Department of Artificial Intelligence and Data Sciences

Work Progress
on
Kidney Stone Detection using Deep Neural Network and Transfer Learning with Image Segmentation and Image Resolution

Submitted By:

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048, 050, 070, 071, 072

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INTRODUCTION

Kidney stones are small, hard mineral and salt deposits that form within the kidneys or urinary tract.Detecting kidney stones is crucial for several reasons, and failure to do so can result in significant threats to the body's health. Nowadays many practitioners are involved in including automation in the field of medical learning, hence we all together decided to indulge in the particular field as we were intrigued to work for it. Hence, we are experimenting with deep neural networks with transfer learning in medical image analysis.

LITERATURE REVIEW

On the basis of the research that has been carried out till date on the medical images, it has been witnessed that the models have outperformed but on a limited number of images, and the accuracy is comparatively low due to presence of noise even after the noise removal and edge detection. Moreover the results for the segmentation of image has been compromised due to the variability of image quality of the dataset.

Hence to overcome the problems listed above we have recommended to provide a solution, which would be addressing the problems in such ways:

- By augmenting the data and using smote technique to avoid the overfitting of the model.
- By removing various types of noises such as gaussian noise, impulse noise, rayleigh noise, uniform noise, periodic noise and many more.
- By improving the quality of image which includes the contrast, sharpness and improving various domains such as spatial and frequency before segmentation.
- Using ReLU activation function to overcome vanishing gradient problem
- Implementing transfer learning for deep neural network for kidney stone detection.

S. No.	Author	Title	Published in	Year	Proposed Methodology and Result	Research gaps
1.	Jyothirmai Joshi, Sai Nikitha, Viswa Chandrika, Sindhu, Jahnvi	Kidney stones detection using Image processing technique	International Journal of Applied Engineering Research ISSN 0973-4562 Volume 16, Number 6	2021	The ultrasound images contain speckle noise. To process the image and detect the location of the stone in the image, we need to remove the noise. Thus, the first step is to enhance the image by using various sharpening and smoothing filters. After the image is enhanced, image segmentation is used to differentiate between the shadow and the stone by separating the foreground and the background. Gabor Filter was effective on a larger number of images though not all. Next Median blur + Laplacian Filter and Gaussian blur + Laplacian Filter worked perfectly with other of the few images which are lesser compared to Gabor Filter.	The main objective of this project is to detect the kidney stone from the digital ultrasound image of the kidney by performing various image processing techniques. Due to the varied texture and existence of speckle noise, detecting regions of interest in ultrasound pictures is a difficult process.
2.	Sesha Vidhya S, Vishmitha D; Yoshika K, Sivalakshmi P, Vineesha Chowdary, Shanthi KG; Yamini M	Kidney Stone Detection Using Deep Learning and Transfer Learning	2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA)	2022		

S. No.	Author	Title	Published in	Year	Proposed Methodology and Result	Research gaps
3.	Rati Goel, Anmol Jain	Improved Detection of Kidney Stone in Ultrasound Images Using Segmentation Techniques	International Journal of Applied Engineering Research ISSN 0973-4562 Volume 16, Number 6	2020		.
4.	YiNan Zhang, MingQiang An	Deep Learning- and Transfer Learning-Based Super Resolution Reconstruction from Single Medical Image	Hindawi Journal of Healthcare Engineering Volume 2017, Article ID 5859727, 20 pages	2017	The proposed method contains one bicubic interpolation template layer and two convolutional layers. The bicubic interpolation template layer is prefixed by mathematics deduction, and two convolutional layers learn from training samples. For saving training medical images, a SIFT feature-based transfer learning method is proposed. Not only can medical images be used to train the proposed method, but also other types of images can be added into training dataset selectively. The method also produces slightly sharper	

RESEARCH GAPS

1.) **Integration of Multiple Techniques:** While previous work acknowledges the importance of image segmentation, image resolution, and disease detection for kidney stones, it often addresses these aspects in isolation. A research gap exists in combining these techniques in a unified framework to provide a comprehensive solution. The proposed project aims to bridge this gap by integrating image segmentation, image resolution enhancement, and kidney stone detection into a single, coherent pipeline.

2.) **Transfer Learning in Medical Imaging:** The utilization of deep neural networks with transfer learning in the medical image analysis domain presents a promising approach. However, there is a need for further research into how transfer learning can be effectively applied to medical image analysis, specifically for the detection of kidney stones. This research can explore the selection of appropriate pretrained models, fine-tuning strategies, and the adaptation of models for domain-specific tasks.

3.) **User-Friendly Disease Detection:** The project recognizes the importance of making disease detection results understandable and interpretable by common people. The research gap lies in developing user-friendly interfaces and visualization methods that can convey the detected kidney stones in a way that is accessible and informative for non-specialists. Effective communication of the diagnostic results to patients and healthcare providers is an area where further investigation is warranted.

