

KIDNEY DISEASE DETECTION

A photograph of a kidney specimen held by a person wearing a blue nitrile glove. The kidney is a reddish-brown organ with visible internal structures like renal pyramids and renal papillae. The background is dark, making the kidney stand out.

Using Transfer Learning Techniques

Team Data Wranglers

CONTENTS

01

Problem Statement

02

Dataset

03

Tools Used

04

Approach &
Outcome

05

Exploring the
Detection Model

06

Future Potential &
Conclusion



01 PROBLEM STATEMENT



This research project aims to create a model that can accurately detect whether a kidney image has a disease and classify the disease as severe or not. By training the model on a large dataset of kidney images, we hope to create a tool that can assist medical professionals in diagnosing kidney diseases quickly and accurately. The project uses state-of-the-art machine learning techniques to improve patient outcomes and reduce the burden on healthcare systems by enabling earlier and more accurate diagnosis of kidney diseases.



02 DATASET



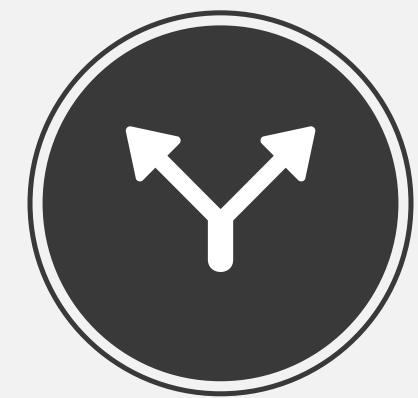
Data Collection

The dataset was collected from PACS (Picture archiving and communication system) from different hospitals in Dhaka, Bangladesh where patients were already diagnosed with having a kidney tumor, cyst, normal or stone findings.



Pre-Processing and Augmentation

The images were resized to (224x250 px) and batch normalization was performed along with Data Augmentation to prevent overfitting and get faster training time



Splitting the Data

The dataset was split into the train (80%), test (10%), and val (10%) datasets for easy usage.

03 TOOLS USED

TEAM DATA WRANGLARS

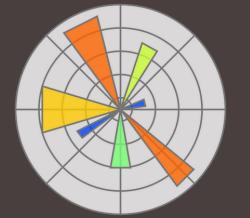
The Model was made using various Python libraries such as NumPy, Pandas, Matplotlib, Seaborn, Scikit-learn and TensorFlow and was deployed using Gradio



NumPy



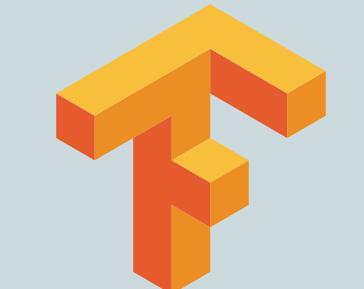
Pandas



Matplotlib



seaborn



Tensorflow

04

APPROACH AND OUTCOME

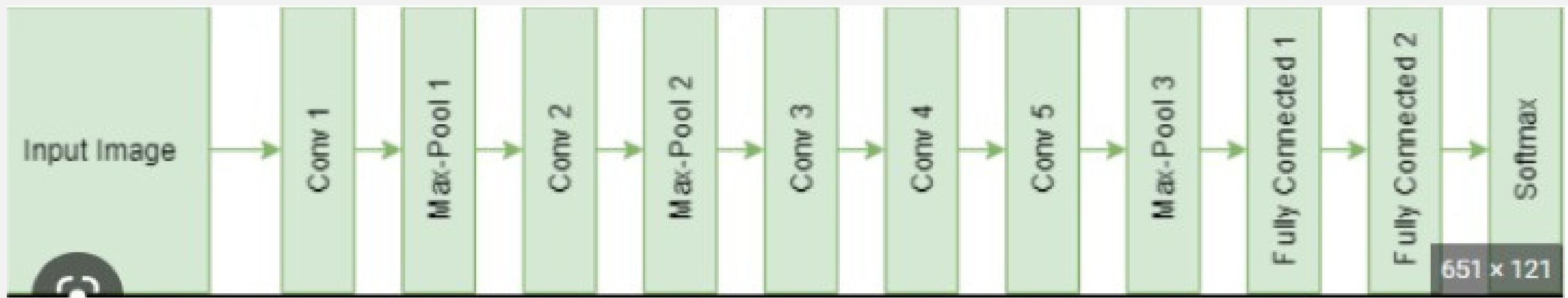
FACTORS CONSIDERED WHILE CHOOSING THE MODEL

-  Type of Dataset
-  Model Complexity
-  Predictive Power
-  Cost
-  Time Efficiency

