Automatic Kidney Abnormalities Detection Using CNN

Final Project Report

by

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EDM16B029 & EDM16B040

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DESIGN AND MANUFACTURING, KANCHEEPURAM

May 2020

Certificate

We, **P SAI PRIDHVI & JEEVAN KUMAR**, with Roll No: **EDM16B029 & EDM16B040** hereby declare that the material presented in the Project Report titled **Kidney Abnormalities Detection Using CNN** represents original work carried out by me in the **Department of Electronics and Communication Engineering** at the **Indian Institute of Information Technology, Design and Manufacturing, Kancheepuram** during the years **2019–2020**. Under the Guidance of **Dr Priyanaka Kokil**. With our signatures, We certify that:

- We have not manipulated any of the data or results.
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- We have explicitly acknowledged all collaborative research and discussions.
- We have understood that any false claim will result in severe disciplinary action.
- We have understood that the work may be screened for any form of academic misconduct.

Date: Student's Signatures

In our capacity as supervisor of the above-mentioned work, We certify that the work presented in this Report is carried out under our supervision, and is worthy of consideration for the requirements of B.Tech. Project work.

Advisor's Name:Dr Priyanka Kokil Advisor's Signature

Abstract

The chronic kidney disease (CKD) is fatal disease. Thus, it is important to diagnose the kidney diseases at an earlier stage before it cause fatality. This Report proposes an algorithm and fully functioning APP for Automatic kidney abnormalities detection Using CNN at an early stage. Kidney abnormalities detection involves two stages: CNN model and Detection using an Android APP. The input images used in this work are kidney ultrasound (US) images which are classified into two categories such as Normal kidney, Abnormal kidney.

Acknowledgements

I would like to acknowledge and extend my heartfelt gratitude to all those people who have been associated with this project and have helped me with it thus making it a worthwhile experience.

I am extremely grateful to **Dr.Priyanka Kokil** for his timely guidance, motivation, interest shown all through the duration of our project which helped me in expanding my knowledge to achieve the goal.

I would also like to thank **Mr.Sudharsan sir & Mr.Pratap** sir for helping me to complete the project successfully.

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- Principal component analysis (PCA)
- Grey-level co-occurrence matrix (GLCM)
- Gradient features [10],

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- An algorithm of FPGA based IoT en-abled ultrasound system.
- Support Vector Machine (SVM) with Multi-Layer Perceptron (MLP)

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- ROI generation algorithm
- ANN-based Classification
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- State-of-the-art feature

1.1.8 Akkasaligar, Prema T.[8]

- K-nearest neighbors classifier (k-NN)
- Maximum a posteriori (MAP)
- Gaussian,Median,Wiener Filters

1.2 Motivation

Statistics of CKD[10]

- 10% of the population worldwide is affected by chronic kidney disease (CKD), and millions die each year because they do not have access to affordable treatment.
- Over 2 million people worldwide currently receive treatment with dialysis or a kidney transplant to stay alive, yet this number may only represent 10% of people who actually need treatment to live.
- More than 80% of all patients who receive treatment for kidney failure are in affluent countries with universal access to health care and large elderly populations.
- It is estimated that number of cases of kidney failure will increase disproportionately in developing countries, such as China and India, where the number of elderly people are increasing.
- In middle-income countries, treatment with dialysis or kidney transplantation creates a huge financial burden for the majority of the people who need it. In another 112 countries, many people cannot afford treatment at all, resulting in the death of over 1 million people annually from untreated kidney failure.
- Noncommunicable diseases (such as heart disease, diabetes, or kidney disease) have replaced communicable diseases (such as influence, malaria, or AIDs) as the most common causes of premature death worldwide. An estimated 80% of this burden occurs in low- or middle-income countries, and 25% is in people younger than 60 years.
- According the 2010 Global Burden of Disease study,it remains among the few growing causes of mortality which made CKD the 13th leading cause of death in 2013; this compared to ranking 27th in 1990, but rose to 18th in 2010.
- Chronic kidney disease can be treated. With early diagnosis and treatment, it's possible to slow or stop the progression of kidney disease.