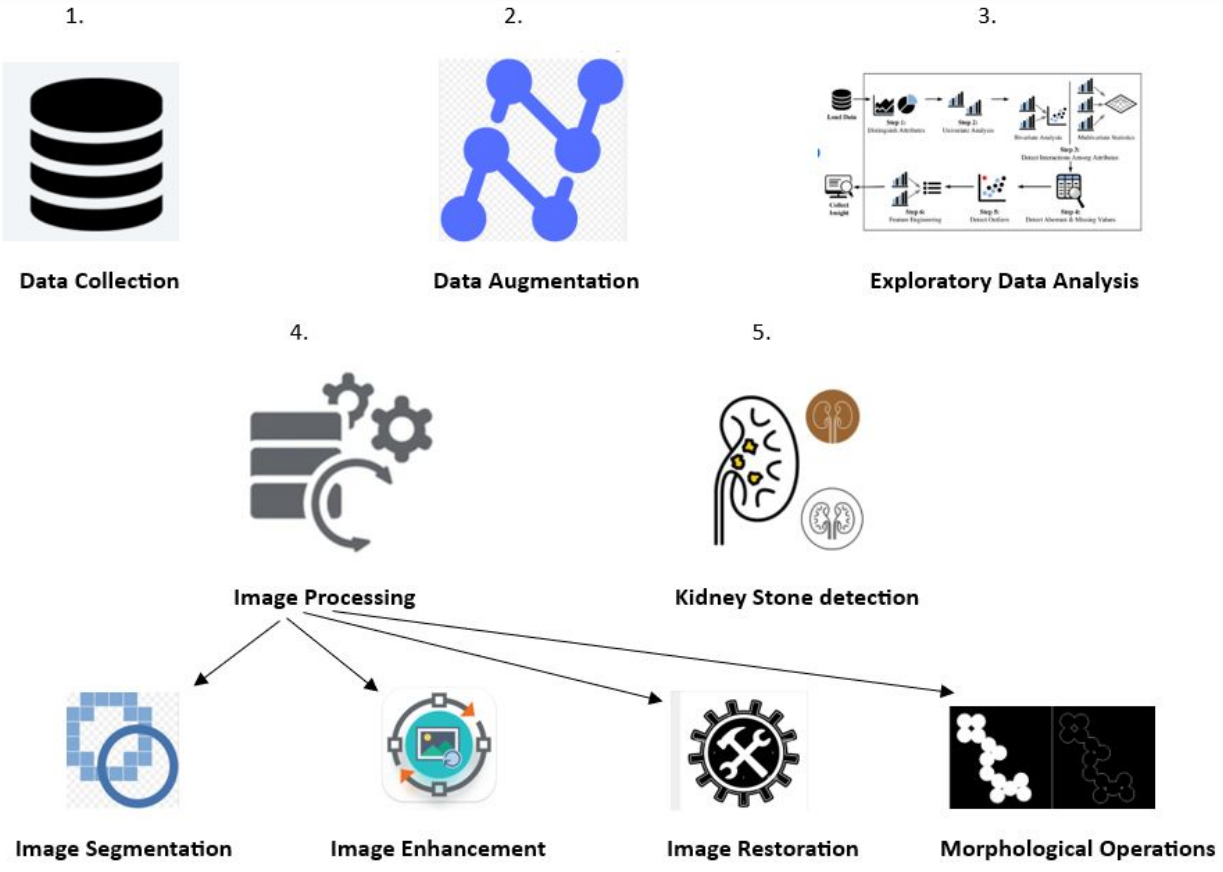
4.) **Evaluation Metrics for Medical Image Analysis:** The proposed project introduces a set of evaluation metrics, including Intersection over Union (IoU), structural similarity index, peak signal-to-noise ratio (PSNR), and mean average precision (mAP). Further research could explore the effectiveness of these metrics in the context of kidney stone detection and assess their robustness and suitability for different stages of the image analysis process. Additionally, comparative studies with existing evaluation metrics commonly used in medical image analysis can help determine the advantages of the proposed metrics.

RESEARCH OBJECTIVES

The main aim of the project is the automated detection of the disease which could be understood and figured out by the common people to some extent, hence, transfer learning will be used where learning from the pretrained models can be very much useful for training the deep neural network.
First of all, we are thinking of dividing the projects in three sections: **image segmentation**, **image resolution** and **Kidney stones detection**, where all would be carried out with transfer learning and convolutional neural networks.

For the evaluation metrics for each of the sections, Intersection over union can be used for image segmentation, structural similarity index and peak signal to noise ratio can be calculated with reference to the reference image which would be our ground truth for our image resolution and mean average precision for accuracy of the detection of the neural networks.

Proposed Methodology



Exploratory Data Analysis

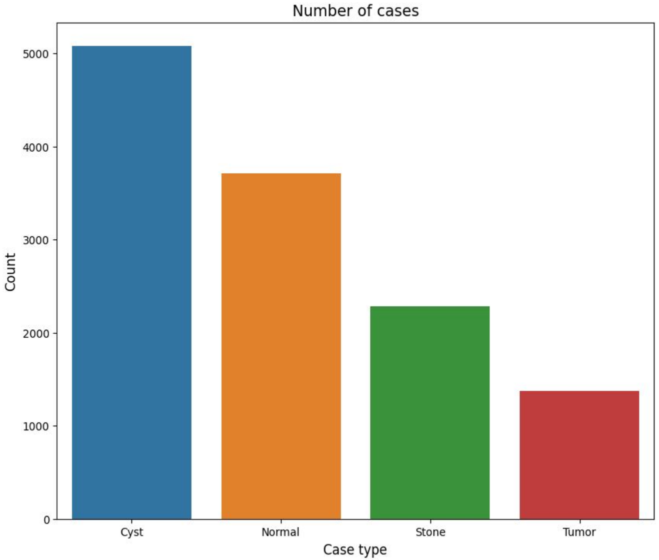
```
Normal    5077
Cyst      3709
Tumor     2283
Stone     1377
Name: Class, dtype: int64
```

