A Comparative Study of Algorithms for Detecting Kidney Stones in CT-Scan Images

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Abstract- *One in seven girls and one in ten males will develop nephrolithiasis (kidney stones) at some point in their lives. For problems to be avoided, nephrolithiasis must be diagnosed early. Imaging methods help to identify kidney stones and to determine where, how many, and how big they are in the renal structure. They also serve as the foundation for kidney stone diagnosis. The most popular algorithm for training neural networks is the back-propagation network. To implement an automated kidney stone identification, it is used to process the image and data. The traditional method for classifying and identifying kidney stones in medical resonance images involves a human assessment.*

Since it is impractical to handle large amounts of data, this method is not accurate. Magnetic Resonance (MR) Images may include intrinsic noise from operator errors. As a result, there are serious errors in the classification of diseases and characteristics in image processing. The region of interest can now be extracted by utilizing the back-propagation network approach in this field employing artificial intelligence-based methodologies, neural networks, and feature extraction.

The goal of this project was to identify kidney stones using a back propagation network. The decision-making process involves two steps: First the feature extraction and then the image classification. The principal component analysis is used for feature extraction, while the back-propagation network is used for picture classification (BPN). In this study, a segmentation approach based on the Fuzzy C-Mean (FCM) clustering algorithm is presented. Training efficiency and classification accuracy were used to estimate the BPN classifier's performance. Comparing the Back Propagation Network to other neural network-based techniques, it offers precise classification.

Keywords- Kidney Stone, Neural Network, Back-Propagation Neural Network, MRI, Image Processing.

I. INTRODUCTION

In the body, the kidneys serve as filters. In addition to producing urine, which is excess water containing urea, ions, toxic ammonia, carbon dioxide, and sodium, these organs are positioned at the sides of the belly and oversee purifying blood through nephrons. Kidney stones are hard lumps that form in the kidney due to a lack of fluid in the body, ions, and other waste products.

The stone will clog the ureter if its size increases to at least 3 millimetres. This creates a lot of pain, mainly in the lower back, which should radiate to the groin. Urinary stones are categorized according to their chemical make-up, where they are in the kidney (nephrolithiasis), ureter (ureterolithiasis), or bladder (cystolithiasis). The kidney's minor and major calyces as well as the ureter may contain the stone. Computed axial tomography is employed in medical imaging techniques because, compared to other techniques, it produces results with the highest degree of precision and has a low noise level. It may also be frightening to have a dysfunctional kidney. Therefore, it is essential to identify calculus early. The success of surgical procedures depends on the accurate diagnosis of urinary calculi.

A picture must first be transformed into numerical form before a computer may process it for processing purposes. The term "pixel" refers to each number in a picture that represents a particular brightness value at a particular location. The size of the digital image used for analysis will be 512 by 512 pixels, or roughly 250,000 pixels. Three fundamental computer operations should be carried out on the image after it has been digitized. A single input pixel in this process creates a single pixel value in the output image. Furthermore, for local operations, a large number of pixels from the input image determine the value of the output image. Finally, in a global operation, every pixel in the input image creates a pixel in the output image. The processes can be used alone or in combination to improve and compress the image. When the information in an image is clearer, the image is said to have been enhanced. An important step in image processing is the recognition of object groups in real-time images.

Because there are greater variances in similarity among objects belonging to the same class, it is seen as a milestone. In addition, the same item may appear differently due to distortions brought on by background clutter, scale, and changes in viewpoint. The appearance of the image, which appears similar despite classification, may be the cause of other issues. These are a few of the probabilities that might be discovered in categorization issues. From now on, object class models should adapt to account for class variability. Additionally, it needs to be discriminatory enough to remove actual item occurrences from disorganized photos. Consequently, it is challenging to recognize an object class model classification. This study describes two methods for identifying and categorizing objects. Persuasion of the region of interest in the image under consideration is the goal of image categorization. This work primarily focuses on a strategy for object class recognition that uses edge information solely. Additionally, compared to fragmented fragments, which call for analyses between every edge pixel, matching between primary pictures can be computed easily (e.g., using geometric attributes). For the image processing described above for the identification of kidney stones, the backpropagation network technique has demonstrated the best results.

