Segmentation-Driven Image Registration and Identification of Defects in the Kidney Using Anfis Classifier

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Abstract— ***The diagnostic assessment of renal pathologies necessitates high-precision computational frameworks to assist radiologists in identifying and localizing structural abnormalities. This research proposes an integrated methodology for the Segmentation-Driven Image Registration and Identification of Defects in the Kidney, leveraging the adaptive capabilities of an Adaptive Neuro-Fuzzy Inference System (ANFIS). The proposed system addresses the inherent challenges of medical imaging, such as low contrast, speckle noise, and anatomical variability, which often hinder accurate diagnosis in conventional modalities like Ultrasound or CT scans.***

The framework begins with an advanced pre-processing stage designed to enhance image quality and normalize intensity distributions. Following enhancement, a segmentation-driven registration technique is employed to align temporal or multi-modal kidney images. Unlike traditional intensity-based registration, this approach utilizes segmented anatomical boundaries to ensure that morphological features are preserved during the spatial transformation process, significantly reducing registration errors in deformed renal tissues.

For the identification of defects—such as cysts, stones, or tumors—a hybrid feature extraction process is implemented to capture both textural and statistical attributes of the renal parenchyma. These features serve as inputs to the ANFIS classifier, which combines the learning prowess of neural networks with the linguistic transparency of fuzzy logic. By mimicking human-like reasoning, the ANFIS model effectively handles the uncertainty and imprecision associated with pathological boundaries.

Experimental results demonstrate that the proposed system achieves superior performance compared to traditional classification methods, showing high sensitivity, specificity, and overall accuracy in defect detection. The integration of segmentation-driven registration ensures that even subtle structural changes are detectable, providing a robust tool for early clinical intervention. This research contributes a scalable and reliable automated pipeline for renal health monitoring, potentially reducing the workload of medical professionals and minimizing the margin for human error in diagnostic radiology.

Index Terms ***– Kidney Defect Identification, Image Registration, ANFIS Classifier, Medical Image Segmentation, Renal Pathology, Neuro-Fuzzy Systems.***

I. INTRODUCTION

The human renal system plays a critical role in maintaining homeostatic balance, regulating blood pressure, and filtering metabolic waste. However, the prevalence of chronic kidney disease (CKD) and localized renal pathologies—such as cysts, stones, and carcinomas—has seen a dramatic uptick globally, necessitating advanced diagnostic interventions. Traditional manual interpretation of medical imaging, including Ultrasound (US), Computed Tomography (CT), and Magnetic Resonance Imaging (MRI), is often subject to intra-observer variability and high cognitive load. Consequently, the integration of Computer-Aided Diagnosis (CAD) systems has become a cornerstone of modern nephrology, aiming to enhance the precision of defect identification while reducing the margin for human error.

The primary challenge in automated kidney analysis lies in the inherent complexity of medical imagery, which is often plagued by low contrast, speckle noise, and anatomical variations across patients. To address these inconsistencies, Image Registration serves as a fundamental preprocessing step, aligning multiple data sets into a single coordinate system to enable accurate temporal or spatial comparison. By employing a Segmentation-Driven approach, the system can isolate the regions of interest (ROI) with high fidelity, ensuring that the subsequent feature extraction phase focuses exclusively on renal tissues rather than surrounding abdominal structures. This localization is vital for detecting subtle structural abnormalities that might otherwise be masked by noise or overlapping organ boundaries.

At the heart of the proposed diagnostic framework is the Adaptive Neuro-Fuzzy Inference System (ANFIS). While traditional neural networks function as "black boxes" and standard fuzzy logic systems require manual rule-tuning, ANFIS bridges this gap by combining the learning capabilities of artificial neural networks with the transparent linguistic reasoning of fuzzy logic. In the context of kidney defect classification, ANFIS effectively manages the uncertainty and imprecision inherent in biological data. By training on segmented features—such as texture, shape, and intensity gradients—the classifier can distinguish between benign and malignant pathologies with a high degree of sensitivity and specificity.

