

# Application of Machine Learning Algorithms in Presumptive Diagnosis of Urinary System Diseases

Presented by: Group 3

Project 5

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# Outline

- Objective
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- Literature Review
- Methodology
- Results
- Conclusion

# Objective

## Problem Statement

- Our goal is to predict whether the patient has inflammation or nephritis or both or none.

## Objectives

- The expert system was developed to assist healthcare professionals in diagnosing and treating patients.
- Trained the dataset on multiple machine learning algorithms and compared the performance metrics such as precision, recall, f1 score and confusion matrix.

# Introduction

The expert system that we had come up with will have 4 consequences for the given 6 features. The table below shows the output consequences.

- Acute Inflammation of urinary bladder is characterized by sudden occurrence of pains in the abdomen region and the urination.
- Acute nephritis of renal pelvis begins with sudden fever, nausea and vomiting.

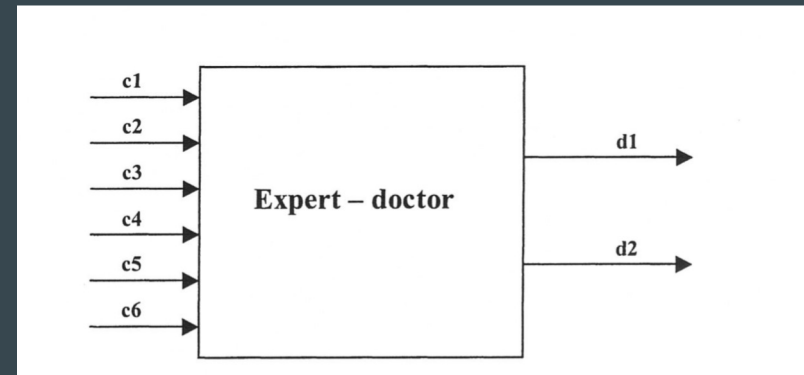
c1	c2	c3	c4	c5	c6	d1	d2
p	no	no	yes	yes	no	yes	no
w	yes	yes	yes	yes	yes	yes	yes
g	no	yes	yes	no	yes	no	yes
p	no	yes	no	no	no	no	no
w	yes	yes	yes	yes	no	yes	yes
p	no	no	yes	yes	yes	yes	no
w	no	no	no	no	no	no	no
p	no	no	yes	no	no	yes	no
n	no	no	yes	yes	yes	yes	no
n	no	yes	no	no	no	no	no
w	yes	yes	no	yes	no	no	yes
w	no	yes	yes	no	yes	no	yes

