Kidney Stone and Tumour Detection Using CT Images

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***Abstract*— The application of the computerised tomography scan has proven to be revolutionary in obtaining the images of various tissues and bones of the human body. CT scans can image these tissues and bones by aggregating X-ray images that have been taken from multiple angles on the desired region in a completely painless way. This imaging method has been used to detect the presence of injuries or chronic diseases in the human body. The following paper talks particularly about the detection of Kidney Stones and Tumor on these images using native image processing techniques and classifier models. This can automate the task of kidney disease detection. In this paper, there is a greater weight on selection of these processing techniques because the intention is to create a simple model and this problem can be tackled only if the images present in the dataset are meaningful and have only those attributes pertaining to the problem. The objective of this paper is thus to discuss efficient algorithms that need to be incorporated during the preprocessing of these images for the task of identification of kidney diseases.**

Keywords—computerised tomography scan, morphological operations, MATLAB, thresholding algorithms, machine learning, CNN X-rays

I. Introduction

Nowadays, overwork that brings out human immunity reduction, excessive salt intake, and worse external environmental factors such as cold, dampness are easy to further cause kidney diseases. The research of the Kidney International [1] shows that the population of the chronic kidney disease (CKD) is beyond 2.8 hundred million and still increasing rapidly. And it is reported the morbidity and mortality of renal diseases has doubled in the last year by the National Institute of Health, and the incidence of renal disease tends younger and younger. The nephropathy will be a more and more serious problem.

CT scans are one of the most common imaging modalities used for the screening, diagnosis and treatment of lesions. It can detect small calcification, stones or negative stones that cannot be clearly detected by standard X-ray examination. CT scans can determine the location, extent and hematoma of the kidney injury, as well as postoperative complications. And compared with standard X-rays, CT scans are more detailed as it involves compiling X-ray images from different angles.

Automating the process of detections of these injuries or chronic diseases can prove very promising in the field of medicine as the time taken for this process in masses can be significantly reduced. The problem at hand can be tackled by using appropriate preprocessing techniques and good segmentation algorithms such as the watershed algorithms and fuzzy c means clustering, etc. to generate meaningful images that can be used to train the machine learning model. These techniques will make it much easier for the model to learn the data and make the process explainable and interpretable which can be beneficial in real life application of disease detection where explainability of the solution is considered very important.

II. Previous work

Previous research has looked to solve kidney stone, cyst and tumour detection using various methods like image processing, machine learning and neural networks. Some of the prominent techniques in each method have been listed below:

Paper [1] analyses CT scan images and automatically detects kidney lesions/cysts using morphological cascade convolution neural networks. In this paper, they've done extensive image processing using morphological operators like dilation and erosion individually. They've taken the sum of these images before inputting to the backbone model. They've defined 3 modes of inutting the images for further analysis to an RCNN model they built to successfully classify cysts. The paper doesn't do extensive pre-processing which is something that could possibly produce higher accuracy in classification.

In [2] they have proposed Fuzzy C means clustering to cluster each region/ pixel in a way that it can belong to more than one cluster. This provides better results than k-means clustering as each pixel/ region is not confined to just one region. The paper also looks at level set segmentation to segment the kidney stones which uses contours to identify and segment out the region of interest. The advantage of this method is that it allows flexible topology change and no previous knowledge about the shape to extract segments.

In [3], discrete wavelet transform is used for removing noise and unnecessary artefacts and brightening up the image. They were able to achieve better preprocessed images working on wavelets rather than on pixel blocks. The paper also uses the grey level co-occurrence matrix as a statistical texture analysis tool. The four aspects looked at in this paper are contrast, correlation, energy, and homogeneity. It is then passed through a back propagation neural network that detects whether a stone is present in the input image. After this, the watershed algorithm is used to segment the kidney stones in the images where their presence is detected by the neural network.