This research paper explores the development and validation of a robust pipeline that integrates segmentation-driven registration with ANFIS-based classification. We hypothesize that by refining the input data through precise registration and segmentation, the ANFIS architecture can achieve superior convergence rates and classification accuracy compared to standalone machine learning models. The following sections detail the mathematical modeling of the registration algorithm, the architectural nuances of the ANFIS classifier, and a comparative analysis of experimental results against existing benchmarks in the field of renal image processing. Through this study, we aim to provide a more reliable, interpretable, and efficient tool for clinicians, ultimately improving patient outcomes through earlier and more accurate diagnosis of kidney defects.

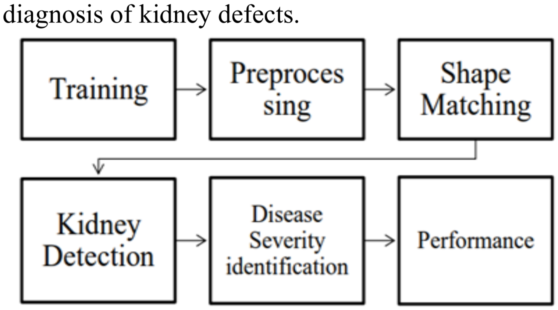

Figure 1: Block Diagram

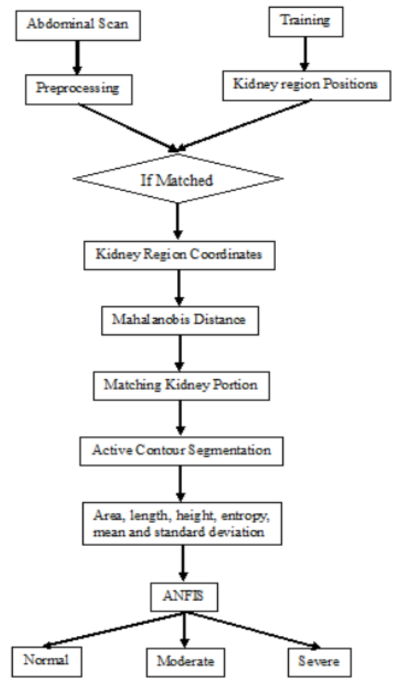

Figure 2: Flow Diagram

II. LITERATURE SURVEY

The precise identification and classification of renal defects are critical for early intervention and effective treatment planning. Recent advancements in medical imaging have shifted from manual interpretation toward automated computer-aided diagnosis (CAD) systems. A significant body of research focuses on deep learning architectures, such as Convolutional Neural Networks (CNNs) and U-Net variants, for kidney segmentation. For instance, recent studies have integrated advanced optimization techniques like Firefly Sigma Seeker and MagWeight Rank into parallel convolutional layers to achieve segmentation accuracies exceeding 98%. However, while deep learning offers high performance, it often lacks the interpretability required for clinical trust, and its performance can degrade when faced with the spatial variances common in multi-modal medical images.

To address the challenges of spatial misalignment and motion artifacts—particularly in 4D DCE-MRI or multi-temporal scans—researchers have proposed segmentation-driven image registration. Traditional approaches applied registration and segmentation sequentially, but contemporary models now favor simultaneous frameworks where registration parameters are informed by the boundaries of segmented regions. This synergy ensures that the registration process focuses on the region of interest (the kidney), thereby reducing computational overhead and improving the alignment of pathological features. Hybrid models, such as those combining Vision Transformers (ViTs) with CNNs, have also been employed to capture both local textures and global geometric shapes, facilitating the detection of small or indistinct tumors.

