Kidney Stone Detection using Image Processing

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Abstract— **Kidney stones are a common ailment affecting millions of people worldwide. Diagnosis of kidney stones typically involves imaging techniques such as X-rays, CT scans, and ultrasounds. However, these techniques are not always accurate and can be costly. This paper proposes an alternative method for kidney stone detection using image processing techniques. The proposed method involves the use of digital image processing to identify and classify kidney stones from CT scan images. A series of image processing steps are applied to the ultrasound images, including image enhancement, segmentation, feature extraction, and classification. The proposed method was evaluated using a dataset of ultrasound images of the kidneys. The results indicate that the proposed method has the potential to be an effective and low-cost alternative to traditional imaging techniques for kidney stone detection.**

I. Introduction

Kidney stones are a common problem in the human urinary system that can cause severe pain and discomfort. The diagnosis and treatment of kidney stones are crucial to prevent complications and improve the quality of life for patients. Traditional diagnostic methods for kidney stones include X-rays, CT scans, and ultrasounds. However, these techniques can be costly, time-consuming, and not always accurate. In recent years, the use of image processing techniques has gained popularity in the field of medical imaging. Image processing techniques can be used to extract relevant features from images, classify them, and provide a quantitative assessment of the condition. In this paper, we propose a novel approach to kidney stone detection using image processing techniques.

The proposed method involves the use of CT scan images of the kidneys, which are commonly used in the diagnosis of kidney stones. The ultrasound images are pre-processed to remove noise and enhance the contrast between the kidney and surrounding tissues. Features such as texture, shape, and size are extracted from the segmented image, and a classification model is trained to distinguish between images with and without kidney stones. The objective of this paper is to present a low-cost and effective alternative to traditional diagnostic methods for kidney stones. The proposed method has the potential to improve the accuracy of diagnosis, reduce the cost of imaging, and provide a quantitative assessment of the condition.

II. Literature Survey

S. No	Title	Author	Year	Algorithm	Applications	Tools	Advantages	Disadvantages	Dataset used and Directory	Future Scope
1.	Interpretable Deep Learning Classifier by Detection of Prototypical Parts on Kidney Stones Images	Daniel Flores-Araiza, Francisco Lopez-Tiro, Elias Villalvazo-Avila	2022	Prototypical Part Network (CNN: ResNet)	This model can be used for ESR by a urologist.	Python	VGG19 with batch normalization on CNN makes better accuracy rate for each of the 6 classes.	Model collapse of the learned ProtoPnet plus is a limitation on the current PPs.	ex-vivo dataset of kidney stone images. Kaggle.	Better Initialization Procedures for PP and loss function adjustments in CNN will be explored.
2.	A deep learning system for automated kidney stone detection and volumetric segmentation on non-contrast CT scans	Daniel C. Elton, Evrim B. Turkbey, Perry J. Pickhardt, Ronald M. Summers	2021	Gradient Anisotropic diffusion denoising, CNN	Can be used in robotic vision to detect kidney stone on AI vision.	Python	Use of anisotropic Diffusion up-to 200 connected components removes noise without blurring the image.	Usage of scan thickness 1mm won't make so accurate result and should be at 0.75 mm.	NNMC-CTC dataset	Future work will study how systems such as this can automatically track kidney stone volume changes over time
3.	DoubleU-Net: A Deep	Debesh Jha, Michael A.	2020	CNN DoubleU-Net	Used for Medical Image	Tensorflow, Volta 100	DoubleU-Net is capable of	It uses more parameters as	CVC-ClinicDB,	Designing simplified

	Convolutional Neural Network for Medical Image Segmentation	Riegler, Dag Johansen, Pal Halvorsen, Havard D. Johansen			Segmentation to differentiate the foreign body from the Human organ	GPU, Nvidia DGX-2 AI system	producing better segmentation mask even for the challenging images	compared to U-Net.	Kaggle	architectures with fewer parameters while maintaining its ability
4.	Detection of kidney stone using digital image processing: a holistic approach	Angshuman Khan, Rupayan Das, M C Parameshwara	2022	Principle Component Analysis (PCA), K-means, Fuzzy C means clustering	Pre-processing, Fragmentation, and the Feature extraction on the input image	Matlab	Higher accuracy rate of the proposed Model.	Not able to achieve the Highest accuracy	Geertsma T 2021 Ultrasound Images & Clips	Extend the work by proposing artificial neural network-based methodology to achieve more accuracy
5.	Detection of Kidney Stones Using Image Processing	M. Kavitha, Kiruba. N	2022	Fuzzy C-Means Algorithm, Histogram Equalization, ROI Model	The resulting image helped in detecting the exact location of stone and further the edge detection method was used to identify the shape and structure of the stones formed	Matlab	Proved to be an accurate method that can be used in the process of detection of kidney stone	Using seperate process for clearing the noises from the ultrasound which is time consuming	Ultrasound Images from Ultrasound Machine	Increasing the accuracy of the algorithm by working with new technologies