In this paper [4], they have preprocessed the images using Discrete Wavelet Transform to dispose of noise and brighten the photograph making it simpler to become aware of the key capabilities. They have done further preprocessing using GLCM feature extraction, dataset education, BPN and watershed set of rules and segmentation of kidney stone using Fuzzy C-Means method. The Gray stage co-incidence matrix helps in determining the texture functions of an image by calculating how frequently the pixel pairs with specific values and in a specific spatial dating arise in an image. First, it creates a GLCM after which extracts the great texture functions from this matrix.

Finally, they make use of a backpropagation neural network to process the enhanced images and use it to detect and classify images with kidney stones.

In this paper[5], the images of interest are first processed via an ROI mask. This is done because the tumour is a mass that exists in the organ; it is our responsibility to use a mask and extract that particular region only. This is followed by grayscale conversion to ease processing. Contrast enhancing is essential as the intensity of the tumour is low and needs to be brought out from the rest of the images. After the preprocessing of these images comes the most important step of the process that's the segmentation of these images to extract the tumour specifically. This is done with the help of the watershed algorithm and fuzzy c means clustering to obtain the tumours.

In this paper [6], the authors have explored various image processing techniques like Canny Edge Detection and thresholding to process the images after which they built and used a Back Propagation neural network to detect and classify kidney stones.

III. Proposed solution

After having selected the dataset, we explored some image processing techniques like histogram equalisation, applying a median filter, power law transformation, morphological operations and binarization using thresholding. We have been successful in processing and enhancing the images to be able to detect kidney stones and tumours. After generating the processed images, we also created a simple CNN classifier and trained it on the generated intermediate images to predict labels for each sample image.

A. *Dataset Acquisition*

The dataset was collected from the PACS (Picture archiving and communication system) from hospitals in Dhaka, Bangladesh with scans from patients that were already diagnosed with having a kidney tumour, cyst, normal or stone findings. A batch of Dicom images of the region of interest for each radiological finding was created and each image finding was again verified by a radiologist and a medical technologist to reconfirm the correctness of the data. The dataset contains a total of 5462 images, in which 848 images contain kidney stones, 1340 images contain tumours and 3274 images are healthy controls with no kidney disease

B. *Pre-processing*

Preprocessing the input data is an essential step to remove any noise and enhance the image for further analysis. The following steps were carried out for the same:

1. Removing soft tissue/ areas around the kidney: We crop the images [Fig. 2] to remove unnecessary regions from the CT scan.

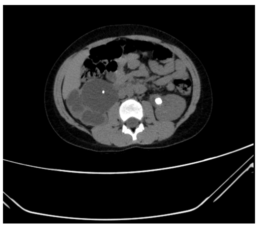

Fig 1. Original image

Fig 2. Image after cropping

1. Converting images from RGB to grayscale to convert the 3 layer RGB image into a single layer grayscale image with values from 0-255. We use the rgb2gray method in MATLAB for the same.
2. Next, we apply a median filter [Fig. 3] to remove noise and smoothen the image. We use the medfilt2 method in MATLAB for the same

Fig 3. Image after filtering with median filter

3. We then use histogram equalisation [Fig. 4] to spread out the intensity values by stretching out the intensity range of the image. We can see that the contrast has reduced, we will use a power-law transformation in the next step to correct this

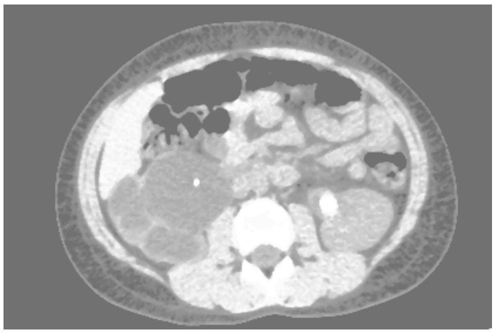

Fig 4. Image after Histogram Equalisation

4. Power Law Transformation [Fig. 5] is then performed to enhance only the lighter areas and suppress the darker areas using appropriate parameter values for c and gamma. The parameter values used were c equal to 1 and gamma as 100.