n=normal temperature( $36^{\circ}$ - $37^{\circ}$ ) C,

p=subfebrile  
temperature( $37^{\circ}$ - $38^{\circ}$ ) C,

g=febrile state( $38^{\circ}$ - $40^{\circ}$ ) C,

w=high fever(above  $40^{\circ}$ ) C,



# Dataset

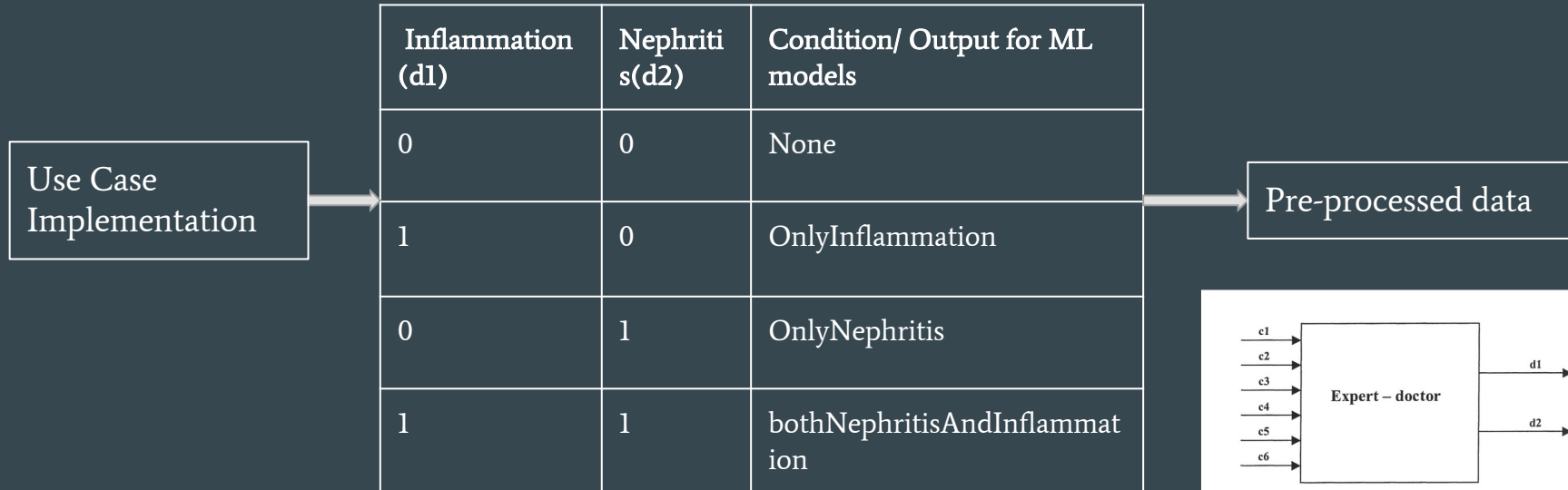
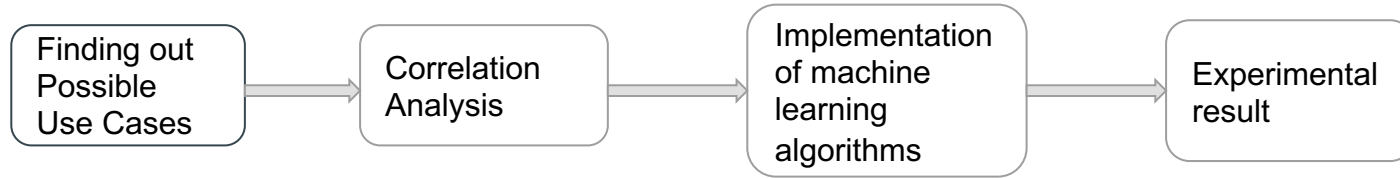
- Acute Inflammation Dataset
- The dataset includes information on 120 patients.
- Each patient is described by six clinical features and two diseases.
- Temperature – continuous.
- Other features – categorical

	Temperature	Nausea	Lumbar Pain	Urine Pushing	Micturition pains	Burning	Inflammation	Nephritis
0	35.5	0	1	0	0	0	0	0
1	35.9	0	0	1	1	1	1	0
2	35.9	0	1	0	0	0	0	0
3	36.0	0	0	1	1	1	1	0
4	36.0	0	1	0	0	0	0	0
...	...	...	...	...	...	...	...	...
115	41.4	0	1	1	0	1	0	1
116	41.5	0	0	0	0	0	0	0
117	41.5	1	1	0	1	0	0	1
118	41.5	0	1	1	0	1	0	1
119	41.5	0	1	1	0	1	0	1