III. METHODOLOGY

The paper proposes a method for kidney stone detection using region-based convolutional neural networks (RCNN) using ResNet-50, a deep residual neural network architecture. The methodology of the paper involves several steps, including data collection, image pre-processing, feature extraction, model training, and evaluation.

1. Data Collection: Collected a dataset of CT scan images of the kidneys, including images with and without kidney stones.
2. The image dataset is resized with a size of 224 x 244 with a minimum scale of 0.75 to the original image and the dataset is split with the split ratio of 0.2 which defines that the dataset is split as 20 percent as validation set and remaining 80 percent is used for training set. After that the training images are taken as batches and is resized 512 x 512 to make as square shape with the method squish.
   The resized images are then passed into the RCNN architecture which performs Region Proposal, Extracting CNN features and classify the region proposals.

Region Proposal:

The RCNN architecture uses selective search algorithm for region proposal. Selective search is a bottom-up approach, meaning it starts with the individual pixel in an image and groups them into larger and larger regions. The Selective Search algorithm operates by first generating a large number of initial candidate regions by combining neighbouring pixels with similar colours, textures, or edges. These initial regions are then merged based on their similarity in colour, texture, or edge, creating increasingly larger and more complex candidate regions. At each stage, the algorithm computes a similarity metric between neighbouring candidate regions and merges them if they exceed a certain threshold. This process is repeated until a set number of candidate regions is generated, or until a desired number of object proposals is reached.

Feature Extraction:

Once the region proposals are generated, they are passed to the CNN to extract features.

CNN:

The Residual Network (ResNet) convolutional neural network works by skipping connections. The ResNet-50 architecture consists of 50 layers including the convolutional layers, max pooling and fully connected layers. The network takes the input as training images and passes it through the series of convolutional layers that extract features at each stride. From the Region proposal images the convolutional layers extract features.

ResNet-50 Architecture:

One 7 x 7 kernel convolution with a 2-sized stride, one max pooling layer with 2 sized strides, nine more layers with 3 x 3 kernel convolution, another with 1 x 1, 64 kernels and a third with 1 x 1, 256 kernels, these three are repeated three times, 12 more layers with 1×1,128 kernels, 3×3,128 kernels, and 1×1,512 kernels, iterated 4 times, 18 more layers with 1×1,256 cores, and 2 cores 3×3,256 and 1×1,1024, iterated 6 times. 9 more layers with 1×1,512 cores, 3×3,512 cores, and 1×1,2048 cores iterated 3 times. The use of ResNet-50 is the use of skip connections and each convolution layer is followed by a batch normalization layer which normalizes the output of the layer to prevent overfitting. The skip connections in ResNet-50 allow the network to learn the identity function, which is added to the output of some of the convolutional layers. These skip connections are added between pairs of convolutional layers, and the output of the first convolutional layer is added directly to the output of the second convolutional layer. This approach helps to propagate gradients more effectively through the network and allows ResNet-50 to be trained effectively even when it has 50 layers. Up to these 50 layers are completed and after this an average pool layer followed by a fully connected layer with 1000 nodes, using the ReLU (Rectified Linear Unit) activation function.

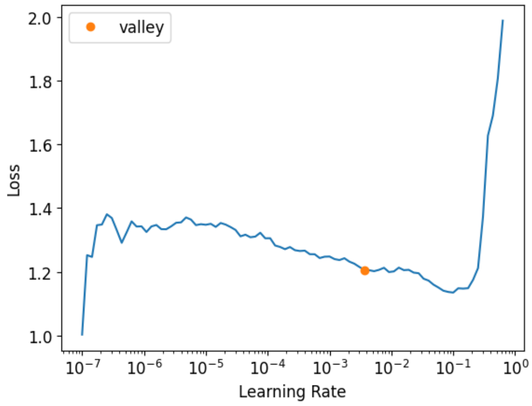
$$\mathrm{ReLU}(x) = \max(0, x)$$

The use of ReLU here is that it introduces non linearity to the network, allowing the model to train more complex relationships and also makes the gradients stable.