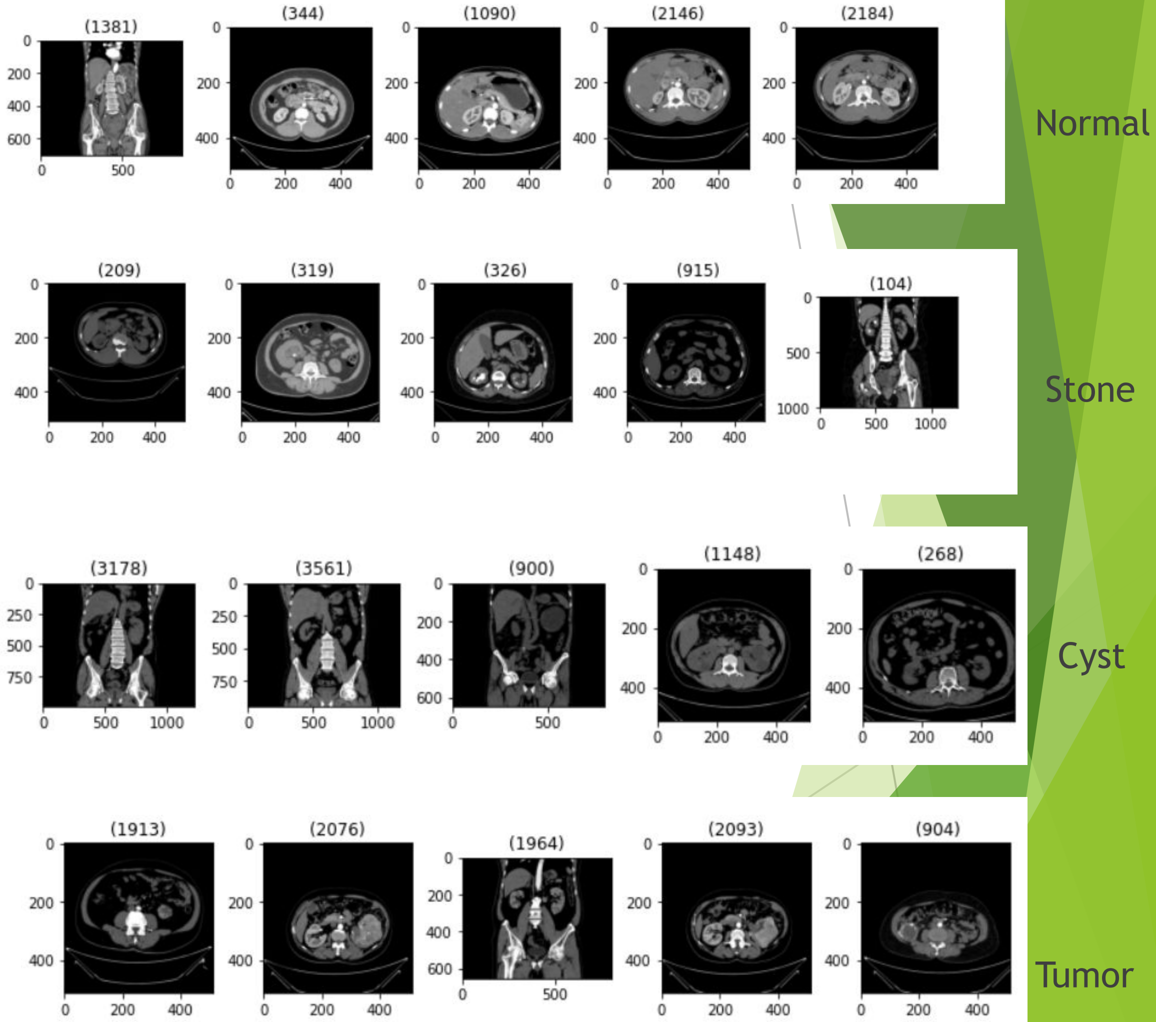
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12446 entries, 0 to 12445
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Unnamed: 0   12446 non-null  int64
 1   image_id     12446 non-null  object
 2   path         12446 non-null  object
 3   diag         12446 non-null  object
 4   target       12446 non-null  int64
 5   Class        12446 non-null  object
dtypes: int64(2), object(4)
memory usage: 583.5+ KB
```

	Unnamed: 0	image_id	path	diag	target	Class
0	0	Tumor- (1044)	/content/data/CT KIDNEY DATASET Normal, CYST, ...	Tumor	3	Tumor
1	1	Tumor- (83)	/content/data/CT KIDNEY DATASET Normal, CYST, ...	Tumor	3	Tumor
2	2	Tumor- (580)	/content/data/CT KIDNEY DATASET Normal, CYST, ...	Tumor	3	Tumor
3	3	Tumor- (1701)	/content/data/CT KIDNEY DATASET Normal, CYST, ...	Tumor	3	Tumor
4	4	Tumor- (1220)	/content/data/CT KIDNEY DATASET Normal, CYST, ...	Tumor	3	Tumor
...	...	...	...	...	...	...
12441	12441	Cyst- (2522)	/content/data/CT KIDNEY DATASET Normal, CYST, ...	Cyst	0	Cyst
12442	12442	Cyst- (2627)	/content/data/CT KIDNEY DATASET Normal, CYST, ...	Cyst	0	Cyst
12443	12443	Cyst- (972)	/content/data/CT KIDNEY DATASET Normal, CYST, ...	Cyst	0	Cyst