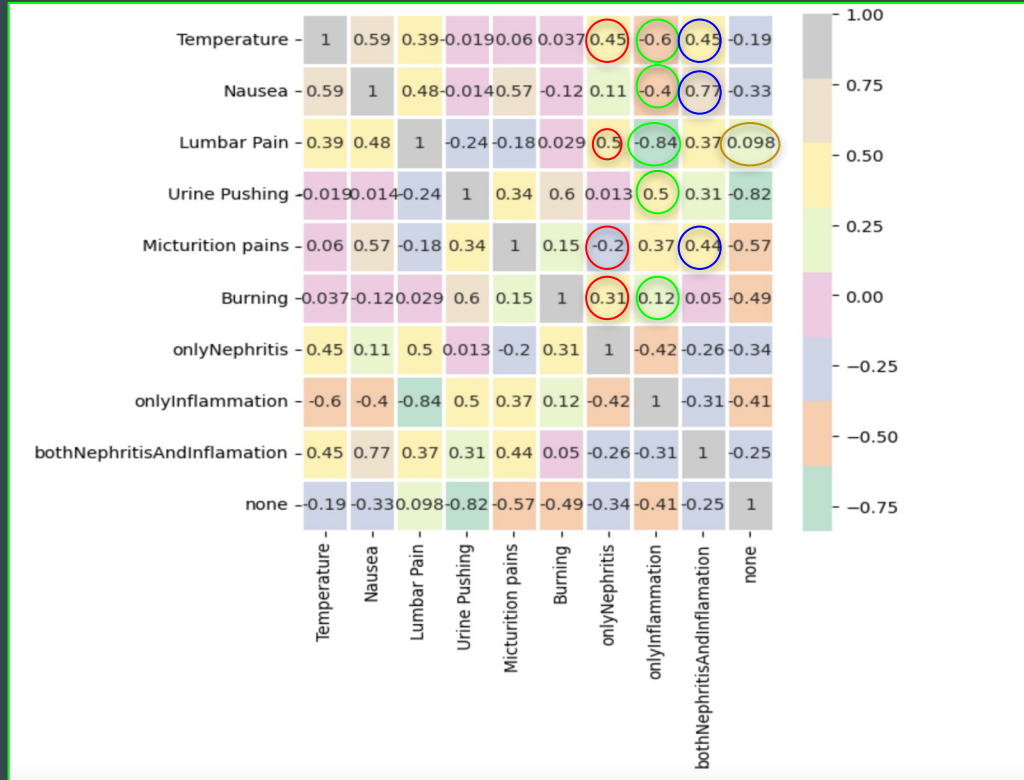
# Literature Review

Authors	Title	Findings/Limitations
Czerniak, J. M., & Zarzycki, H. (2003)	Application of rough sets in the presumptive diagnosis of urinary system diseases.	Introduces an expert model system which performs presumptive diagnosis on acute Nephritis and acute Inflammation
(Baxt, 1995) (Saritas, 2012)	Application of artificial neural networks to clinical medicine, Prediction of Breast Cancer Using Artificial Neural Networks	AI implemented in the field of medicine for several purposes, including the categorization and diagnosis of illnesses, the suggestion of treatments.
Ozkan et al. (2018)	Diagnosis of urinary tract infection based on artificial intelligence methods	Implemented classification task to diagnosis UTI with Decision Tree, SVMs. Random Forest and ANN .