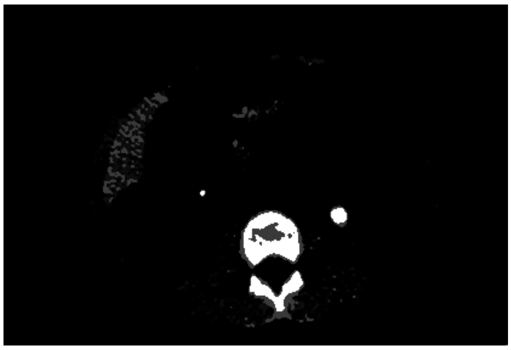

Fig 5. Result after power-law transformation

5. Morphological Operations such as erosion and opening were used in sequence with a disk structuring element [Fig. 6]. For erosion, a structuring element disk of radius 1 and n is 4 where n is the number of periodic structuring

elements used to approximate the shape. For the opening operation, we use a structuring disk element of radius 4 and n as 4.

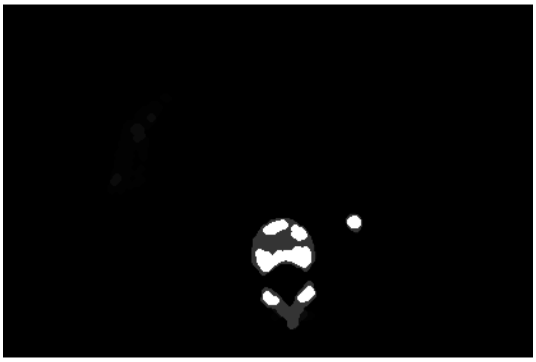

Fig 6. Result after morphological operations

6. Thresholding: We used various threshold values[Fig. 7-10] in a hit and trial fashion and found the optimal threshold value to be 30. The results after thresholding are as below.

Fig 7. Using T= 0.7

Fig 8. Using T=5

Fig 9. Using T= 10

Fig 10. Using T=30

For tumour detection, we carried out a similar procedure to that for kidney stones.

The preprocessing for tumour detection results are as shown below-

Similar to kidney stone detection, we first crop the image and get rid of the soft tissues and bone area. We then convert it to a grayscale as processing in a single component is less compute resource expensive compared to processing in 3 components(RGB. We then apply a median filter to remove noise from the image without losing important information. We then apply morphological operations. We are using a disk structuring element with a radius of 2 along with 4 line structuring elements.

Using the structuring element we have dilated the image and applied thresholding to this image. The threshold value we found optimal is 0.67 [Fig. 11-14] as values lower than this value retain too much noise and values higher than the optimal value do not retain the tumour region.

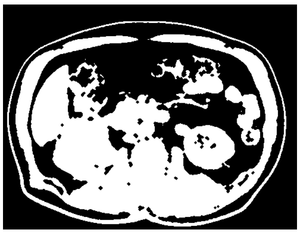

Fig 11. T = 0.20

Fig 12. T = 0.45

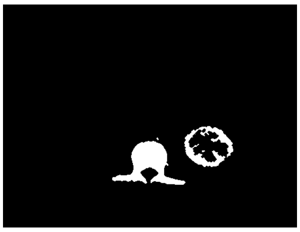

Fig 13. T = 0.67

Fig 14. T = 0.80

To remove the other part of the kidney and other tissues/structures that could be identified as a tumour are removed using erosion. For erosion, we use the same structuring element [Fig. 18].

