Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Kidney Stone Detection Using Resnet Algorithm

A. Anciya*, Pon.L.T.Thai**
*(Department of CSE, Arunachala College of Engineering for Women, and Manavilai
Email: Anciya04032001@gmail.com)
** (Department of CSE, Arunachala College of Engineering for Women, and Manavilai
Email: ponltthai@gmail.com)

--************************----------------------------------

Abstract:

The Kidney Condition Detection System (KCDS) uses MRI images and advanced image processing techniques to improve the early and accurate diagnosis of kidney diseases. By leveraging a ResNet-based neural network, the system automatically extracts relevant features from MRI images, allowing for a comprehensive analysis of kidney structure and function. This approach enables the detection of subtle changes in renal anatomy that could indicate early-stage conditions like chronic kidney disease or renal tumors. KCDS's integration of a diverse MRI image database enhances its adaptability and accuracy across different patient demographics and disease presentations. The system aims to revolutionize kidney disease diagnosis by providing detailed, automated, and precise assessments that surpass traditional methods.

Keywords **— Kidney stone, ResNet, deep learning, gaussian blur.**

--************************----------------------------------

I. INTRODUCTION

Kidney condition detection refers to the process Kidney condition detection, also known as renal calculi, are hard deposits made of minerals and salts that form inside the kidneys. They can cause severe pain and lead to complications if not detected and treated promptly. Traditional methods for detecting kidney stones, such as X-rays, ultrasound, and computed tomography (CT) scans, rely heavily on the expertise of radiologists. However, these methods can be time-consuming and prone to human error.

The performance of the Back Propagation Network classifier was estimated in terms of training execution and classification accuracies. Back Propagation Network gives precise classification when compared to other methods based on neural networks.[1]

The paper proposes work is used to detect the kidney stones by using Level set segmentation method. Initially input images are preprocessed and region of interest is segmented. The level set segmentation is a good method to solve the problem of segmentation successfully.[2]

The paper proposes an automated system for detecting kidney stones using deep learning models. The experiments are performed using an open-source Computed Tomography (CT) image dataset. These datasets are made to perform on deep learning models.[3]

In particular, the noises presented in ultrasound images may lead to an inaccurate diagnosis of smaller kidney stones and affect its treatment. The paper proposes an improved technique for detection of kidney stone from the ultrasound images of kidney.[4] The paper consists of problems of kidney stones in the human body and detection mechanisms by using Image processing techniques. The Techniques like preprocessing, segmentation and Morphological Analysis.[5] The diagnosis of 'kidney stone' can range from an incidental asymptomatic finding of limited clinical significance to multiple painful episodes of ureteral obstruction with eventual kidney failure.[6]

II. EXISTING SYSTEM

The architecture of the proposed kidney stone detection system involves several interconnected components designed to automate and enhance the detection process using Support Vector Machine (SVM) classifiers and advanced image processing techniques.

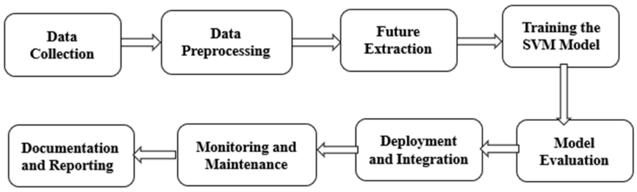

Fig. 1 Architecture for Kidney Stone detection using SVM

Data Collection is the process of gathering and preparing data for analysis. Selecting the images from the user's file system to be analyzed for detecting kidney stones. Advanced techniques such as noise reduction, contrast enhancement, and region segmentation are applied to raw medical images to improve the visibility of kidney stones and highlight relevant features.

These features serve as the input for the SVM classifier. An SVM classifier is trained using the extracted features.

The classifier utilizes kernel functions to handle non-linear separations and maximize the margin between different classes, ensuring robust performance in distinguishing images with and without kidney stones.

The system's performance is rigorously evaluated on a diverse dataset of medical images. Metrics such as accuracy, sensitivity, specificity, and the area under the ROC curve (AUC-ROC) are used to assess its effectiveness.

