Automated Detection of kidney Stone through Neural Networks

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***Abstract* — The Back Propagation Network algorithm is widely utilized in training neural networks, particularly in the context of automated kidney stone classification using image and data processing. Traditional methods for classifying and detecting kidney stones in medical resonance images rely on human examination, which is inherently imprecise when handling large datasets. Magnetic Resonance (MR) Images may exhibit noise due to operator errors, leading to significant inaccuracies in image processing for disease classification. However, the integration of artificial intelligence, neural networks, and feature extraction has demonstrated significant promise in accurately identifying regions of interest using the back propagation network algorithm. In this study, we employed the Back Propagation Network for kidney stone detection, involving two key stages: 1. Feature extraction using principal component analysis and 2. Image classification using Back Propagation Network (BPN). Additionally, we introduced a segmentation method utilizing the Fuzzy C-Mean (FCM) clustering algorithm. The performance of the BPN classifier was evaluated in terms of training execution and classification accuracies. Notably, the Back Propagation Network exhibited precise classification compared to alternative neural network-based methods.**

Keywords— Renal Calculi, Back Propagation Network, Magnetic Resonance Imaging, Artificial Neural Networks.

I. INTRODUCTION

The entities within the provided image undergo processing using conventional image manipulation techniques, including noise reduction and feature extraction, aimed at identifying specific textured areas in the image.

To facilitate computer-based processing, the image is initially converted into numerical format, enabling the computer to analyze it. Each numerical value in the image corresponds to a specific brightness level at a designated location, referred to as a pixel. A digital image chosen for analysis typically comprises 512 × 512 pixels, totaling approximately 250,000 pixels. Modern computing systems may handle larger-sized images.

Once digitized, three fundamental operations are carried out on the image within the computer. Firstly, in point operation, a single pixel in the input image contributes to generating a pixel value in the output image. Secondly, for local operations, the output image's value is influenced by multiple pixels in the input image. Finally, in global operations, each pixel in the input image contributes to producing a pixel in the output image. These operations can be applied individually or in combination to enhance and compress the image. Image enhancement occurs when the information within the image becomes more discernible.

Identifying object groups in real-time images represents a significant breakthrough in image processing, marked by the intricate challenges posed by variations in object similarity within the same class. The complexity is further compounded by distortions arising from cluttered backgrounds, changes in scale, and shifts in viewpoint, resulting in disparate appearances of identical objects. Another layer of difficulty arises from images that may look similar despite distinct classifications, adding to the intricacies of classification problems. Consequently, models designed for object classification must dynamically adapt to accommodate class variability while maintaining the necessary discriminative power to sift through true object occurrences in visually chaotic images.

This paper delves into two distinct approaches for recognizing and classifying objects, with a particular emphasis on addressing the inherent challenges associated with object class recognition. The primary goal of image classification is to accurately pinpoint the region of interest within the analyzed image. The proposed approach in this work concentrates on object class recognition using exclusively edge information. This focused methodology allows for efficient computations of matches between primary images, leveraging geometric properties. This stands in contrast to fragmented approaches that necessitate intricate analyses between each individual edge pixel or changes in technical terminology

The back propagation network algorithm has demonstrated superior performance in the context of kidney stone detection within the aforementioned image processing framework. The term "back propagation" signifies the reverse propagation of error, wherein an error computed at the outer layer is retroactively disseminated throughout the network's layers. Geometric properties present a more straightforward challenge, as they can be easily rectified to address similarities across various scales. However, contour fragments lack scale invariance, requiring additional steps to achieve it. One viable solution involves rescaling through the introduction of aliasing effects, such as adjusting the placement of edge pixels. Alternatively, remodeling the imaging sizing before fragment extraction represents another strategy, albeit at the cost of potential reductions in image resolution or alterations in technical terminology.

The back propagation network algorithm has shown best result for the above explained image processing for the kidney stone detection. The phrase back propagation states the backward propagation of error as an error determined at the outer layer is distributed backwards throughout the network's layers. Geometric properties can be fixed easily, they solve similarities across scales. But, contour fragments are not scale invariant. It must be rescaled by introducing aliasing effects (for e.g., placement of edge pixels apart), or to remodel the imaging sizing before extracting fragments from the image. This may further reduce image resolution.