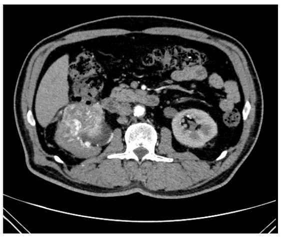

Fig 15. Kidney with tumour

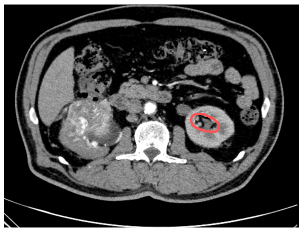

Fig 16. Tumour circled in red

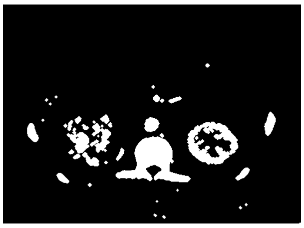

Fig 17. Image after binarizing

Fig 18. Image after morphological operations

After generating the images for the three categories-kidney stone, tumour, and normal (no disease) we create a simple classifier model that can take the generated images as input and classify them into the three mentioned classes. For the purpose of identification and classification, we have used a very simple convolutional neural network with the following layers

1. Conv 2D layer which is the first layer in the CNN and is tasked with learning low level features like edges, etc. We use a kernel with 100 filters
2. Relu Activation layer is used as the intermediate activation function to introduce non-linearity into the model

3. Max pooling layer consisting of filter size 3 x 3 is used to reduce the dimensionality by reducing the number of pixels in the intermediate output.
4. Flattening layer is used to convert all the intermediate 2D arrays from the max pooled layer into a single linear vector similar to a column or row vector
5. Softmax Activation layer is used in the output layer of neural network models that predict a multinomial probability distribution for the multi-class classification problem i.e. kidney stone, tumour and normal.

We split our data into training and testing sets using a split ratio of 8:2 and the data is passed to the CNN to train for 20 epochs.

IV. Results

The CNN model was trained and tested for binary classification of just the kidney stone first and we further extended that to the multi-class classification of the categories stone-tumour-normal.

The crux of these results stems from the fact that our dataset was fully pre-processed using image processing techniques we applied after experimentation. This preprocessed dataset being fed into the CNN is what enabled us to achieve the high accuracy values we have been successful in attaining.

A visual representation of our results is as shown below:

For kidney stones:

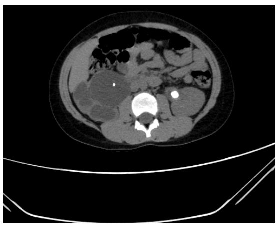

Fig 19. Original image

Fig 20. After image processing

For kidney tumour:

Fig 21. Original image

Fig 22. After image processing

For normal kidney:

Fig 23. Original image

Fig 24. After image processing

We use validation accuracy and loss as the main metric to judge the performance of our model. The accuracy [Fig. 25]on the validation set is 0.99452 and the validation loss is 0.0337

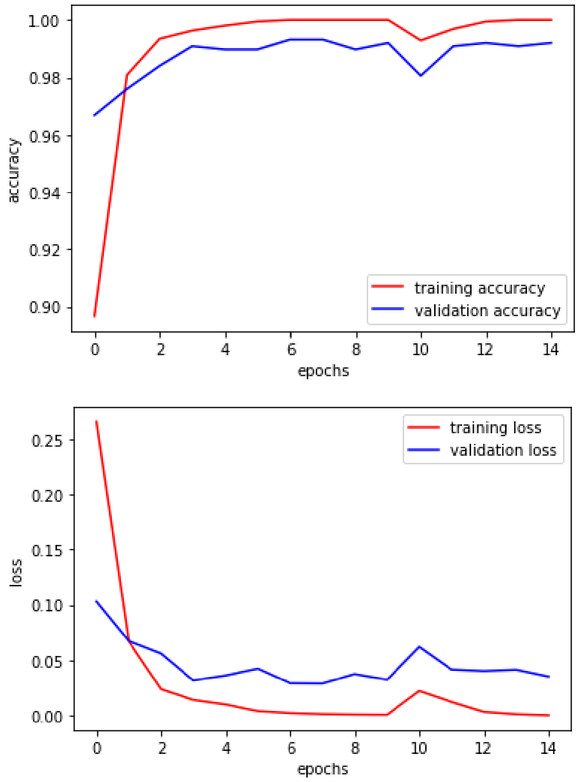

Fig 25. Accuracy and Loss for the Training set and Validation set

We use validation accuracy and loss as the main metric to judge the performance of our model. The accuracy[Fig. 26] on the validation set is 0.985 and the validation loss is 0.015