1.3 What is Chronic Kidney Disease?

Chronic kidney disease (CKD) is a major Global health issue because of its high risk of end-stage renal disease (ESRD). CKD is decrease in functionality of kidney.The kidneys filter waste and excess fluid from the blood. As kidneys fail, waste builds up in the blood. In the early stages of the disease, most people do not have symptoms. But as CKD gets worse, wastes can build up in your blood and make you unhealthy .Once kidneys fail, dialysis or a kidney transplant is needed to stay alive. This stage of CKD is known as end-stage renal disease (ESRD).[9]

1.4 Types in Kidney Abnormalities

- Kidney Cysts
- Kidney Stones
- Kidney Cancer(Tumor)

1.5 How is CKD Treated?

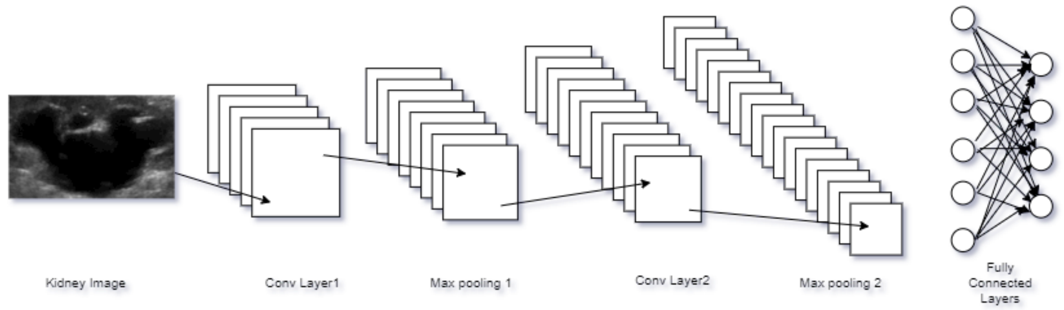
The best treatment of CKD is early detection, when the disease can be slowed or stopped. However, once kidneys fail, treatment with dialysis or a kidney transplant is needed.

1.6 Detection Method

Medical image classification plays an essential role in clinical treatment. However, the traditional method has shown less performance. Moreover, by traditional methods, much time is needed to be spent on extracting and selecting classification features. The deep neural network is an emerging machine learning method that has proven its high Efficiency for different classifications.The convolutional neural network dominates with the best results on varying image classifications.

1.7 CNN

A Convolutional Neural Network (CNN) is a class of deep neural networks, most commonly applied to analyzing visual imagery. Convolutional neural networks have been one of the most influential innovations in the field of computer vision. It indicates that the network employs a mathematical operation called convolution. It is a specialized kind of linear operation.



1.7.1 Convolutional Layers

The convolutional layer is the core building block of a CNN. The layer's parameters consist of a set of learn-able filters (or kernels), which have a small receptive field, but extend through the full depth of the input volume.

1.7.2 Max pooling

The Pooling layer is responsible for reducing the spatial size of the Convolved Feature. This is to decrease the computational power required to process the data through dimensionality reduction.

1.7.3 Kernel size

CNN are basically a stack of layers which are defined by the action of a number of filters on the input. Those filters are usually called kernels.

1.7.4 Pooling size

It reduces the spatial size of the convoluted features in Pooling layers.

1.7.5 Activation

Activation functions are mathematical equations that determine the output of a neural network. The function is attached to each neuron in the network, and determines whether it should be activated or not.

Functions : 'sigmoid', 'relu', 'tanh'

1.7.6 Weights

Each neuron in a neural network computes an output value by applying a specific function to the input. The function that is applied to the input values is determined by a vector of weights and a bias.

1.7.7 Dense layer

A linear operation in which every input is connected to every output by a weight. Generally followed by a non-linear activation function.

1.7.8 L2 Regularisation

In L2 regularization, regularization term is the sum of square of all feature weights as shown above in the equation. L2 regularization forces the weights to be small but does not make them zero and does non sparse solution.

1.7.9 Flatten

Flattening transforms a two-dimensional matrix of features into a vector that can be fed into a fully connected neural network classifier.