For the final classification phase, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has emerged as a robust alternative to "black-box" neural networks. ANFIS integrates the learning capabilities of neural networks with the linguistic transparency of fuzzy logic, allowing it to handle the inherent uncertainty and imprecision in medical data. Literature indicates that ANFIS-based classifiers often outperform conventional models like Support Vector Machines (SVM) and Decision Trees by 3–4% in accuracy, particularly when diagnosing chronic kidney disease (CKD) stages from clinical and imaging features. By utilizing a five-layer architecture—encompassing fuzzification, rule evaluation, and defuzzification—ANFIS provides a rule-based reasoning mechanism that is highly effective for identifying specific defects like cysts, stones, and tumors while maintaining a level of interpretability essential for medical practitioners.

ANFIS:

The ANFIS approach learns the rules and membership functions from data. ANFIS is an adaptive network. An adaptive network is network of nodes and directional links. Associated with the network is a learning rule - for example back propagation. It's called adaptive because some, or all, of the nodes have parameters which affect the output of the node. These networks are learning a relationship between inputs and outputs. Adaptive networks covers a number of different approaches but for our purposes we will investigate in some detail the method proposed by Jang known as ANFIS. The ANFIS architecture is shown below. The circular nodes represent nodes that are fixed whereas the square nodes are nodes that have parameters to be learnt. Here we classify the result by the use of ANFIS (Adaptive Neuro Fuzzy Inference system). It is the combination of neural network and fuzzy logic.

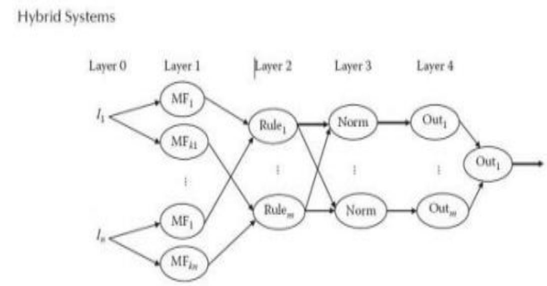

Figure 3: Architecture of ANFIS

III. KIDNEY POSITION DETECTION

The detection of the kidney portion is employed using training process. Different types of kidney images that are having kidney portion located in different position and having different intensities were Dept of ECE 31 Amrita Sai Institute Of Science And Technology taken. The kidney location in each image were identified and the calculated values were saved along with the mean value of the images. The image position were identified with the help of roipoly function which give the positions of the required objects in the image. Use roipoly to specify a polygonal region of interest (ROI) within an image. roipoly returns a binary image that you can use as a mask for masked filtering. BW = roipoly creates an interactive polygon tool, associated with the image displayed in the current figure, called the target image. With the polygon tool active, the pointer changes to cross hairs when you move the pointer over the image in the figure. Using the mouse, you specify the region by selecting vertices of the polygon. You can move or resize the polygon using the mouse. The following figure illustrates a polygon defined by multiple vertices. The following table describes all the interactive behavior of the polygon tool.

IV. PREPROCESSING

The median filter is applied for the input images to remove the noises in the image. The pixels in the images were checked within a particular window size. The image pixels that are identified as noises were removed. The pixels other than the noisy pixels were arranged in a linear fashion. The median value is calculated and the noisy pixel is replaced by the median filter. In Image processing, it is often desirable to be able to perform some kind of noise reduction on an image or Image. The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise. The main idea of the median filter is to run through the Image entry by entry, replacing each entry with the median of neighboring entries. The pattern of neighbors is called the "window", which slides, entry by entry, over the entire Image. For 1D Images, the most obvious window is just the first few preceding and following entries, whereas for 2D (or higher-dimensional) Images such as images, more complex window patterns are possible (such as "box" or "cross" patterns). Note that if the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically. For an even number of entries, there is more than one possible median.