Back propagation is the process by which a mistake that is discovered at the outer layer spreads backwards through all the network's layers. Geometric qualities are simple to fix and eliminate scale-related similarities. It seems to be less distinctive when viewed as separate structures. The same qualities improve when combined, giving the impression that they are sufficiently discriminatory. A basic bi-level abstraction is being carried out. It is initially done with pairs of primitives at the top layer. Later, a variety of shape clues were learned. There is no requirement that shape-tokens have specified values. However, it also enables repetition and adaptability to an object class. The capacity of a combination to represent a form is influenced by this value, with simple shapes favouring fewer shape-tokens than complex shapes.

The diagnosis of kidney stones can be made using a variety of techniques, including blood tests, CT scans, MRI scans, and urine tests. In the case of enormous volumes of data, operator-assisted kidney stone diagnosis is not viable. This article uses imaging and data processing along with back propagation neural networks to provide an automated categorization of kidney stones. There is a lot of potential in classifying kidney stones using neural networks. The Gray level co-occurrence matrix and fuzzy c- mean clustering technique are used in this study's feature extraction to segment the test image and identify the kidney stone. The effectiveness of the BPN classifier is assessed based on its training efficiency and classification precision.

II. LITERATURE REVIEW

Tanzila Rahman and Uddin Mohammad (2013) used a Gabor filter to minimize speckle noise, and histogram equalization was used to enhance the images. To extract the renal sections, two segmentation techniques were used: cell segmentation and region-based segmentation [1]. Kidney ultrasound images were divided into categories by Wan Hafizah, Eko Supriyanto, Arooj and Yeoh (2011), who built a database using the features they extracted. Nineteen features from the grey level co-occurrence matrix (GLCM) and five features from the intensity histogram were used to extract the features [2].

A method for segmenting the human brain for tumour identification was proposed by V.P.Gladis Pushpa Rathi. & S.Palani. (2011). With the help of a hierarchical self-organizing map, images are segmented (HSOM). Artificial Neural networks and Wavelet packets were used to determine the aberrant spectra and type of abnormality [3].

Bommanna Raja, Madheswaran Muthusamy and Thyagarajah K. (2007) used ultrasound to classify renal illnesses and identify critical content descriptive feature characteristics [4]. To ascertain the feedforward neural network's susceptibility to weight mistakes, Maryhelen Stevenson, Rodney Winter and Bernard Widrow, conducted an analysis [5].

In this study, kidney stone segmentation is carried out utilizing the fuzzy C-means method and GLCM feature extraction for feature extraction. Back Propagation Neural Network is then used to classify kidney stones.

III. CLASSIFICATION OF IMAGES

From a perspective, pixel colour is the primary factor used to categorize images. Any of the following types of photos can be used in their original form or transformed into another form depending on the effectiveness of the output needed. As a result, the system's processing time to produce an output is prolonged and computational complexity is reduced. The several categories are listed below with an explanation of each.

BINARY IMAGE

If you think about it at the pixel level, it has two beneficial effects. Black and white are typically the two colours used to represent binary images. But you can substitute any two colours for black and white. The colour used for objects in the foreground. The background of the considered image is represented by the leftover image.

Binary images are frequently referred to as two-level or bi-level images. This means that each pixel is stored as a single bit in the memory (0 or 1). This method is frequently referred to as black and white, monochrome, or monochromatic, although it can also refer to any images that include one sample per pixel.