# Methodology



# Results -Correlation Analysis



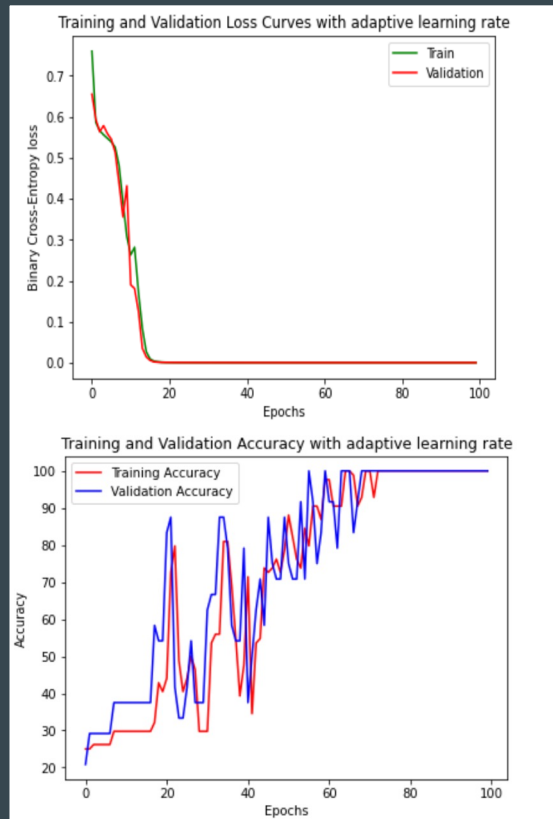


# Results -ANN

## Baseline Settings

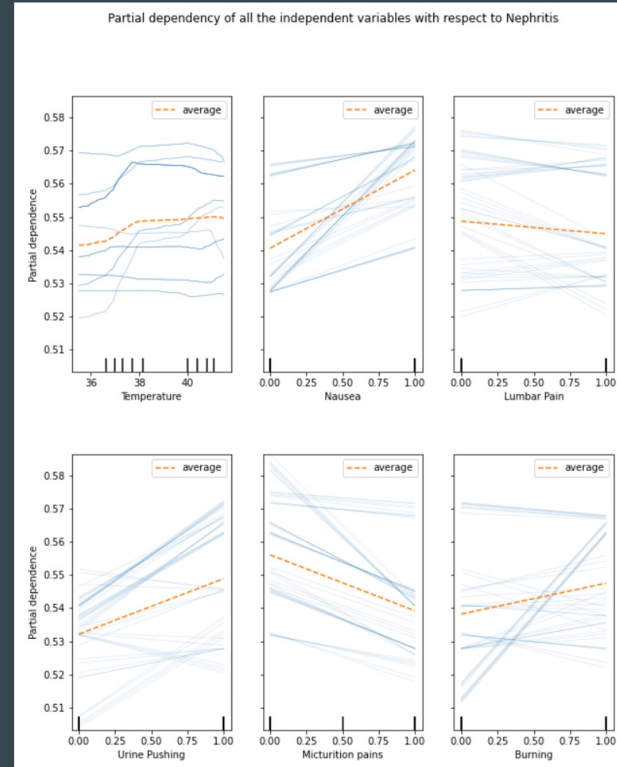
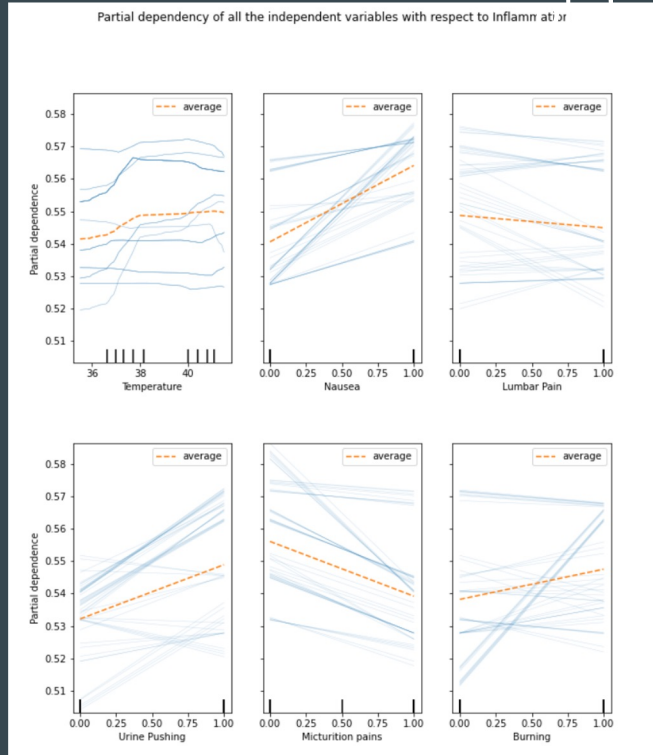
## Training and Validation Loss and Accuracy

```
1 import torch.nn.functional as F
2 class Net(T.nn.Module):
3     def __init__(self, InputNumbers):
4         super(Net, self).__init__()
5         self.hid1 = T.nn.Linear(InputNumbers, 128)
6         self.bn1 = T.nn.LayerNorm(128)
7         self.hid2 = T.nn.Linear(128, 64)
8         self.bn2 = T.nn.LayerNorm(64)
9         self.oupt = T.nn.Linear(64, 4)
10
11         T.nn.init.xavier_uniform_(self.hid1.weight)
12         T.nn.init.zeros_(self.hid1.bias)
13         T.nn.init.kaiming_normal_(self.hid2.weight)
14         T.nn.init.zeros_(self.hid2.bias)
15         T.nn.init.xavier_uniform_(self.oupt.weight)
16         T.nn.init.zeros_(self.oupt.bias)
17         self.dropout = T.nn.Dropout(0.25)
18
19         self.leakyRelu = T.nn.LeakyReLU(0.1)
20         self.sigmoid = T.nn.Sigmoid()
21
22     def forward(self, x):
23         z = self.leakyRelu(self.hid1(x))
24         z = self.leakyRelu(self.hid2(z))
25         z = self.leakyRelu(self.bn2(z))
26         z = self.oupt(z)
27         z = self.sigmoid(z)
28         return z
29
30 criterion = T.nn.BCELoss()
31 # optimizer = T.optim.SGD(net.parameters(), lr=lrn_rate)
32 optimizer = T.optim.RAdam(net.parameters(), lr=lrn_rate)
33
34 " ReduceLRonPlateau: implements apative learning rate "
35 #Reduces the learning rate after 2 epochs if there is no improvement with the model"
36 scheduler = T.optim.lr_scheduler.ReduceLRonPlateau(optimizer, mode='min', patience=3)
37
```