12444	12444	Cyst- (2323)	/content/data/CT KIDNEY DATASET Normal, CYST, ...	Cyst	0	Cyst
12445	12445	Cyst- (2145)	/content/data/CT KIDNEY DATASET Normal, CYST, ...	Cyst	0	Cyst

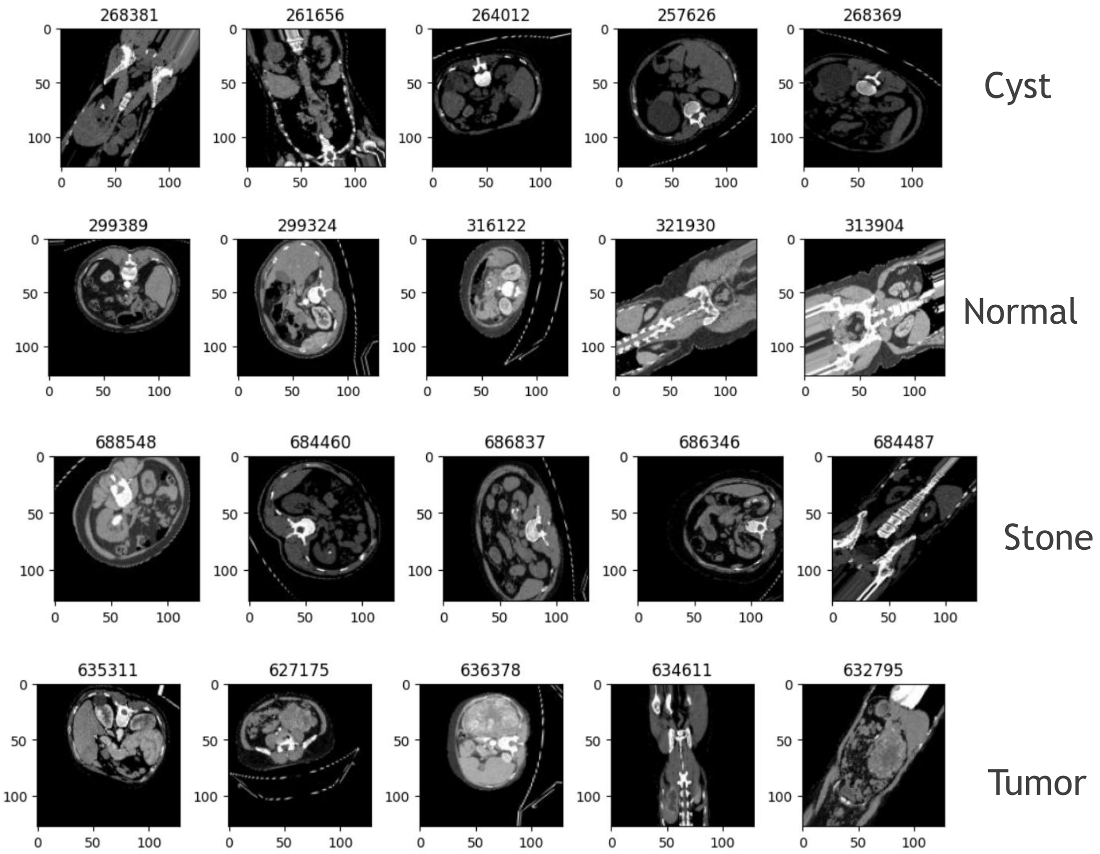
12446 rows × 6 columns

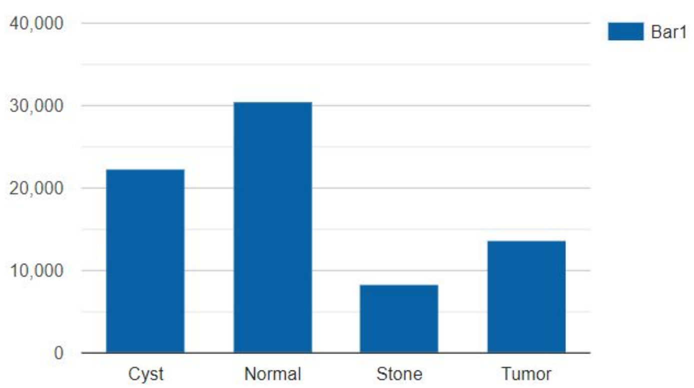




The dataset contains 12,446 unique data within which the cyst contains 3709, normal 5077, tumor 2283 and stone 1377 images.

Data Augmentation



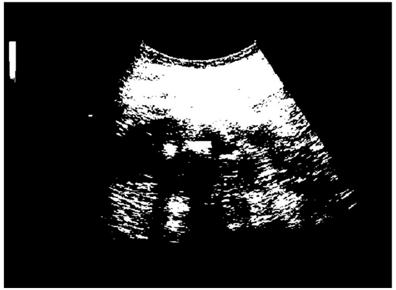


After Augmentation of the original dataset, the augmented dataset contains 22251 cyst , 30455 normal, 8259 stone, 13690 tumor images.

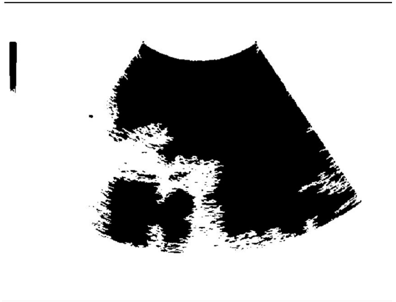
Image Preprocessing Techniques

Image segmentation:

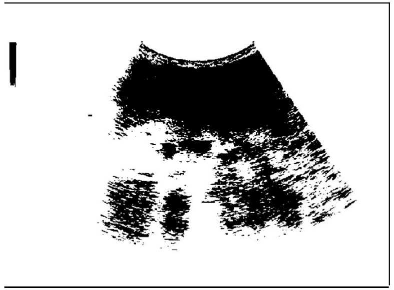
1.) Threshold based segmentation

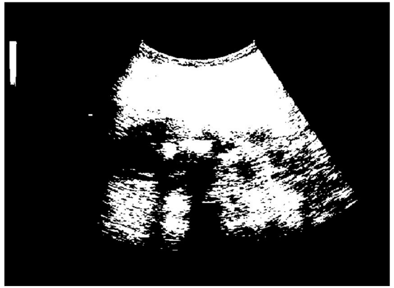


2.) Region Based segmentation

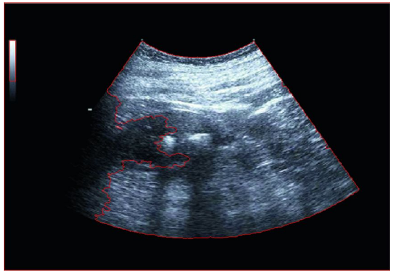


3.) Cluster based segmentation





4.) Watershed segmentation



5.) Edge based Segmentation

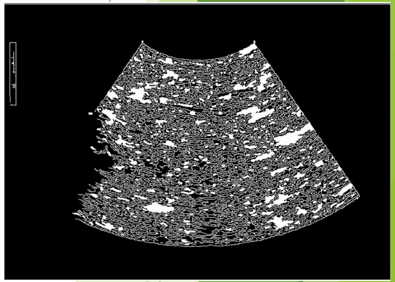
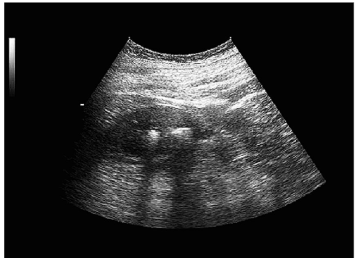


Image enhancement:

1.) Histogram Equalization

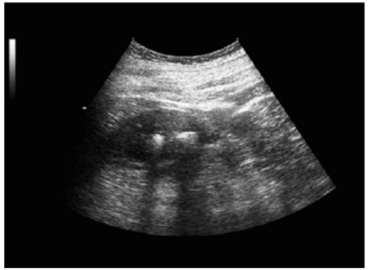