GREYSCALE IMAGE

Each pixel's value in a grayscale image is a single sample that solely contains information about intensity. These photos have unique grayscale tones with a value range of 0-255. The differences continue from black (0), which can be interpreted as the lowest shade, to white (255), which can be interpreted as the highest. One-bit black and white images can be used to create sharp grayscale images. These continue to be the fundamental ideas behind computer imaging. Black and white are the only colours seen in these pictures (also called bi-level or binary images). Images in grey scale contain a variety of grey colours. Images in grey scale contain characteristics such as being monochromatic, which means shifts in colour are not present.

COLOR IMAGE

Every pixel in a colour image has access to colour information. Three numbers are used to calculate the unique value of each pixel. It provides a breakdown of the colour into the three primary hues of red, blue, and green. To put it another way, an image is a sizable two-dimensional array. The characteristics of the pixels and colours define it. They are all encoded in three bytes each. The three primary colours can be described in this way. The combination of these three colours, referred to as RGB encoding and adaptable to the human eye, results in 256x256x256 = 16.8 million distinct colours in total.

IV. PROPOSED METHODOLOGY

The identification of kidney stones is done using a back propagation network (BPN). In terms of performance and classification metrics, the propagation network is chosen. Quick and accurate categorization is provided through a back propagation network. Additionally, it works well as a tool for detecting kidney stones. Malignant and benign cancer patterns are also categorized using BPN. Network weights and biases are often changed using the backpropagation understanding.

Additionally, it lowers a network's squared error. The block diagram for kidney stone extraction is shown in Figure

1. To obtain pictures of both normal and diseased kidneys, a two-stage technique is used. The technique for training with a known data set initially aids in training. Additionally, while testing a sample picture, first-level classification based on feature extraction using the GLCM approach is feasible. When preprocessing is used before feature extraction, classification accuracy is increased. The process of operating the pictures at the lowest level of abstraction is known as image preprocessing.

Images of intensity are the input and output of it. The goal of preprocessing is to make the picture data better by minimizing undesirable distortions or enhancing a select number of essential image attributes. The output indicates whether the input picture is a normal or abnormal image following the categorization of the input image by a back propagation network. If the picture is normal, a kidney stone

cannot be inferred from it. Like this, if the picture is aberrant, the kidney stone is inferred from it.

The renal CT-Scan pictures are used to apply the suggested procedure. Preprocessing using DWT, feature extraction from the GLCM dataset, dataset training, BPN classification, and segmentation of kidney stones using the fuzzy C-means method are all steps in the process. MATLAB is the simulation software utilized.

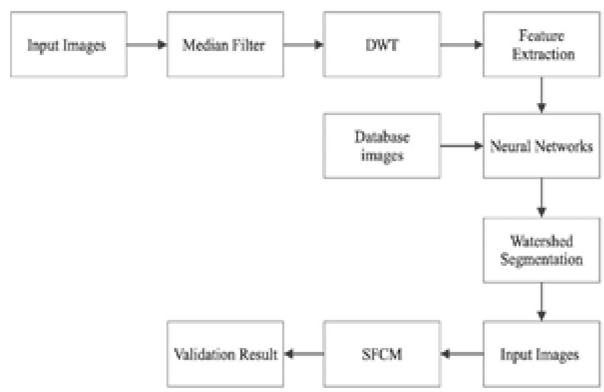

Figure 1: Block diagram of the proposed methodology

IMAGE PRE-PROCESSING

The Discrete Wavelet Transform is used to preprocess the input test picture. To make it simpler to spot the important details, noise is removed from the image during image enhancement or pre-processing. With wavelets, an input image is transformed into a collection of wavelets, which may be stored more effectively than pixel blocks.

Using high pass and low pass filters, the discrete wavelet transform divides the input picture into high pass and low pass components. The LL sub-band includes the majority of the information whereas the other higher order bands contain the edges in the vertical, diagonal, and horizontal directions. The picture is now divided into four sub-bands as

LL, LH, HL, and HH.