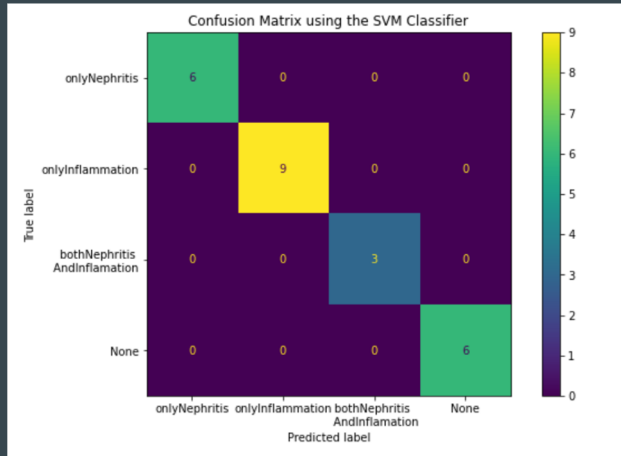


# Results -ANN

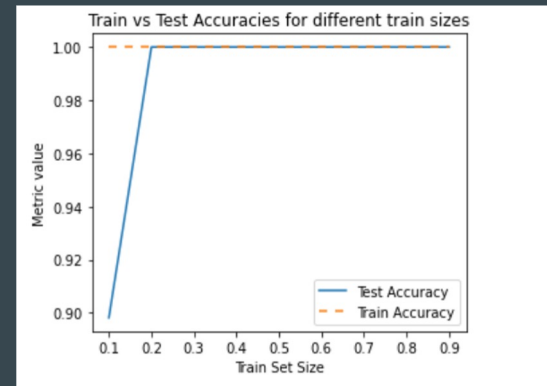
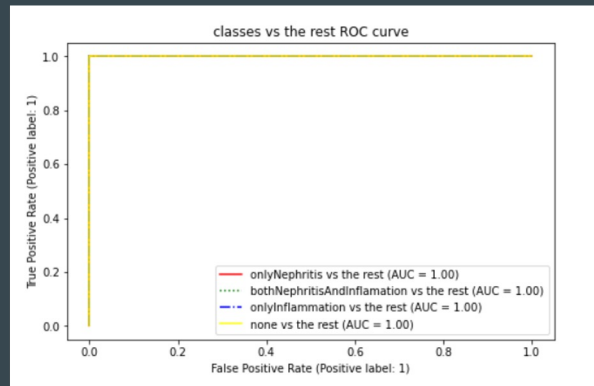
## Partial Dependence