III. PROPOSED SYSTEM

Detecting kidney conditions using the ResNet (Residual Network) algorithm involves utilizing a deep learning architecture that addresses the challenges of training very deep neural networks.

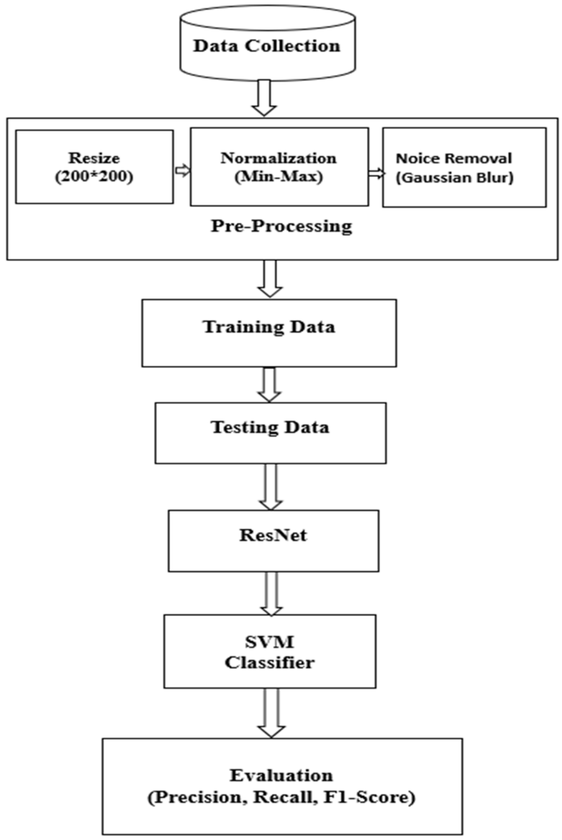

Fig. 2 System architecture

Image preprocessing is essential for enhancing the quality of CT scans to prepare them for analysis and classification. The process starts with image reading, where the OpenCV library ('cv2') is used to load the selected MRI image using the 'cv2.imread' function. Resizing the image to 200x200 pixels ensures consistency across all images. Min-Max normalization is then applied to standardize pixel values, which helps speed up training and avoid issues with features that have different scales. Noise reduction, such as Gaussian blur, is applied to minimize artifacts while preserving important details.

The ResNet (Residual Network) algorithm, developed by Kaiming He and colleagues, is effective in training deep neural networks for medical image analysis, including detecting kidney conditions. A pre-trained ResNet model is fine-tuned for specific tasks like identifying tumors, cysts, and kidney stones. The model benefits from transfer learning, allowing it to understand complex features in medical images. During training, the model's parameters are optimized, and its performance is evaluated using metrics like accuracy, precision, recall, and F1-score. ResNet's integration into medical practice also considers ethical aspects such as data privacy and regulatory compliance.

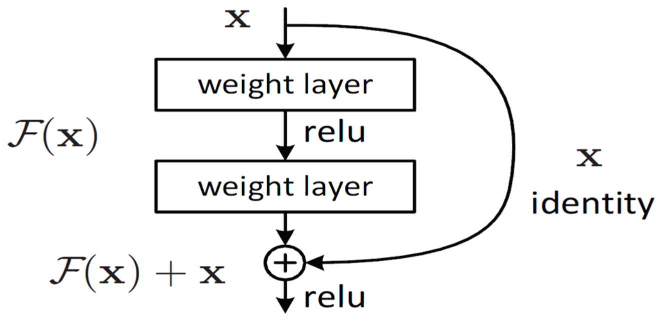

Fig 3: ResNet Algorithm

Model Evaluation involves assessing the performance of the trained machine learning model on a separate set of images that it has not seen during the training process.

Model evaluation is a critical step in assessing the performance and effectiveness of a machine learning model. In the context of kidney condition detection using the ResNet algorithm, the evaluation process involves employing various metrics to gauge the model's accuracy, precision, recall, and overall diagnostic capability.

