases such as polycystic kidney disease, lupus nephritis, renal parenchymal disease, and kidney graft rejection. A study conducted by Global Burden of Diseases, reveals that Chronic Kidney Disease (CKD) is the seventeenth leading cause of death worldwide, and it is the eighth leading cause of death in India [2]. Chronic kidney disease (CKD) has become a global health issue and is an area of concern. It is a condition where kidneys become damaged and cannot filter toxic wastes in the body [3]. The two main causes of CKD remain diabetes and high blood pressure. High blood glucose also commonly known as blood sugar, from diabetes can damage the blood vessels of kidney. Almost 1 in 3 adults with diabetes have CKD. Analogous to the blood sugar, high blood pressure can also damage the blood vessels in kidney. Almost 1 in 5 adults with high blood pressure have CKD [4]. Currently methods are available in radiology which includes Ultrasound, CT scan, X-Ray, MRI, etc. But US is always preferred more than the others due to its advantages.

A. Ultrasound Detection

Ultrasound is the most popularly used medical imaging technique for kidney disease detection. Ultrasound (US) is a preferred image modality for examination in case of renal diseases, mainly because of its safety and cost-effectiveness in comparison to Computer Tomography (CT). Ultrasound imaging technique is far more feasible than other radiologic methods since there are no harmful rays used. Several limitations of US images make segmentation a particularly difficult task: poor signal-to-noise ratio, missing boundaries, misplaced boundaries and reconstruction errors [5]. A major disadvantage of US also exists, i.e., noise present and low clarity which deteriorate the efficiency of detection. Speckle is a type of noise that exists while imaging and decreases the visual appearance of the ultrasound images. It affects the finer details like edges and boundaries which is crucial in diagnosis. Speckle noise is harder to eliminate since it is a multiplicative noise and not as easy as to remove like additive noise [6]. The presence of speckle noise in kidney stone images may sometimes mimic a small stone and make the ultrasound imaging as inefficient in detecting small stone of size less than 5mm. In order to detect the kidney disease more efficiently and accurately, it is extremely important to extract and select features from the US images properly.

1) Feature Extraction

Feature extraction describes the relevant shape information contained in a pattern so that the task of classifying the pattern is made easy by a formal procedure. The main goal of feature extraction is to obtain the most relevant information from the original data and represent that information in a lower dimensionality space. The process of transforming the large input data into the set of features is called feature extraction [7]. To extract the features from images lot of methods are available such as PCA, kernel PCA, Fourier transforms etc. some of the features that can be extracted from the images are; GLCM features, statistical features, texture features, region-based feature and wavelet features etc. In our work, we have focused on the GLCM features.

2) GLCM Features

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixels with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. The following table lists the statistics. These statistics provide information about the texture of an image [8].

Statistic	Description
Contrast	Measures the local variations in the gray-level co-occurrence matrix.
Correlation	Measures the joint probability occurrence of the specified pixel pairs.
Energy	Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment.
Homogeneity	Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

Table 1: Statistics and their description

3) *Feature Selection*

Feature selection of a feature extraction method is the single most important factor in achieving high recognition performance. Selecting the most meaningful features is a crucial step in the process of classification problems. A good feature set contains discriminating information, which can distinguish one object from other objects. It must be as robust as possible in order to prevent generating different feature codes for the objects in the same class [7]. Feature selection process increases the classification accuracy and minimizes the computation complexity. Nowadays, number of optimization algorithms and machine learning algorithms are used for feature selection process, such as; ANOVA, lasso, CFA etc. Some of them are discussed in the next section.

II. Related Work

Various researchers in the past decades have developed different techniques that can reduce the effect of noise in images and as well as extract and select features effectively. Among these techniques, few are explained here; A. Nithya, et al., [9], proposed a kidney stone detection using artificial neural network and segmentation using multi-kernel k-means clustering algorithm. K. Viswanath and R. Gunasundari., [10], proposed a method to remove speckle noise by using Gabor filter for smoothening and Multilayer Perceptron (MLP) and Back Propagation (BP), ANN for classification. ShiYin, et al., [11], proposed a subsequent boundary distance regression and pixel classification networks to segment the kidneys automatically. T. Rahman and M. S. Uddin., [12], implemented a system that can segment different kidney diseases from ultrasound images by using Gabon filter and histogram equalization. R. M. Pujari and V. D. Hajare., [13], presented analysis of Ultrasonography (USG) images for detection of Chronic Kidney Disease (CKD) at early stages by focusing on detecting the proportion of fibrosis conditions within kidney tissues. M. P. Pawar et.al., [14], proposed a model that removed speckle noise by using Gaussian filter and segmentation is done by using Gradient vector flow (GVF). S. M. K. Chaitanya et.al., [15], proposed a method for classifying abnormal kidney images by using grey-scale conversion for pre-processing and wavelet-based Gabor method, cuckoo search for optimization. Ravindra B et al., [16], discusses the classification of chronic and non-chronic kidney disease NCKD using support vector machine (SVM) neural networks.