# Results– SVM Classifier

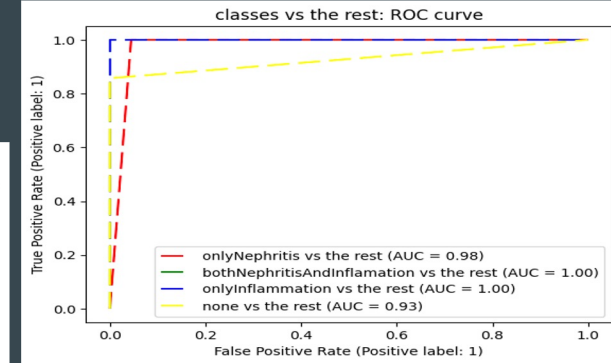
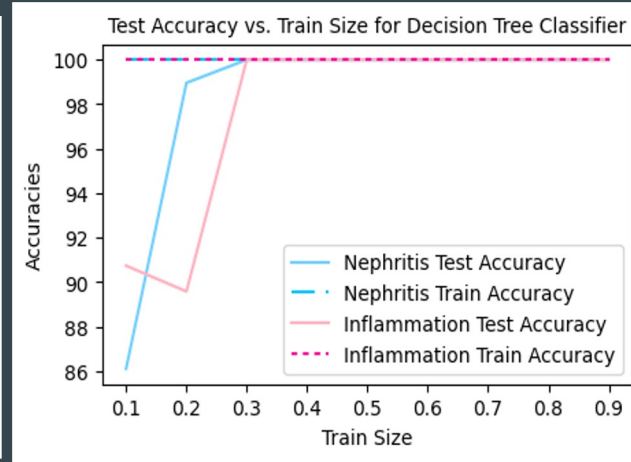
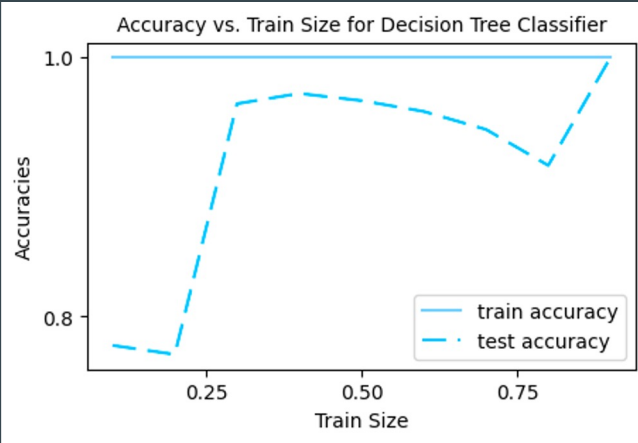


	precision	recall	f1-score	support
onlyNephritis	1.00	1.00	1.00	6
onlyInflammation	1.00	1.00	1.00	9
bothNephritisAndInflammation	1.00	1.00	1.00	3
None	1.00	1.00	1.00	6
accuracy			1.00	24
macro avg	1.00	1.00	1.00	24
weighted avg	1.00	1.00	1.00	24

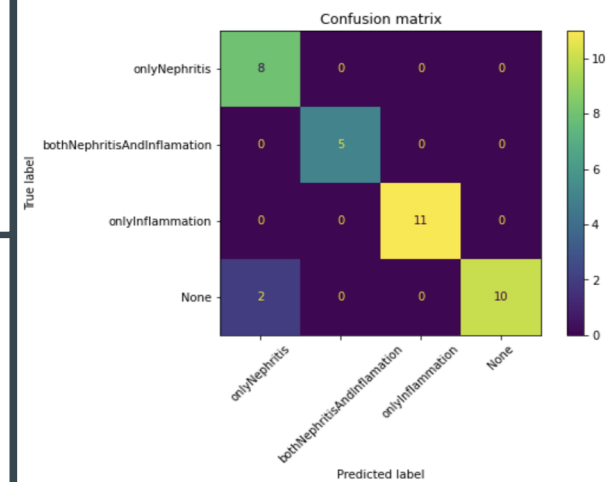


# Results -Decision Tree Classifier

Train Size =0.7

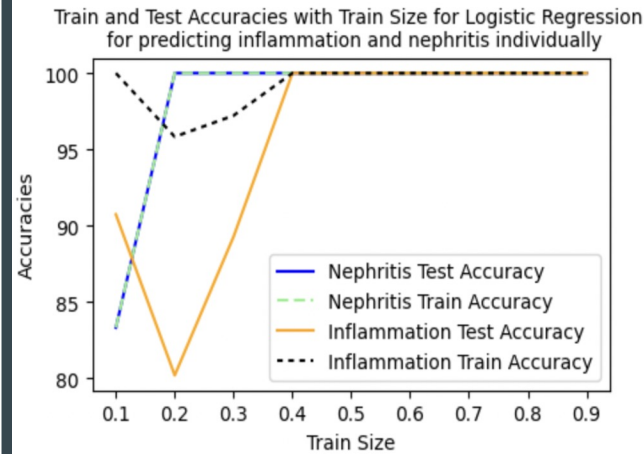
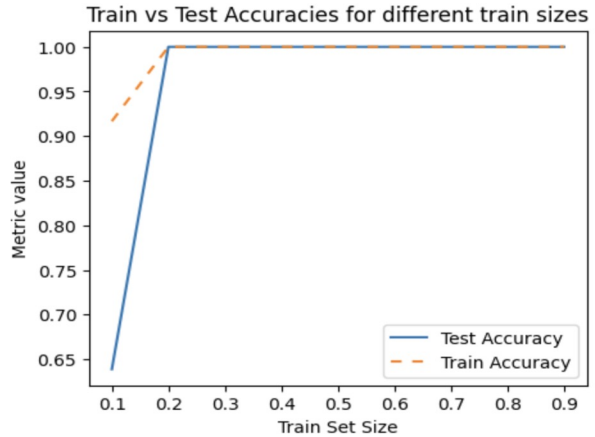