In literature, it is shown that the standard nature of line segments and definite shapes meet the requirements of the ability to portrait intricate shapes and structures. As individual structures, it appears to be less unique. When the same features are combined, their features are enhances and thereby appears to be adequately discriminative. A bi-level basic abstraction is being performed. Initially, at the first layer it is performed with pairs of primitives. Later, a learned number of shape indications. No constraint is imposed to have standard values of shape-tokens. But it also allows it to be repeated and adaptable to an

Object class. This value influences a combination's ability to represent shapes, where simple shapes favor fewer shape-tokens than challenging ones. Continuously, discriminative combinations of varying complexity can be exploited to represent an object class. We study this combination by exploiting, demarcating the shape, geometric, and fundamental restrictions. The shapes inhibit, describes the visual approach of shape tokens, while geometric constraints describe its spatial outline. Structural constraints establish possible structures of an object by the relationships between shape- tokens./change in technical word

II. IMAGE CATEGORIZATION

Primarily, image classification is founded on pixel color considerations. Depending on the desired output effectiveness, images can be maintained in their original state or transformed into a different format. This minimizes computational complexity and enhances system processing time to yield efficient outcomes. The ensuing list delineates various image types, each explained below.

A. Binary Image

A binary image exhibits two distinct pixel-level outcomes. Typically, the colors black and white are employed, but any two colors can be substituted. The foreground color represents objects, while the rest of the image constitutes the background. Binary images are often referred to as bi-level or two-level, signifying that each pixel is stored as a single bit (0 or 1). While commonly associated with black and white, monochrome, or monochromatic terminology, it can encompass any image with a single sample for each pixel.

B. Gray Scale Image

In a grayscale image, each pixel holds a single sample, conveying information solely based on intensity. These images exhibit varying shades of gray within the 0-255 value range, with black (0) representing the weakest shade and white (255) the strongest. Grayscale images are distinct from one-bit black-and-white images, which are fundamental in computer imaging. Unlike binary images, grayscale images feature multiple shades of gray and are characterized by their monochromatic nature, indicating the absence of color-based changes.

Grayscale images convey light intensity at each pixel across the electromagnetic spectrum, captured at a single frequency, rendering them monochromatic.

C. Color Image

A color image assigns color information to every pixel, determined by three numbers. These values signify the color decomposition in the three primary hues: red, blue, and green. Essentially, an image is a vast two-dimensional array, encoding properties of colors and pixels. Each pixel is coded in 3 bytes, representing the three primary colors. Employing RGB encoding, a total of 16.8 million distinct colors (256x256x256) can be generated, adjustable to human vision.

II. METHODOLOGY

The detection of kidney stones is accomplished through the utilization of a Back Propagation Network (BPN), which is evaluated in terms of performance and classification metrics. BPN proves to be an efficient and accurate tool for both quick classification and the identification of kidney stones. Moreover, it is adept at classifying patterns associated with malignant and benign cancer. The back-propagation mechanism is instrumental in adjusting the weights and biases of networks, contributing to the minimization of squared error within the network.

A graphical representation of the kidney stone detection process is commonly referred to as a "Schematic Diagram for Kidney Stone Detection" or simply a "Kidney Stone Detection Block Diagram." Such diagrams visually outline the sequential stages and components involved in the detection methodology, providing a clear overview of the entire process.

In Figure 1, the block diagram illustrates the process of kidney stone extraction, which involves a two-stage approach to distinguish between normal and abnormal kidney images. The initial stage involves training the network with a known dataset. Subsequently, when subjecting a sample image, initial level classification is achieved through feature extraction using the GLCM method. The classification accuracy is further enhanced through preprocessing before feature extraction. Image preprocessing, a term commonly used, operates on images at the lowest level of abstraction, with intensity images as input and output. The primary objective of preprocessing is to refine image data by reducing unwanted distortions and enhancing essential image features for subsequent processing.

Following the back propagation network's classification of the input image, the results indicate whether the input images represent normal or abnormal kidney conditions. If the image is classified as normal, the deduced image does not depict a kidney stone. Conversely, if the image is deemed abnormal, the deduced image is identified as depicting a kidney stone.