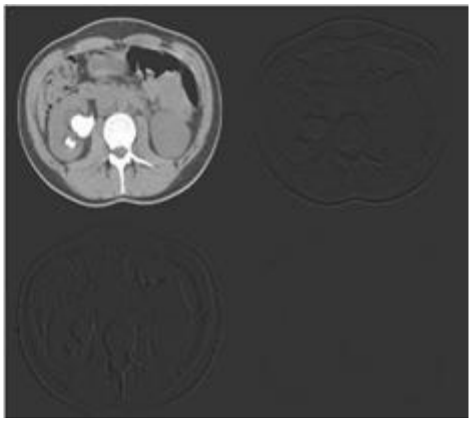

Figure 2: Four sub-bands LL, LH, HL, HH by DWT.

GLCM FEATURE EXTRACTION

Extraction By calculating how frequently pixel pairings with certain values and in a given spatial relationship occur in an image, the grey level co-occurrence matrix produces the textural characteristics of the picture. It first builds a GLCM, and from this matrix, it then extracts the important texture characteristics. As indicated in the table below, we will primarily focus on five significant elements in this study.

KEY FEATURE	DESCRIPTION
Contrast	It is used to measure the local variations in the gray-level cooccurrence matrix.
Correlation	It calculates the joint probability occurrence of the specified pixel pairs.
Energy	It provides the sum of squared elements in the GLCM and is also known as uniformity or the angular second moment.
Homogeneity	It measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.
Entropy	It refers to the intensity level that the individual pixels can adapt.

Table 1: Feature Description

DATASET TRAINING:

The training dataset is a collection of 20 photos that include both normal and pathological kidneys. Training is a method of learning that is typically used in image processing to identify features, shapes, and even patterns. Pre-processing and feature extraction are steps that are also included in the training process as they are in the processing of the test picture. Comparing the features derived from the training set with those extracted from the test picture. The neural network's Back Propagation approach compares the training data with test data to accurately classify kidney stones.

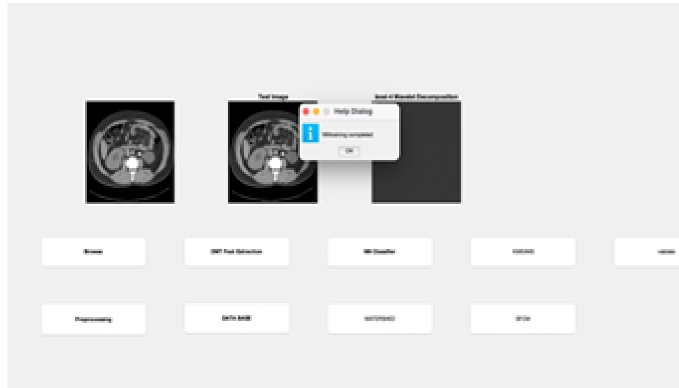

Figure 3: Dataset training completed

BACK PROPAGATION NEURAL NETWORK

To calculate the gradient required in the calculation of the weights to be utilized in the network, the backpropagation approach in artificial neural networks employs a process called gradient descent. Backpropagation refers to the spreading of mistakes backwards through the network's layers because of a computation error at the output layer. The primary goal of the learning method known as backpropagation is to reduce the error function by varying the weight. A given collection of input patterns with established classifications of normal and diseased kidneys are used to train a specified feed-forward multilayer neural network. When the network is presented with the sample set including the input test picture, it checks its output response to the training data set's sample input pattern. The output response received is then compared to the known and intended output. The incorrect value is determined. The sample patterns are continually provided to the network until the error value is reduced. As a result, the back propagation neural network classifies whether the supplied input test picture contains a kidney stone.