From the literature study, it is analyzed that the Ultrasound images are mostly used in detecting various kidney diseases. However, the quality of these images gets distorted by noise effects caused by machines which make it difficult to extract features from them. A large number of methods were suggested by different experts that eliminated the speckle noise from these images and enhanced their quality. But these techniques were complex and not able to preserve the edges of the images. Furthermore, in traditional methods, more focus on feature extraction, however, selecting important and crucial features also plays a critical role in detecting kidney diseases. Therefore, it is mandatory to select features appropriately by using different optimization algorithms. Inspired from these findings, the proposed work developed a method that can overcome these limitations.

III. Proposed Work

In order to overcome the limitations of the conventional models, this paper presented a new model for detecting different kidney diseases in an effective way. As the images obtained from US is of poor quality which makes the processing complex and difficult. Thus, to enhance the image quality in the proposed work, Kuwahara filter is utilized. The main application of using Kuwahara filter is that it minimizes the noise in images while preserving its edges.

In addition to this, the proposed system utilizes the CFA algorithm for feature selection which reduces the overall complexity of the system. The CFA is used so that only informative and crucial features are selected from the available features in order to reduce the dimensionality space. Also, PNN classifier is used in the proposed work that maps input patterns in a number of class levels. It has multiple features and advantages over traditional ANN. Thus, by applying the PNN, CFA and kuwahara filter the quality and accuracy of the ultrasound images can be increased, which in turn increases the overall efficiency of the proposed model.

IV. Methodology

The detailed process opted for the proposed model is shown in fig1.1, along with its explanation.

Step 1: The first step opted in the proposed system is to select different medical images from the available dataset. The medical images can be taken from the dataset that is available on the internet or can be collected from the real world.

A. *Dataset used*

In the proposed work, the dataset is chosen from the Kaggle.com in which CT images of 100 kidney patients is available. Out of these 100 medical images, 40 images belong to normal persons, 30 are tumor images and rest 30 are stone images.

Step 2: Once the medical images are selected, the next step is to refine these images so that noise can be removed. For this, the proposed model utilized the kuwahara filter. The main job of the kuwahara filter is to preserve edges of the image so that it becomes easy to segment and classify the tumor and non-tumor images.

Step 3: The next step is to extract various features from these refined images. In proposed work, a total of seven GLCM features are extracted from the refined medical images, which include contrast, correlation, energy, homogeneity. In addition to this, pixel value, min pixel value and max pixel value of the images is also evaluated.

Step 4: In order to reduce the complexity of the proposed system, it is extremely important to minimize the total feature count of images. For this, CFA optimization algorithm is used that will select only those features which contain important and crucial information for segmenting and classifying different kidney diseases. The different configurationally parameters of the CFA, along with their specific values are given in table 2.

Sr No.	Parameter	Value
1	Population Count	10
2	Iterations	100
3	Lower Limit	1
4	Upper Limit	5
5	Awareness Probability	0.1
6	Flight Length	2

Table 2: Configuration setup of proposed system

Step 5: The selected important features are then divided into two parts for training and testing purpose. The data is firstly passed to the proposed PNN network for training. Once the network is trained, another set of data is given to it for testing. The proposed model then classifies the input medical images into normal and abnormal categories on the basis of the trained network.

Step 6: Finally, the performance of the proposed model is evaluated in terms of various performance factors that are given briefly in the next section.