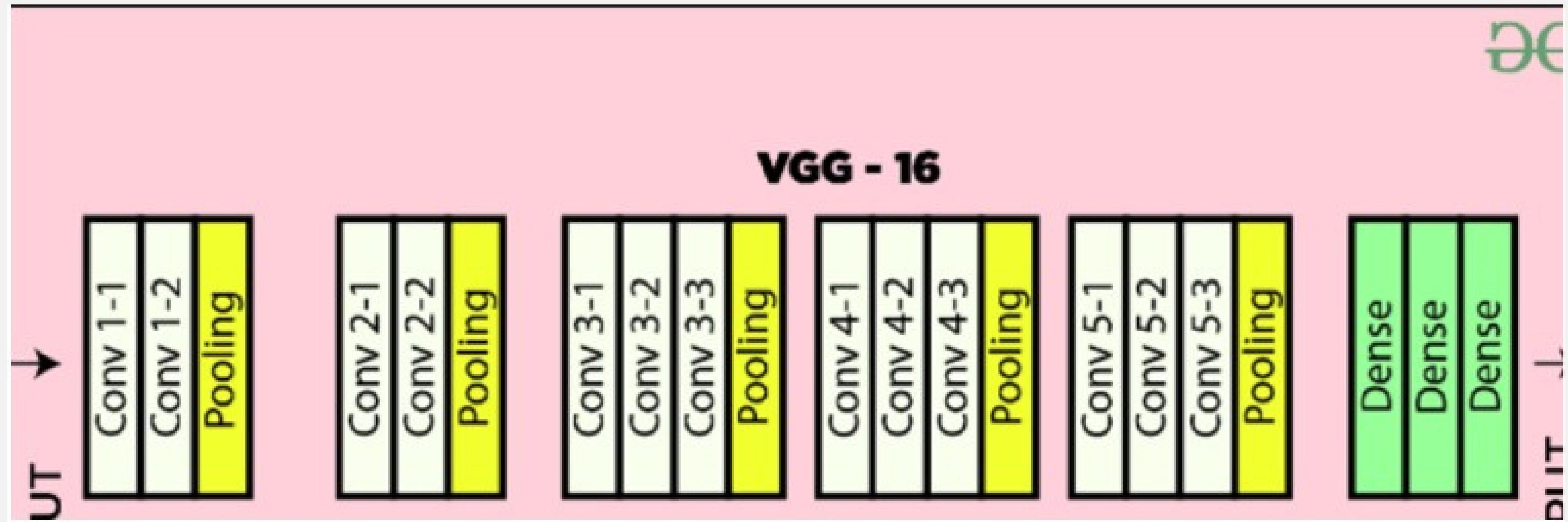
EFFICIENT-NET B3

| Stage i | Operator $\hat{\mathcal{F}}_i$ | Resolution $\hat{H}_i \times \hat{W}_i$ | #Channels \hat{C}_i | #Layers \hat{L}_i |
|--------------|-----------------------------------|--------------------------------------------|--------------------------|------------------------|
| 1 | Conv3x3 | 224×224 | 32 | 1 |
| 2 | MBConv1, k3x3 | 112×112 | 16 | 1 |
| 3 | MBConv6, k3x3 | 112×112 | 24 | 2 |
| 4 | MBConv6, k5x5 | 56×56 | 40 | 2 |
| 5 | MBConv6, k3x3 | 28×28 | 80 | 3 |
| 6 | MBConv6, k5x5 | 14×14 | 112 | 3 |
| 7 | MBConv6, k5x5 | 14×14 | 192 | 4 |
| 8 | MBConv6, k3x3 | 7×7 | 320 | 1 |
| 9 | Conv1x1 & Pooling & FC | 7×7 | 1280 | 1 |

ALEX-NET



VGG-16



CLASSIFICATION REPORT

Classification Report:

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Cyst | 0.9946 | 0.9928 | 0.9937 | 556 |
| Normal | 0.9987 | 0.9948 | 0.9967 | 762 |
| Stone | 0.9810 | 0.9952 | 0.9880 | 207 |
| Tumor | 0.9942 | 0.9971 | 0.9956 | 342 |
| accuracy | | | 0.9946 | 1867 |
| macro avg | 0.9921 | 0.9950 | 0.9935 | 1867 |
| weighted avg | 0.9947 | 0.9946 | 0.9947 | 1867 |

Accuracy: 0.8262610088070457
Precision: 0.8950967554197584
Recall: 0.7648047745590447
F1_score: 0.7971625228913921

| Classes | Precision | Recall | F1-Score |
|---------|-----------|--------|----------|
| 0 | 0.99 | 0.94 | 0.97 |
| 1 | 0.49 | 0.87 | 0.63 |
| 2 | 0.86 | 0.95 | 0.90 |
| 3 | 0.30 | 0.91 | 0.45 |