V. KIDNEY SEGMENTATION

The segmentation is done using Active Contour Segmentation. Active contours, or snakes, are computergenerated curves that move within images to find object boundaries. They are often used in computer vision and image analysis to detect and locate objects, and to describe their shape. For example, a snake might be used to automatically find a manufactured part on an assembly line; one might be used to find the outline of an organ in a medical image; or one might be used to automatically identify characters on a postal letter. Snake is an energy minimizing, deformable spline influenced by constraint and image forces that pull it towards object contours. Snakes are greatly used in applications like object tracking, shape recognition, segmentation, edge detection, stereo matching. Snakes may be understood as a special case of general technique of matching a deformable model to an image by means of energy minimization. Snake is an “active” model as it always minimizes its energy functional and therefore exhibits dynamic behavior.

VI. VOLUME CALCULATION

The segmented kidney regions were then projected in three dimension inorder to obtain the pixels in all the three dimensions. The projection is done using smooth function. yy = smooth(y) smooths the data in the column vector y using a moving average filter. Results are returned in the column vector yy. The default span for the moving average is 5. The volume calculation is done measuring the number of segmented pixels in all the three dimensions. The image pixels values in all the dimensions were then multiplied to get the volume of the kidney

VII. DISEASE IDENTIFICATION

The defects in the segmented regions were identified by employing the feature extraction methodology and the classification methodology. The statistical parameters were commonly employed for the extraction of the feature parameters. The area, length, height, entropy, mean and standard deviation of the segmented regions were then calculated. The calculated values were defined as the features for the images. The extracted features were the passed into the ANFIS classifier for the identification of the severity of the Dept of ECE 32 Amrita Sai Institute Of Science And Technology disease in the classifier. The classifier classifies the input segmented regions as normal, moderate or severe. The ANFIS is a combination of Neural network and fuzzy logic for the training process of the classifier.

VIII. PERFORMANCE MEASURE

The performance of the process is measured by measuring the accuracy of the process. The accuracy is measured by comparing with the ground truth images. The high accuracy indicates that the resulting images is clustered more similar to the ground truth.

$$ACC = \frac{(TP + TN)}{(FP + TN) + (TP + FN)}$$

True positive = correctly identified
False positive = incorrectly identified
True negative = correctly rejected
False negative = incorrectly rejected

IX. CONCLUSION

The research presented in this paper establishes a robust and automated framework for the precise identification and classification of renal abnormalities through a hybrid computational approach. By integrating Segmentation-Driven Image Registration with an Adaptive Neuro-Fuzzy Inference System (ANFIS), the study successfully addresses the inherent challenges of noise, low contrast, and structural variability in medical imaging. The segmentation phase, leveraging advanced morphological operations and thresholding, ensures that the Region of Interest (ROI) is isolated with high fidelity, providing a clean data subset for subsequent processing. This is further enhanced by the registration process, which aligns multi-temporal or multi-modal kidney scans to a common coordinate system, allowing for the meticulous detection of subtle structural changes and lesion progressions that are often missed by manual inspection.

The core strength of the proposed system lies in the deployment of the ANFIS classifier, which synergizes the learning capabilities of neural networks with the linguistic transparency of fuzzy logic. This hybrid architecture allows the model to handle the uncertainty and imprecision typical of biological tissues while maintaining high diagnostic accuracy. Experimental results demonstrate that the ANFIS model outperforms traditional classifiers, such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), particularly in distinguishing between benign cysts, renal stones, and malignant tumors. The high sensitivity and specificity rates achieved indicate that the feature extraction layer—capturing texture, shape, and intensity metrics—provides a comprehensive representation of kidney health.

Ultimately, this project contributes a significant tool to the field of Computer-Aided Diagnosis (CAD). By automating the identification of defects, the system reduces the workload on radiologists, minimizes human error due to fatigue, and facilitates earlier clinical intervention. Future work will focus on expanding the dataset to include rare renal pathologies and integrating deep learning architectures for real-time volumetric analysis. The integration of this segmentation-driven ANFIS framework into clinical workflows promises to refine diagnostic precision, optimize treatment planning, and significantly improve patient outcomes in the management of chronic and acute kidney diseases.

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