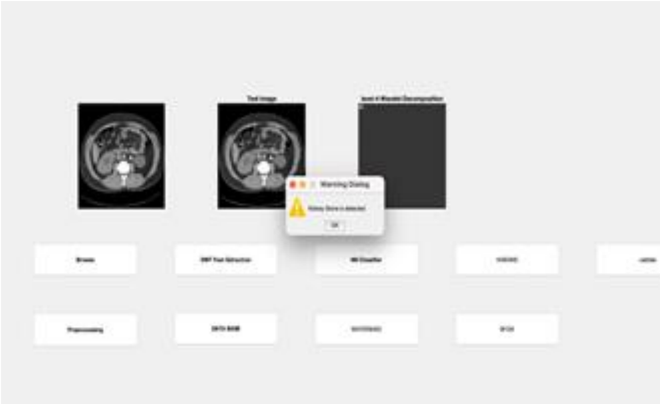

Figure 4: BPN Classification

WATERSHED ALGORITHM

The goal of the watershed method is to convert a grayscale image into a topographic representation by classifying it into three fundamental concepts: minima, catchment basins, and watershed lines. As a result, in the input test image, the dark parts are presumed to have low elevations while the bright areas are supposed to have high altitudes, giving the appearance of a topographic surface. As a result, the watershed method has a lot of promise in picture segmentation and correctly segments the indicated aberrant regions.

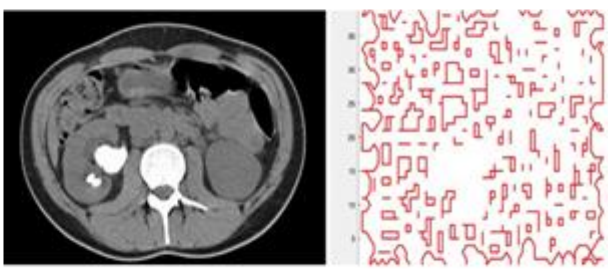

Figure 5: Watershed segmentation of CT-Scan Containing Kidney Stone

K-MEANS CLUSTERING ALGORITHM

The K-means clustering algorithm technique computes centroids and then repeats the process until the best centroid is discovered. It is assumed that the number of clusters is known. The flat clustering algorithm is another name for it. The letter 'K' in K-means denotes the number of clusters discovered from data by the approach. This approach assigns data points to clusters so that the sum of the squared distances between the data points and the centroid is as little as feasible. It is critical to notice that decreasing variety within clusters results in more data points that are identified inside the same cluster. In the first instance, records are organized in a unique fashion, such that if a positive datum belongs to a distinct cluster, it cannot be covered in any other cluster. On the other hand, the second kind, overlapping clustering, uses fuzzy units to cluster information, therefore everything might potentially belong to two or more clusters with highly excellent club stages. In this situation, statistics may be linked to the ideal club fee. A hierarchical clustering technique is essentially based on the union of the various two adjacent clusters. Setting each datum as a cluster determines the first situation. After a few cycles, it reaches the desired clusters.