Histogram Matching

2.) Contrast convolution

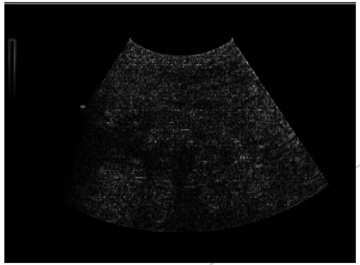


Correlation

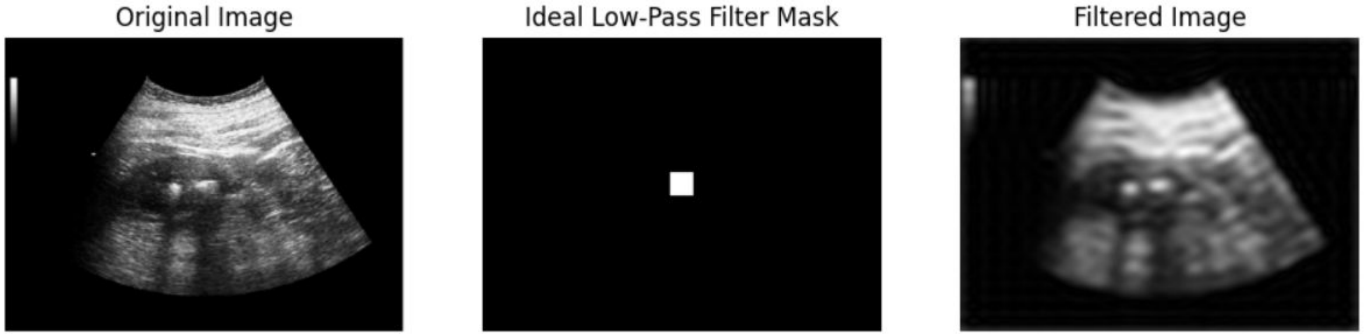
3.) Smoothing Spatial Filter



Sharpening Spatial Filter



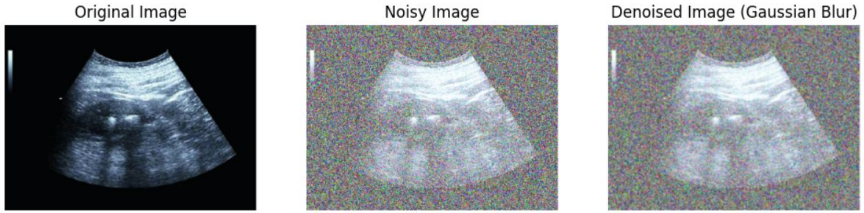
5.) High pass Frequency Domain (ideal)



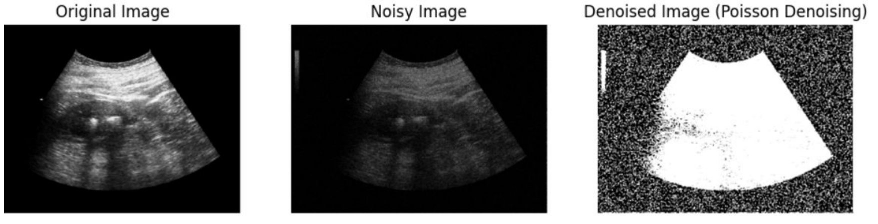
6.) Low pass Frequency Domain (ideal)

Image restoration:

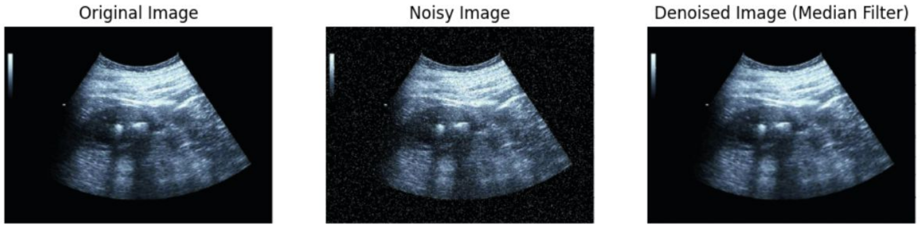
1.) Gaussian Noise/Gaussian Blur



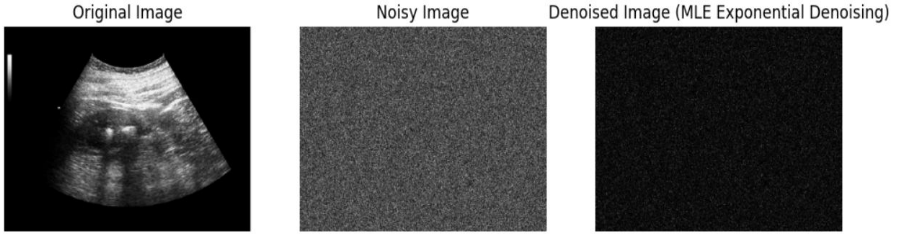
3.) Poisson Noise



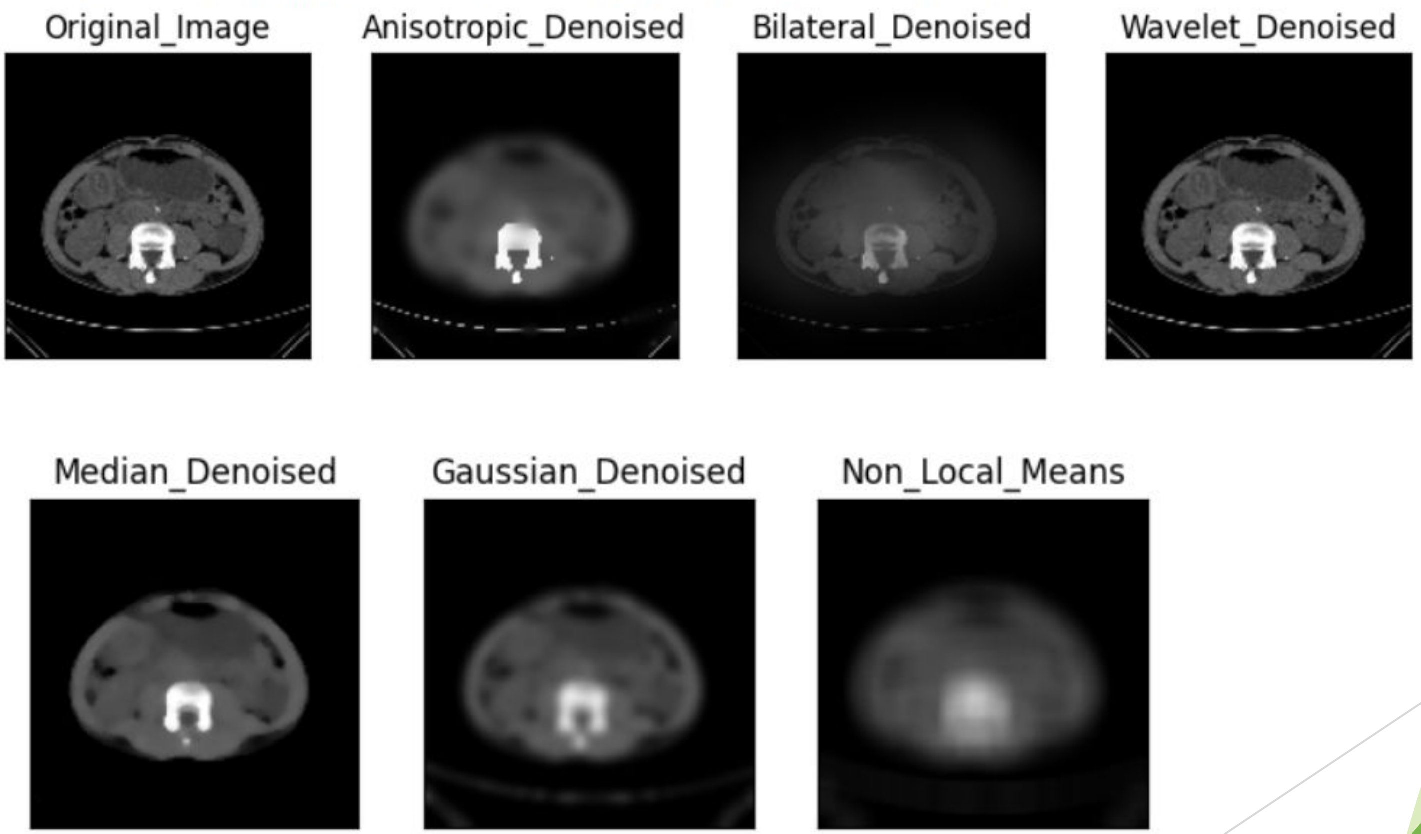
2.) Impulse Noise



4.) Exponential Noise

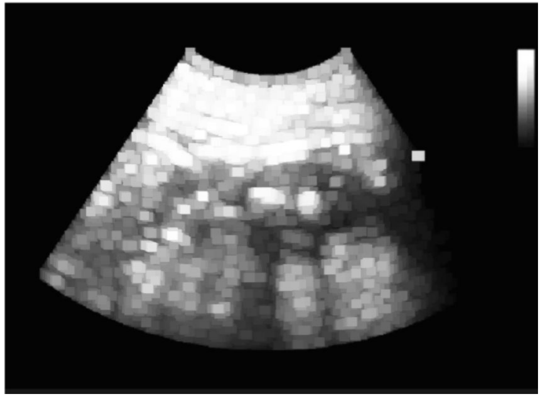


Denoised Images After Processing

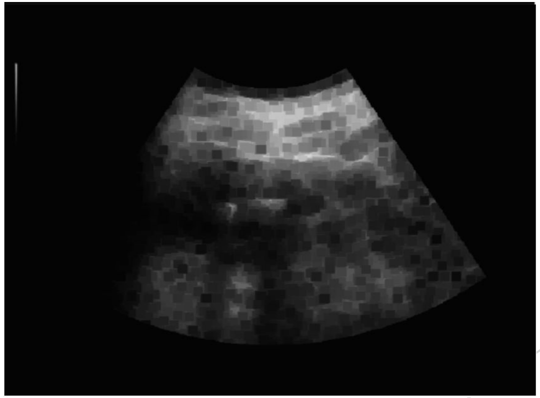


Morphological Processing:

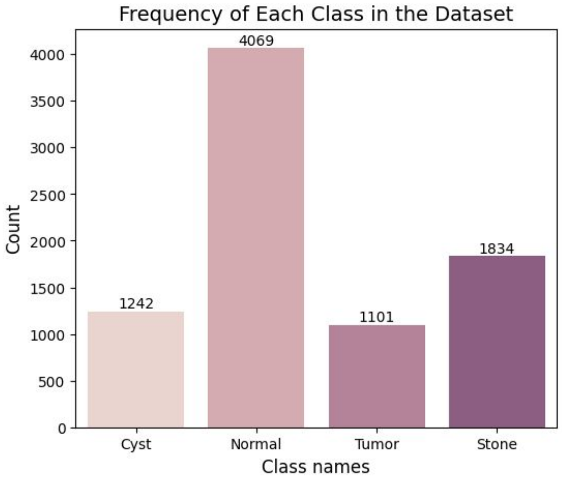
1.) Dilation

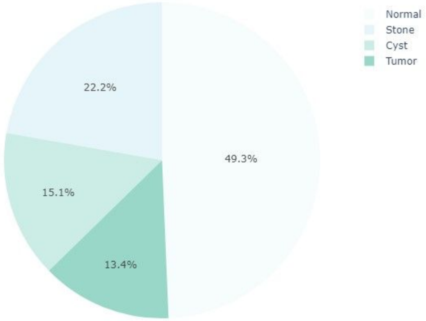


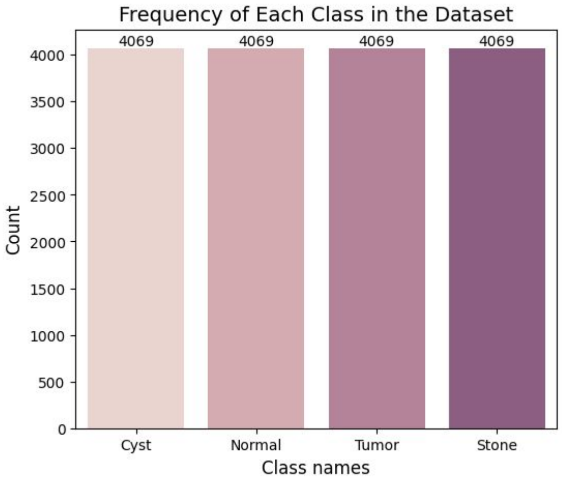
2.) Erosion

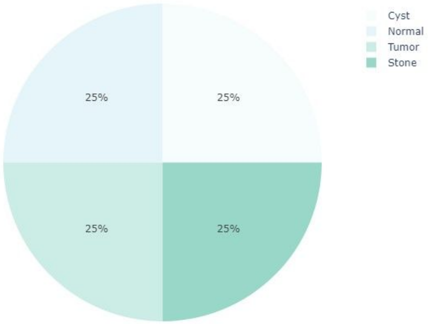


TRAINING DATA BEFORE AND AFTER CLASS BALANCING









Model

We have used CNN, VGG16 and Mobilenet for the detection of kidney stones in two ways:

- **Application of models with Preprocessing and Class balancing**

CNN :-