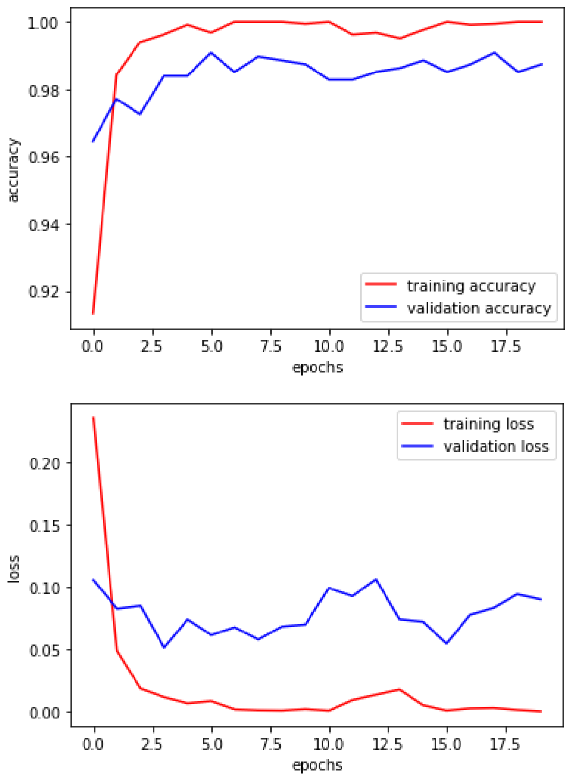

Fig 26. Accuracy and Loss for the Training set and Validation set

The images in the original dataset have been acquired from different hospitals in the same region, therefore having the same scanning standards and using similar resolution scanners for the imaging. The images acquired and are fairly clean in terms of artefacts like motion, blur, tilt etc. and therefore our approach performs very well on this data. If we were to merge multi-site data where images are scanned at different resolutions and with varying parameters of size and time of acquisition, some of the static crop functions and thresholds will need to be changed accordingly as our approach does not fall into the category of a one size fits all solution. This solution however can be applied to most of the standard kidney CT scans without having to change the values of the parameters.

V. Conclusion

We were successful in automating the process of tumour and kidney stone detection using efficient preprocessing techniques and feeding these pre-processed images to a simple convolutional neural network to classify the images. The main objective of this paper was to build a very strong preprocessing pipeline that can be used for CT scan images, this pipeline was developed on MATLAB. It consisted of cropping the images, converting them to grayscale, applying a median filter, using morphological operations such as opening, dilation and erosion, and finally thresholding it to binarize the image. Collectively these methods were able to remove any irrelevant parts of the image and only extract the object of interest (tumour/stone) from these images. This essentially made it possible to use only a single-layered convolutional neural network as we did not need the extremely good feature extraction capabilities of CNN. The final model had an accuracy of 98.5% with a validation loss of 0.15.

Contributions of each team member-

a. Anisha Ghosh: Code implementation for neural network, initial image processing of kidney stone, presentation, paper contribution for literature survey, methodology, and conclusion.
b. Anupama Nhavalore: Code implementation for image processing for tumour, paper contribution - introduction, literature survey, methodology & results
c. Gayathri Sunil: Code implementation for image processing of kidney stone and tumour, presentation, paper contribution for methodology, introduction
d. Tushar Shetty: Code implementation for neural network and presentation, paper contribution for abstract, literature survey and data acquisition

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