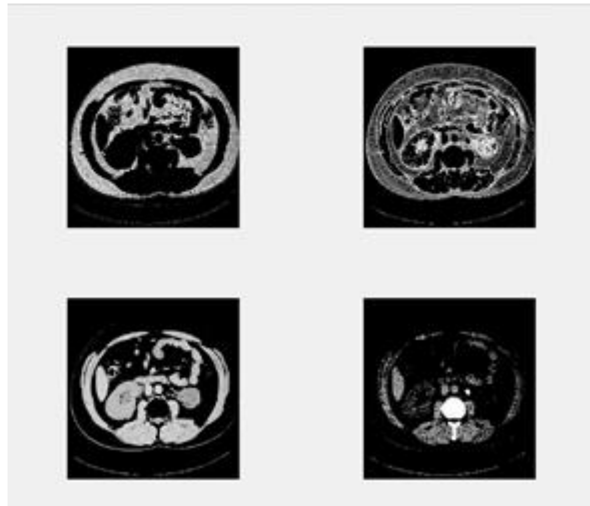

Figure 6: Image Segmentation

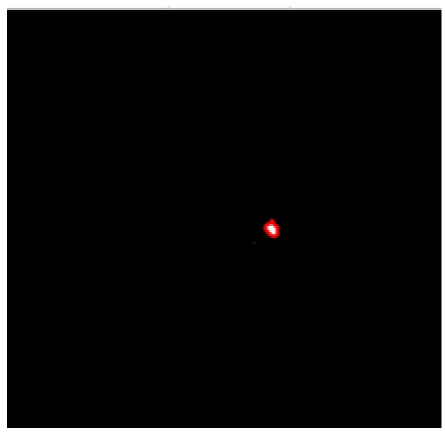

Figure 7: Kidney Stone Localization

SPATIAL FUZZY C-MEANS ALGORITHM

Fuzzy clustering is an unsupervised clustering approach in which the clustering criteria are determined without the need for human intervention. It works based on distance metrics between the data point and the cluster centre by giving a membership function to each data point that corresponds to a cluster centre.

It divides vast amounts of data into smaller amounts of related data. In comparison to k-means clustering, fuzzy-c means works well for overlapping data sets, allowing us to pinpoint the exact position of the kidney stone.

This technique with spatial restrictions (FCM-S) is an efficient image segmentation algorithm. Its efficacy contributes not only to the introduction of fuzziness for each pixel's belongingness but also to the utilization of spatial contextual information.

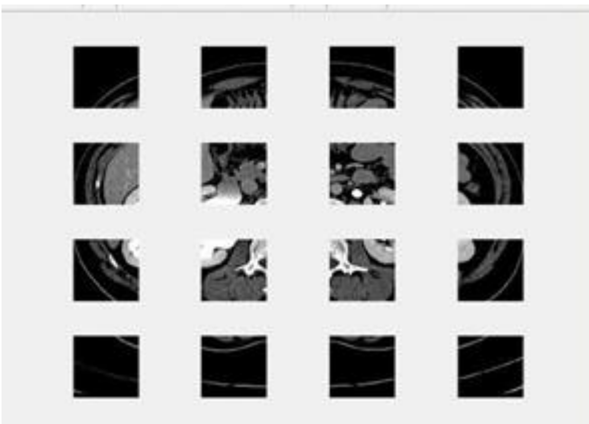

Figure 8: Segmentation

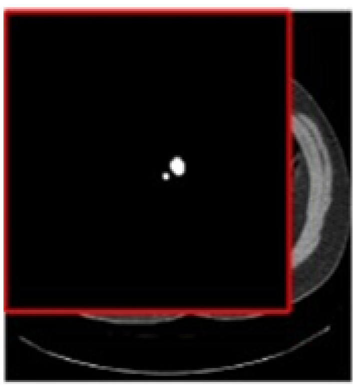

Figure 9: Detected Kidney Stone

V. CONCLUSION

The purpose of this study is to detect the existence of a kidney stone. To acquire the proper number every time, we need to design the optimal algorithm for detecting kidney stones. In our study, we employed three distinct methods; now we must determine which of these three algorithms provides the most accuracy: the Watershed Algorithm, the K- Means Clustering Algorithm, and the Spatial-Fuzzy-C-Means Algorithm.

GLCM and DWT have demonstrated significant promise in feature extraction, resulting in a classification rate accuracy of 98.8 percent. In the situation of overlapping data, the fuzzy C-means method outperforms the K-means clustering algorithm. In Fuzzy C-means, data points can belong to more than one cluster centre, but in K-means, data points can only belong to one cluster centre.

We may infer from this study that the Spatial-Fuzzy-C- Means (SFCM) Algorithm provides the best accuracy of roughly 98 %. When compared to K-means Clustering and the Watershed Algorithm, it can therefore identify kidney stones more successfully.

VI. FUTURE SCOPE

The suggested technology might be adapted for real-time deployment in the future by integrating it with scanning equipment. The obtained kidney image can be submitted to the proposed set of guidelines to become aware of the damaged area and accurately classify kidney stones. Except for the Back Propagation technique, we may compare the impacts of various neural networks to get higher accuracy.

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