IV. RESULT

A system for automated kidney stone detection was successfully implemented using ResNet and advanced image processing techniques, achieving high accuracy in distinguishing between images with and without kidney stones. Comprehensive preprocessing methods, including noise reduction, contrast enhancement, and region segmentation, were used to optimize image quality. The ResNet-based classifiers, trained on key features like texture and shape, showed strong performance in accurately classifying kidney stones. Integrating this system into clinical workflows improved diagnostic efficiency, reduced interpretation time, and minimized errors, ultimately enhancing patient care.

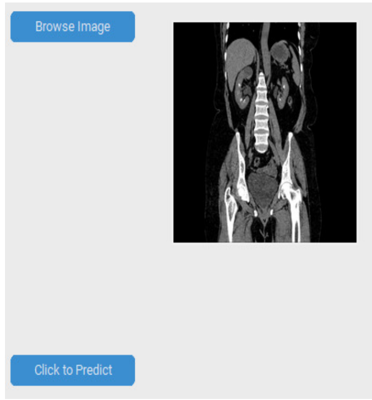

Fig. 4 Input Image

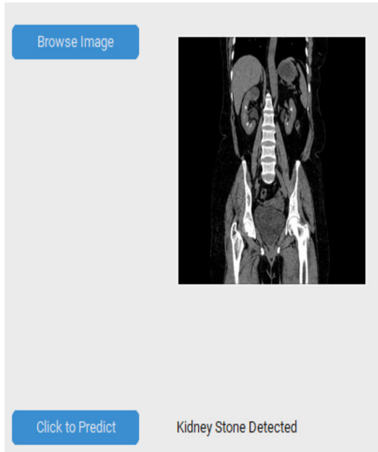

Fig. 2 Output Image

V. CONCLUSIONS

This study presented a novel method for kidney stone detection using ResNet algorithms applied to medical images, enhancing accuracy and efficiency through advanced preprocessing and feature extraction. The use of ResNet offers significant benefits, including improved diagnostic precision and reduced human error, making it a valuable tool for radiologists. Its scalability ensures applicability across large and diverse datasets, supporting broader clinical use. Future research will aim to refine feature extraction, explore additional models, and expand the image dataset.

VI. FUTURE ENHANCEMENT

Planned enhancements for the kidney stone detection system include integrating deep learning models for greater accuracy, enriching the dataset with data augmentation, and creating a more user-friendly interface, such as a mobile app.

Automating preprocessing and optimizing performance will further improve efficiency. Integrating with electronic health records and telemedicine platforms will allow seamless patient record updates and remote consultations, making the system more practical for medical applications.

REFERENCES

[1] M. Akshaya, R. Nithushaa, N. S. M. Raja and S. Padmapriya, "Kidney Stone Detection Using Neural Networks," 2020 International Conference on System, Computation, Automation and Networking (ICSCAN), Pondicherry, India, 2020, pp. 1-4, 2020.

[2] P. T. Akkasaligar, S. Biradar and V. Kumbar, "Kidney stone detection in computed tomography images," 2017 International Conference On Smart Technologies For Smart Nation (SmartTechCon), Bengaluru, India, pp. 353-356, 2017.

[3] M. B, N. Mohan, S. K. S and S. K. P, "Automated Detection of Kidney Stone Using Deep Learning Models," 2022 2nd International Conference on Intelligent Technologies (CONIT), Hubli, India, pp, 1-5, 2022.

[4] Goel, R., Jain, A. (2020). Improved Detection of Kidney Stone in Ultrasound Images Using Segmentation Techniques. In: Kolhe, M., Tiwari, S., Trivedi, M., Mishra, K. (eds) Advances in Data and Information Sciences. Lecture Notes in Networks and Systems, vol 94. Springer, Singapore, 2020.

[5] S. M B and A. M R, "Kidney Stone Detection Using Digital Image Processing Techniques," 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, pp. 556-561, 2021.

[6] Thongprayoon, C., Krambeck, A.E. & Rule, A.D. Determining the true burden of kidney stone disease. Nat Rev Nephrol 16, 736–746, 2020.