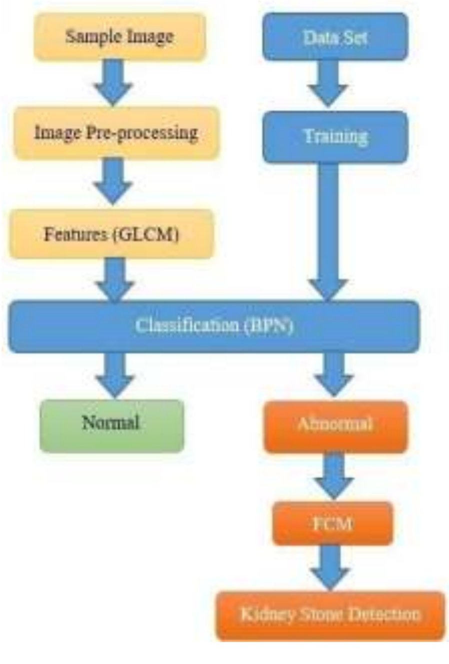

Fig 1 Block Diagram for Kidney stone Detection

III. RESULTS AND DISCUSSIONS

In Figure 2, the input image serves as the sample image for the training system. Subsequently, the image undergoes preprocessing, and through the utilization of GLCM-based feature detection, the detection process is initiated. The preprocessed image is visualized in Figure 3, revealing clearly defined edges from the original image. This enhancement is instrumental in focusing on the region of interest within the image, facilitating the initial stage classification of image detection as normal or abnormal.

Figure 4 portrays the image after feature extraction, highlighting the salient features obtained from the preprocessing stage. Finally, Figure 5 illustrates the segmentation of stones from the image, showcasing the successful isolation of kidney stones based on the applied methodology.

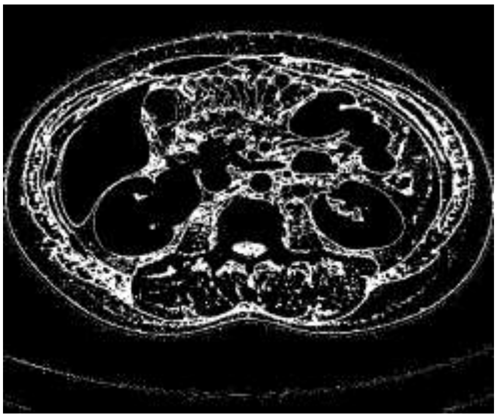

Fig 2 Input Image

Fig 3 Processed Image

Fig 4 Feature extracted image

Fig 5 Output Image

These results collectively demonstrate the effectiveness of the proposed approach in detecting kidney stones through a systematic process of preprocessing, feature extraction, and segmentation. The discussion will further delve into the quantitative measures of classification accuracy and performance metrics, providing a comprehensive evaluation of the proposed kidney stone detection methodology.

The isolated stone region plays a pivotal role in the early detection of kidney stones. Additionally, individuals undergoing medical treatment can be closely monitored to document their response to the intervention. The method allows for precise monitoring of stone sizes, presenting a distinct advantage over alternative approaches. Due to elevated levels of noise associated with other methodologies, the efficiency of early detection and continuous monitoring is notably superior in the analysis of MR images.

IV. CONCLUSIONS

This study employs the Back Propagation Network (BPN) for the detection of kidney stones in MR images. The two-stage detection process, involving feature extraction and classification, successfully identifies stones within the kidney. Through qualitative analysis, the method proves effective in pinpointing the position of even small-sized stones within the kidney. Notably, the Back Propagation Network demonstrates superior precision in classification compared to alternative neural network-based methods.

The method's advantages lie in its ability to accurately separate stone regions from the images, making it well-suited for the precise classification of kidney stone images and enabling early detection. The results of this study highlight the efficacy of utilizing the Back Propagation Network for kidney stone detection in MR images, showcasing its potential as a reliable and accurate tool in medical imaging applications. Further research may explore enhancements and optimizations to refine the methodology for broader clinical applications.

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