```
Epoch 1/5
458/458 [==============================] - 435s 945ms/step - loss: 2.9105 - accuracy: 0.9679 - val_loss: 0.0168 - val_accuracy: 0.9855
Epoch 2/5
458/458 [==============================] - 418s 912ms/step - loss: 7.4624e-06 - accuracy: 1.0000 - val_loss: 0.0076 - val_accuracy: 0.9952
Epoch 3/5
458/458 [==============================] - 396s 864ms/step - loss: 1.5293e-06 - accuracy: 1.0000 - val_loss: 0.0125 - val_accuracy: 0.9952
Epoch 4/5
458/458 [==============================] - 388s 846ms/step - loss: 7.1301e-07 - accuracy: 1.0000 - val_loss: 0.0193 - val_accuracy: 0.9952
Epoch 5/5
458/458 [==============================] - 387s 845ms/step - loss: 3.6595e-07 - accuracy: 1.0000 - val_loss: 0.0246 - val_accuracy: 0.9952
```

MobileNet :-

```
Epoch 1/5
458/458 [==============================] - 23s 41ms/step - loss: 0.3202 - accuracy: 0.8911 - val_loss: 0.2273 - val_accuracy: 0.9053
Epoch 2/5
458/458 [==============================] - 21s 45ms/step - loss: 0.0894 - accuracy: 0.9702 - val_loss: 0.2515 - val_accuracy: 0.8762
Epoch 3/5
458/458 [==============================] - 22s 46ms/step - loss: 0.0645 - accuracy: 0.9805 - val_loss: 0.2538 - val_accuracy: 0.9029
Epoch 4/5
458/458 [==============================] - 22s 47ms/step - loss: 0.0561 - accuracy: 0.9808 - val_loss: 0.2185 - val_accuracy: 0.9248
Epoch 5/5
458/458 [==============================] - 18s 39ms/step - loss: 0.0438 - accuracy: 0.9857 - val_loss: 0.2244 - val_accuracy: 0.9102
```

VGG16 :-