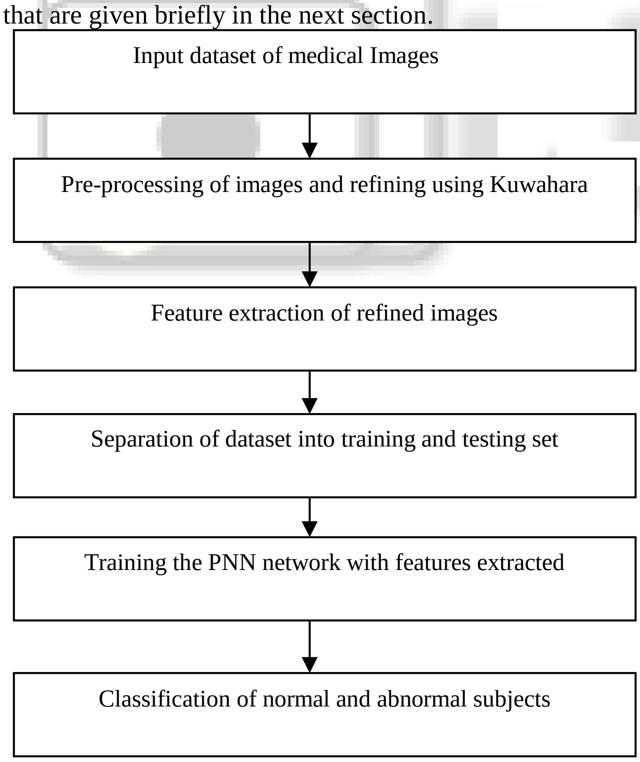

Fig. 1.1: Flow diagram of the proposed model

V. Results and Discussion

The performance of the proposed model is analysed and compared with traditional models in MATLAB environment. The simulation outcomes were obtained in terms of various performance factors which include accuracy, sensitivity, specificity, precision, recall and Fscore and are explained briefly in this section.

A. *Performance Evaluation*

To check the efficiency of the proposed model, its performance is analysed for various dependency factors, those are; accuracy, sensitivity, specificity, precision, recall and Fscore.

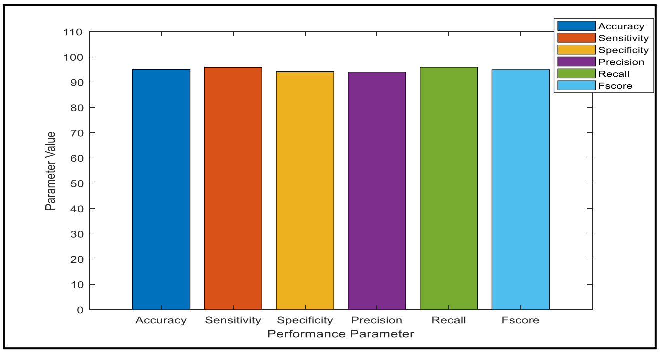

Fig. 1.2: Different performance parameters

Figure 1.2, represents the performance of the proposed model in terms of various performance parameters i.e., accuracy, sensitivity, specificity, precision, recall and fscore. From the graph, it is observed that the value of accuracy, sensitivity and specificity attained in the proposed model came out to be 95%, 95.91% and 94.11% respectively. While as the value of precision, recall and fscore came out to be 94%, 95.91% and 94.94% respectively. The specific values of these performance parameters are given in table 3.

Sr No.	Evaluation parameters	Values (%age)
1	Accuracy	95
2	Sensitivity	95.9184
3	Specificity	94.1176
4	Precision	94
5	Recall	95.9184
6	Fscore	94.9495

Table 3: Performance matrix for proposed system

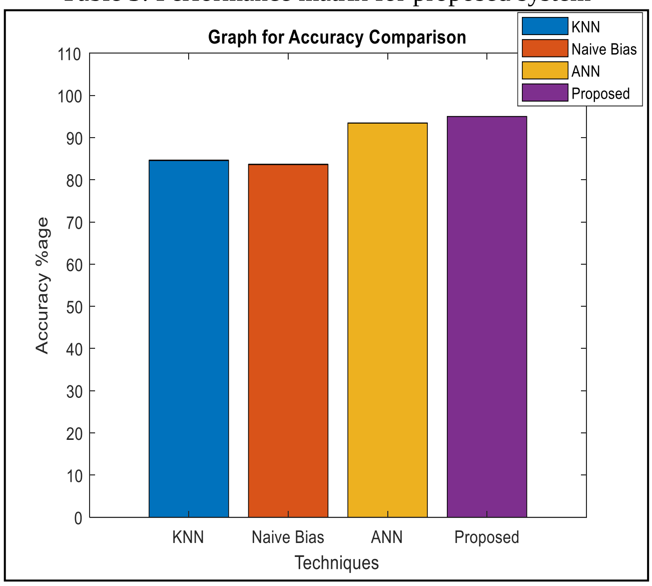

Fig. 1.3: Accuracy of proposed and traditional models

Moreover, the performance of the proposed model is observed and compared with the conventional KNN, Naïve Bias and ANN models in terms of accuracy. Fig 1.3, illustrates the comparison graph of the traditional KNN, Naïve Bias and ANN models and proposed model in terms of accuracy. From the graph, it is observed that the value of accuracy attained in traditional KNN is 84.6%, Naïve Bias is 83.6% and ANN is 93.4% respectively. While as the value of accuracy attained in the proposed model came out to be 95%. This proves that the results produced by the proposed model are more accurate.

Furthermore, the performance of the proposed model is observed and compared with the traditional models in terms of sensitivity and is shown in Fig 1.4.