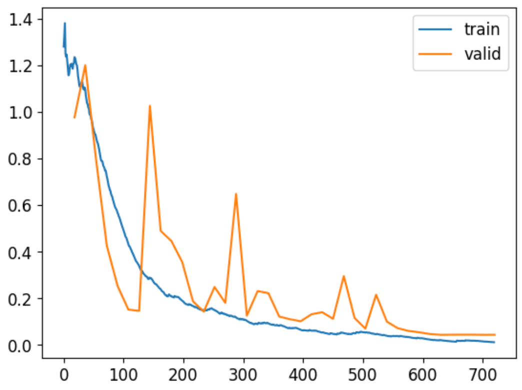
The input shape of the image will be 224 x 224 into the sequential layers and fitting of the model done with 40 epochs with the learning rate of 1e-2.

IV. EXPERIMENT RESULTS

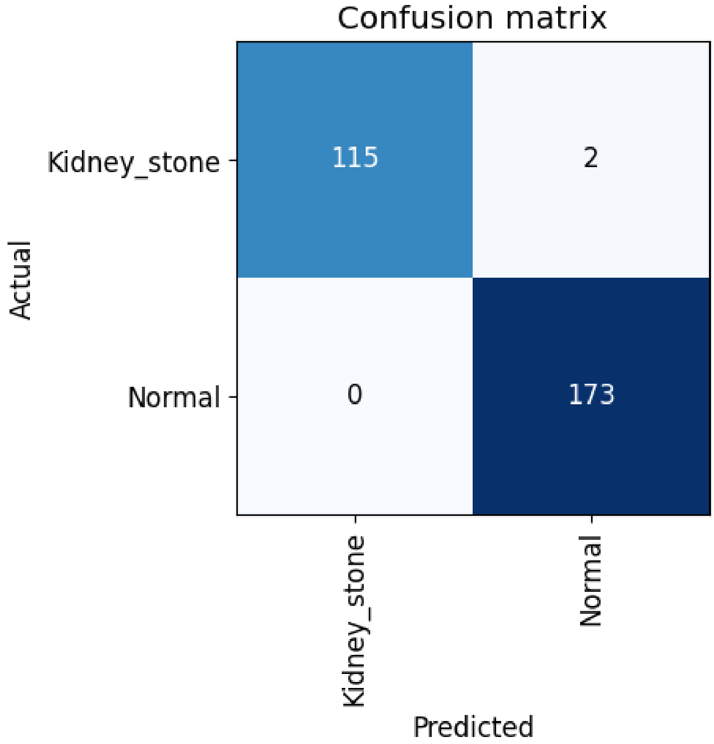
The Learning Rate for the fitted model's graph:



After fitting the model, the training and validation loses during the training of the model are plotted.



The Test Image data is given into the Trained model, the Confusion Matrix obtained,



Evaluation Metrics:

	Precision	Recall	F1-score	Support
Kidney stone	1.00	0.98	0.99	117
Normal	0.99	1.00	0.99	173
Accuracy			0.99	290
Macro avg	0.99	0.99	0.99	290
Weighted avg	0.99	0.99	0.99	290

V. CONCLUSION

Kidney stone detection is a challenging task in medical image analysis, which can be efficiently performed using the Region-based Convolutional Neural Network (RCNN) algorithm. In this project, the implementation of the RCNN model using the ResNet50 architecture to detect kidney stones in ultrasound images. The FastAI library is used to create data loaders, train the model, and evaluate its performance. This model achieved the precision of 1 and recall of 0.98, when predicting the input image contains the kidney stone and when deciding the normal(without) kidney stone the model achieves 0.99 and recall of 1, so total accuracy of this model when applied on the validation image data is 0.99. The accuracy is pretty high as it is applied on the validation data, while applying this trained model on the test data the accuracy is around 93% which is good for a deep learning model. The less test data gives this much accuracy, using of more test images will reduce the accuracy and increase the computational cost and time.

The future scope for this study is to apply different region proposal methods like RPN which will make the model to train and compare the accuracy of the trained models.

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