```
Epoch 1/5
458/458 [==============================] - 46s 84ms/step - loss: 0.3372 - accuracy: 0.8809 - val_loss: 0.1130 - val_accuracy: 0.9515
Epoch 2/5
458/458 [==============================] - 34s 74ms/step - loss: 0.0971 - accuracy: 0.9670 - val_loss: 0.1068 - val_accuracy: 0.9587
Epoch 3/5
458/458 [==============================] - 35s 75ms/step - loss: 0.0718 - accuracy: 0.9754 - val_loss: 0.0585 - val_accuracy: 0.9854
Epoch 4/5
458/458 [==============================] - 34s 73ms/step - loss: 0.0709 - accuracy: 0.9757 - val_loss: 0.0960 - val_accuracy: 0.9587
Epoch 5/5
458/458 [==============================] - 35s 76ms/step - loss: 0.0562 - accuracy: 0.9812 - val_loss: 0.0652 - val_accuracy: 0.9806
```

- **Application of models with Preprocessing**

CNN :-

```
Epoch 1/15
351/351 [==============================] - 42s 96ms/step - loss: 0.1371 - accuracy: 0.9562 - val_loss: 0.0012 - val_accura
cy: 1.0000
Epoch 2/15
351/351 [==============================] - 4s 12ms/step - loss: 4.6098e-04 - accuracy: 1.0000 - val_loss: 1.9573e-04 - val
_accuracy: 1.0000
Epoch 3/15
351/351 [==============================] - 4s 12ms/step - loss: 1.1702e-04 - accuracy: 1.0000 - val_loss: 9.8322e-05 - val
_accuracy: 1.0000
Epoch 4/15
351/351 [==============================] - 4s 12ms/step - loss: 5.9907e-05 - accuracy: 1.0000 - val_loss: 6.1083e-05 - val
_accuracy: 1.0000
Epoch 5/15
351/351 [==============================] - 4s 12ms/step - loss: 3.5668e-05 - accuracy: 1.0000 - val_loss: 4.1480e-05 - val
```

MobileNet :-