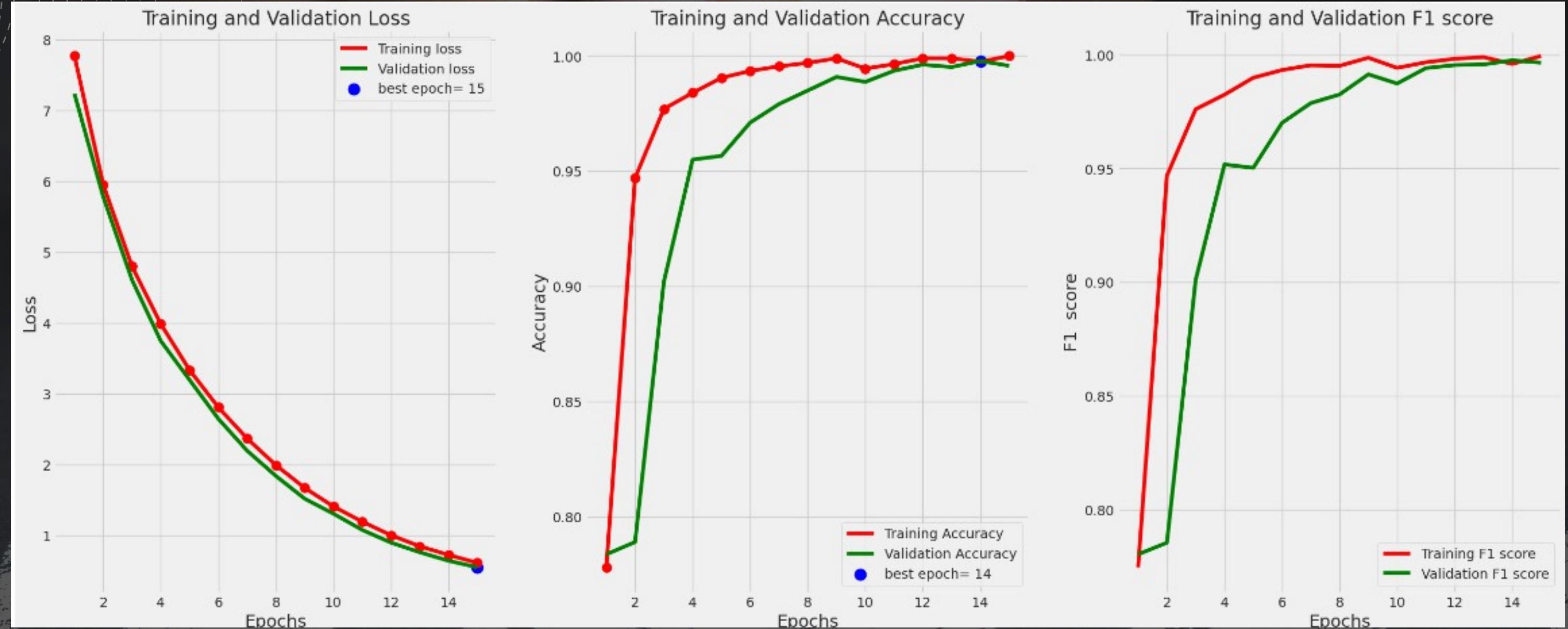
05

EXPLORING THE DETECTION MODEL

The Transfer Learning technique was used to fine-tune the EfficientNet 3 model. The model was enhanced by adding a batch normalization layer, a dense layer with 256 neurons, a dropout layer, and a final output dense layer with the number of neurons equal to the number of classes. Techniques like Resolution Scaling and Width Scaling were used to further improve the model.

Classification Report:

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Cyst | 0.9964 | 0.9856 | 0.9910 | 556 |
| Normal | 1.0000 | 0.9987 | 0.9993 | 762 |
| Stone | 0.9626 | 0.9952 | 0.9786 | 207 |
| Tumor | 1.0000 | 1.0000 | 1.0000 | 342 |
| accuracy | | | 0.9946 | 1867 |
| macro avg | 0.9897 | 0.9949 | 0.9922 | 1867 |
| weighted avg | 0.9948 | 0.9946 | 0.9947 | 1867 |



06 FUTURE POTENTIAL & CONCLUSION

- Kidney stones affect approximately **1 in 11 people worldwide**, and the number of cases is **increasing every year**. Delayed diagnosis and treatment of kidney stones can lead to **serious complications**, including kidney damage, infection, and sepsis.
- With the **increasing prevalence of kidney stones**, the need for a **predictive tool** that can **accurately diagnose** and assess the severity of the condition is critical.
- The Future Versions of this application will be able to provide **actionable advice to medical professionals** and would be able to **track and monitor the patient's health** over time, as well as provide detailed information about the patient's medical history and current treatment plan.
- With the help of this application, medical professionals can better manage the patients and provide **timely treatment**. Additionally, this application can also be used to **educate patients** about the **risks and causes of kidney stones**, as well as provide them with **preventative measures** to reduce the risk.

PRESENTED BY

Shivansh Goel
Divyanshu Singh

Team Data Wranglers