	precision	recall	f1-score
0	0.80	1.00	0.89
1	1.00	1.00	1.00
2	1.00	1.00	1.00
3	1.00	0.83	0.91
accuracy			0.94
macro avg	0.95	0.96	0.95

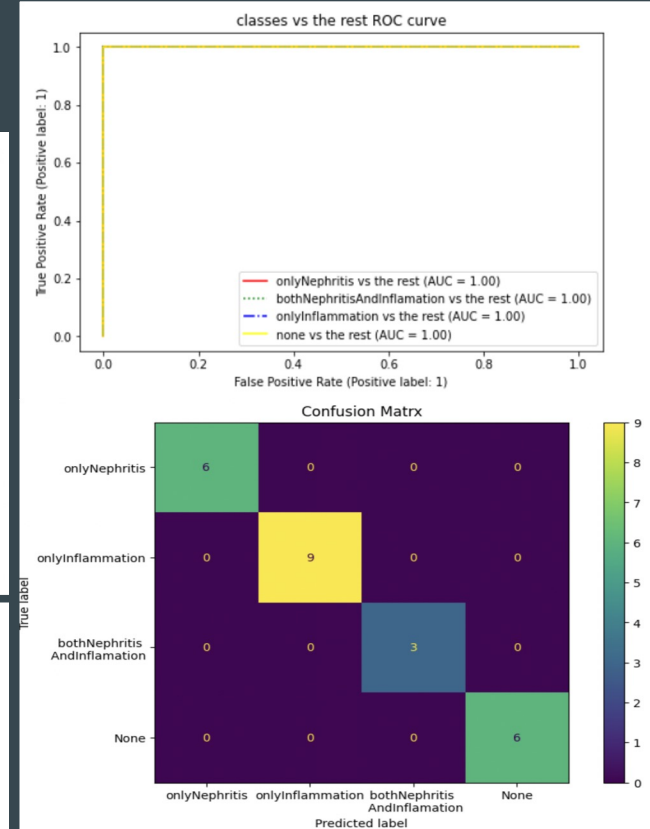


# Results -Logistic Regression

Train Size =0.8



	precision	recall	f1-score
onlyNephritis	1.00	1.00	1.00
onlyInflammation	1.00	1.00	1.00
bothNephritisAndInflammation	1.00	1.00	1.00
None	1.00	1.00	1.00
accuracy			1.00
macro avg	1.00	1.00	1.00
weighted avg	1.00	1.00	1.00



# Conclusion

- All the algorithms that we used performed well with 100% accuracy.
- There is a probability of getting overfitting as our dataset is small.
- For further work one can work on generate synthetic data using GAN so that we might have more dataset.
- Further research can be carried out integrating weighted average of each model to give the final prediction.

# References

- Czerniak, J. M., & Zarzycki, H. (2003). Application of rough sets in the presumptive diagnosis of urinary system diseases. In *Springer eBooks* (pp. 41–51). Springer Nature. [https://doi.org/10.1007/978-1-4419-9226-0\\_5](https://doi.org/10.1007/978-1-4419-9226-0_5)
- Baxt, W. G. (1995). Application of artificial neural networks to clinical medicine. *The Lancet*, 346(8983), 1135–1138. [https://doi.org/10.1016/s0140-6736\(95\)91804-3](https://doi.org/10.1016/s0140-6736(95)91804-3)
- Ozkan, I. A., Koklu, M., & Sert, I. U. (2018). Diagnosis of urinary tract infection based on artificial intelligence methods. *Computer Methods and Programs in Biomedicine*, 166, 51–59. <https://doi.org/10.1016/j.cmpb.2018.10.007>