```
Epoch 1/15
351/351 [==============================] - 188s 520ms/step - loss: 0.3924 - accuracy: 0.8579 - val_lo
ss: 0.2259 - val_accuracy: 0.9140
Epoch 2/15
351/351 [==============================] - 172s 491ms/step - loss: 0.1282 - accuracy: 0.9582 - val_lo
ss: 0.0652 - val_accuracy: 0.9807
Epoch 3/15
351/351 [==============================] - 178s 507ms/step - loss: 0.0831 - accuracy: 0.9735 - val_lo
ss: 0.0579 - val_accuracy: 0.9811
Epoch 4/15
351/351 [==============================] - 188s 537ms/step - loss: 0.0568 - accuracy: 0.9813 - val_lo
ss: 0.0241 - val_accuracy: 0.9960
Epoch 5/15
351/351 [==============================] - 187s 534ms/step - loss: 0.0460 - accuracy: 0.9858 - val_lo
ss: 0.0533 - val_accuracy: 0.9803
```

VGG16 :-

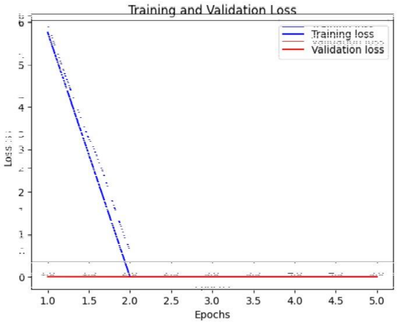
```
Epoch 1/15
351/351 [==============================] - 755s 2s/step - loss: 0.5184 - accuracy: 0.8094 - val_loss:
0.2237 - val_accuracy: 0.9164
Epoch 2/15
351/351 [==============================] - 812s 2s/step - loss: 0.2185 - accuracy: 0.9226 - val_loss:
0.1765 - val_accuracy: 0.9293
Epoch 3/15
351/351 [==============================] - 789s 2s/step - loss: 0.1642 - accuracy: 0.9401 - val_loss:
0.2315 - val_accuracy: 0.9032
Epoch 4/15
351/351 [==============================] - 804s 2s/step - loss: 0.1270 - accuracy: 0.9554 - val_loss:
0.1635 - val_accuracy: 0.9325
Epoch 5/15
351/351 [==============================] - 796s 2s/step - loss: 0.1138 - accuracy: 0.9597 - val_loss:
0.0770 - val_accuracy: 0.9755
```

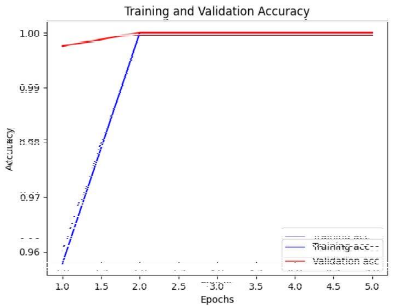
Evaluation Matrices

- Application of models with Processing and class balancing

Loss

Accuracy

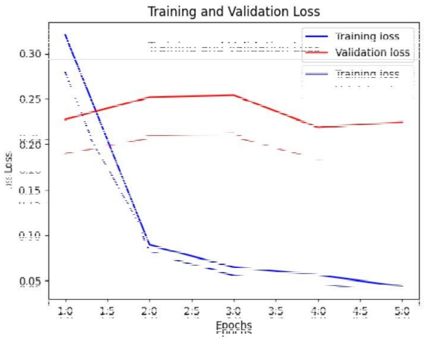


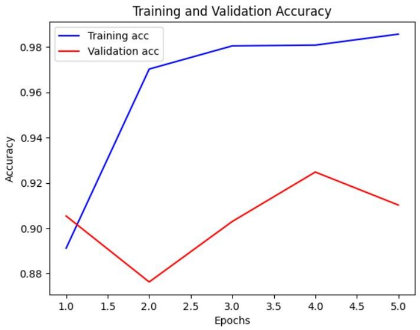


CNN

Loss

Accuracy

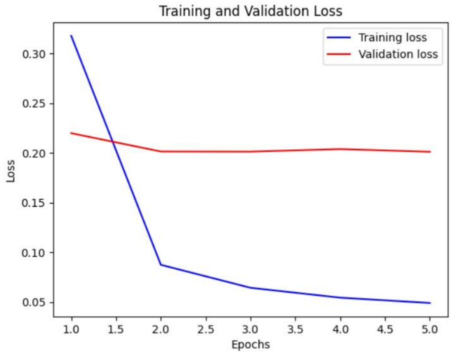


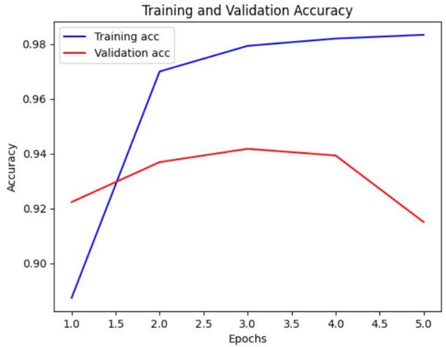


MobileNet

Loss

Accuracy



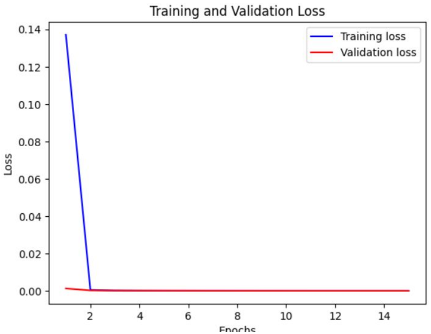


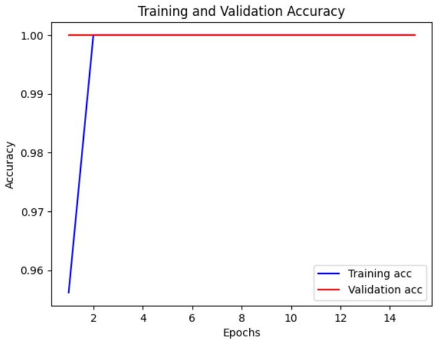
VGG16

- Application of models with Preprocessing

Loss

Accuracy

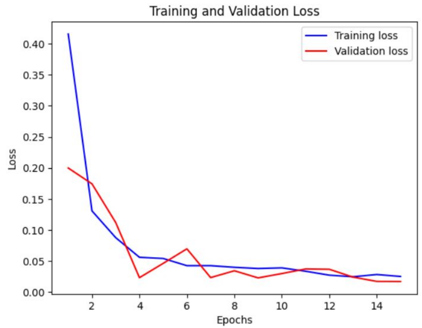


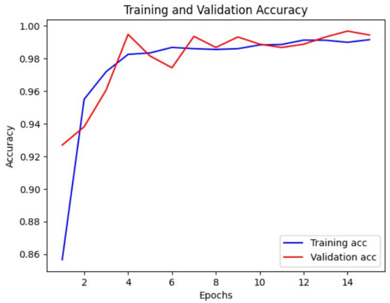


CNN

Loss

Accuracy

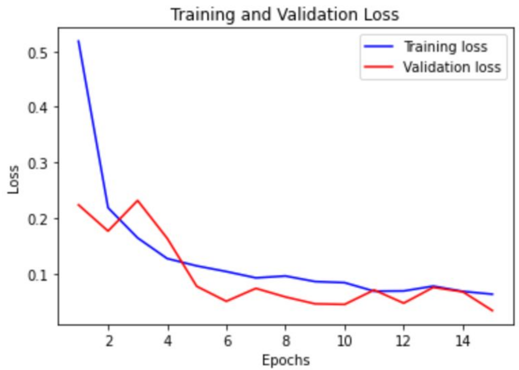


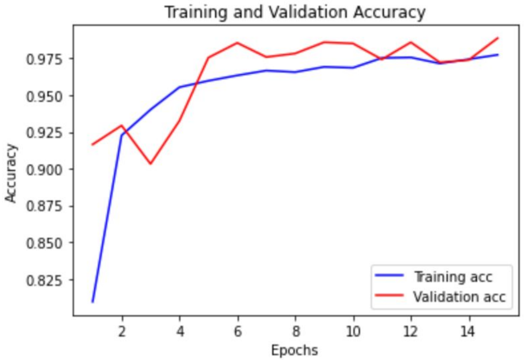


MobileNet

Loss

Accuracy





VGG16

Experimental Results

Performance Metrics for the Entire Dataset

- IoU(Intersection over Union): 0.6789
- PSNR (Peak Signal-to-Noise Ratio) : 33.7666067946768 dB
- MSE: 27.316162109375
- SSIM (Structural Similarity Index Measure) : 0.9398392577862035

Application of models with preprocessing & class balancing

Model	Training Accuracy	Validation Accuracy
CNN	100%	100%
VGG16	97.33%	90.50%
MobileNet	98.57%	91.02%

Application of models with preprocessing

Model	Training Accuracy	Validation Accuracy
CNN	99.124%	100%
VGG16	91.744%	93.138%
MobileNet	95.134%	97.042%

Conclusion and Future Scope

Data Augmentation has helped in more accurate predictions of kidney related diseases, where the application of SMOTE technique for class balancing has helped in solving the problem of overfitting of the models.

We are getting better visible results from **Watershed segmentation** for image segmentation,For enhancing the image quality, **histogram equalisation** has shown good results for the **contrast** of image, **convolution operation** for **sharpening** of image, moreover sharpening filter like **laplacian filter** and smoothing filter like **gaussian filter** has performed well for the spatial domain. For edge detection we have preferred **dilation** over erosion.Various types of noise have also been removed such as **Gaussian noise, Impulse noise, Rayleigh noise** and many more. The images of the entire dataset were denoised with Anisotropic, bilateral, wavefront denoising and etc.

For the prediction and detection of the diseases we have applied CNN in neural networks and used Transfer Learning with the use of MobileNet model, which resulted in high prediction accuracy of the models.

For future scope, the project can be extended to provide the prescription for the disease and the prediction of the duration of the disease and medication time period .

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