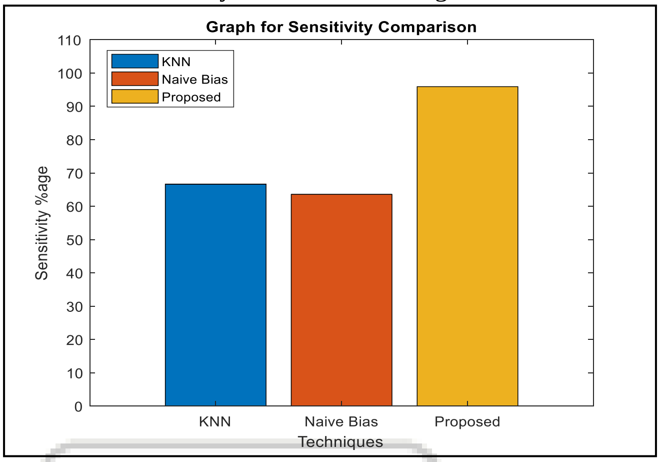

Fig. 1.4: Comparison Graph for sensitivity

Fig 1.4 depicts the comparison graph of proposed and traditional KNN and Naïve Bias models in terms of sensitivity. From the graph, it is observed that the value of sensitivity attained by the conventional KNN and Naïve Bias models came out to be 66.6% and 63.5% respectively. On the other hand, the value of sensitivity attained by the proposed model is 95.91%. Finally, the performance of the proposed model is analyzed and compared with the classical KNN, Naïve Bias and ANN models in terms of the specificity. The value of specificity is shown in fig 1.5.

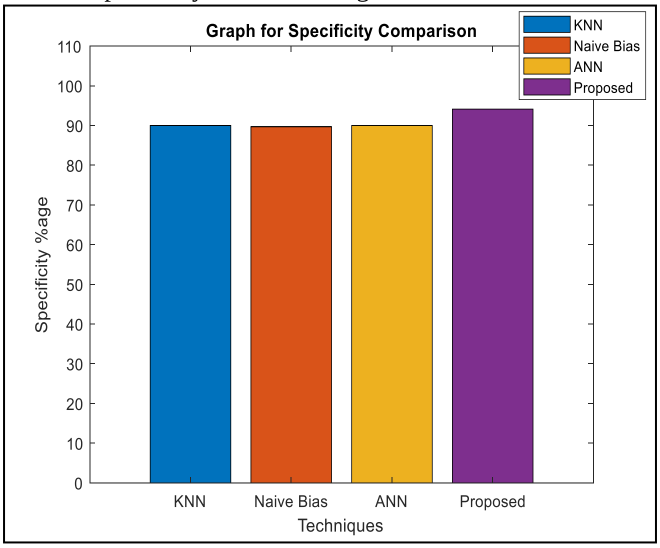

Fig. 1.5: comparison graph for specificity

Fig 1.5 represents the Comparison graph of proposed and traditional KNN, Naïve Bias and ANN models in terms of specificity. From the graph, it is observed that the value of specificity achieved in the conventional KNN, Naïve Bias and ANN model came out to be 90%, 89.7% and 94.1176% respectively. On the other hand, the specificity value in the proposed model is equal to 94.11%. The specific values attained by the traditional KNN, Naïve Bias, ANN models and proposed model are given in table 4.

	KNN	Naive Bias	ANN	Proposed
Accuracy	84.61	83.64	93.45	95
Specificity	90	89.7	90	94.1176
Sensitivity	66.66	63.57	100	95.9184

Table 4: Comparative analysis of proposed and traditional schemes

From the Graphs and tables, it is observed that the proposed model is more accurate, reliable and efficient in identifying different kidney diseases.

VI. Conclusion

In this paper, a new technique is introduced that's based on CFA and PNN to identify different kidney diseases. The performance of the proposed model is evaluated and compared with the traditional KNN, Naïve Bias and ANN models in the MATLAB simulation software. The results were obtained in terms of number of factors which include Accuracy, sensitivity, specificity, precision, recall and Fscore. The accuracy attained in the suggested model is 95 percent, but in traditional KNN, Nave Bias, and ANN models, that's only 84.61 percent, 83.64 percent, and 93.45 percent, respectively. Moreover, the value of sensitivity and specificity in proposed model came out to be 95.9184% and 94.1176% respectively. While the value of sensitivity and specificity in traditional KNN, Naïve Bias and ANN model came out to be 66.66%, 100%, 63.57% and 90%, 89.7%, 90% respectively. In addition to this, the suggested model's effectiveness is shown in terms of precision, recall, and Fscore, with values of 94 percent, 95.9184 percent, and 94.9495 percent, respectively. The simulation outcomes showed that the suggested approach is more precise, effective, and successful at predicting different types of kidney tumors.

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