1.7.10 Dropout

Dropout is a technique used to prevent a model from over fitting. Dropout works by randomly setting the outgoing edges of hidden units (neurons that make up hidden layers) to 0 at each update of the training phase.

1.8 Compilation & Saving Model

1.8.1 Compile

Render the model of weights for a required no of classifications.

1.8.1.1 Optimizer

Optimizers are algorithms or methods used to change the attributes of your neural network such as weights and learning rate in order to reduce the losses.

Optimizers : 'adam', 'rmsprop', 'SGD'

1.8.1.2 Loss function

A loss function is used to optimize the parameter values in a neural network model.

Loss functions : 'binary_cross-entropy', 'sparse_categorical_cross-entropy'

1.8.1.3 Fit the model

- Batch size - It is a number of samples processed before the model is updated
- Epoch (Iterations) - the number of complete passes through the training data-set.

1.8.2 Saving Model

An H5 file is a data file saved in the Hierarchical Data Format (HDF).It is a file format to store structured data.Keras saves models in this format as it can easily store the weights and model configuration in a single file.

Chapter 2

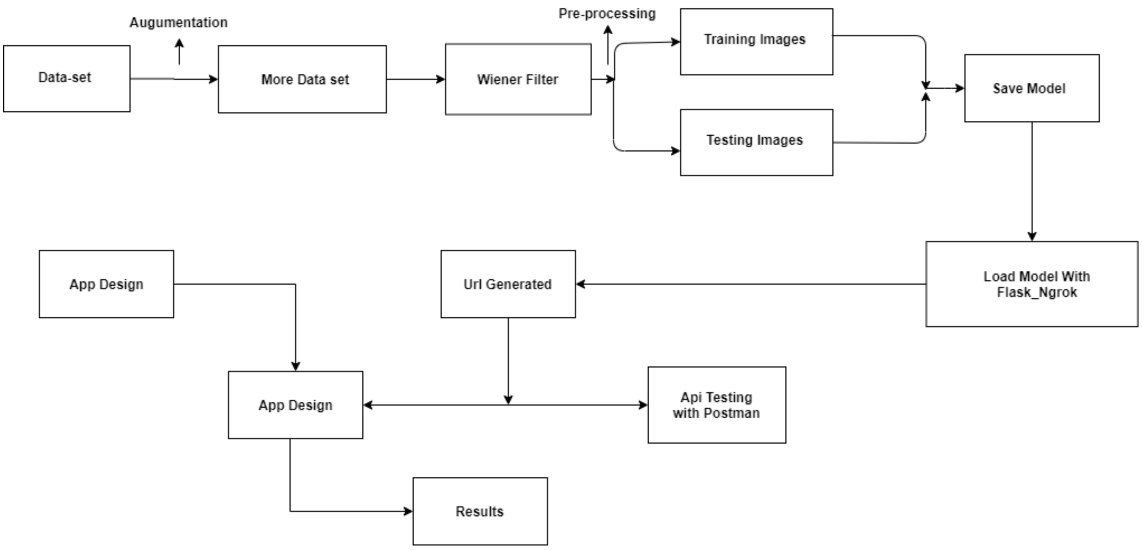
Objectives

- **Collecting as much as Data set Images possible for Training CNN Model.**
- **Increasing Data set Images by Augmentation Technique.**
- **Removing Speckle Noise from Ultrasound Medical Images.**
- **Training a CNN model Effectively for high training & testing accuracy's.**
- **URL generating via Flask.**
- **API testing URL via Postman.**
- **Creating interface between android app and flask URL (Tunnel) via Ngrok.**
- **API testing URL via Designed Android APP.**
- **Results.**
- **Analysis of results of Ultrasound kidney image in the APP shows us the requirement of doctor.**

Chapter 3

Methodology

3.1 Algorithm



3.2 Data-set

- Normal Kidney Images = 60
- Abnormal Kidney Images = 50

3.3 Augmentation

Image data augmentation is a technique that can be used to artificially expand the size of a training data-set by creating modified versions of images in the data-set. There are 6(including the original) modified versions of images.

- (a) Original Image
- (b) rotation_range = 40,
- (c) shear_range = 0.2
- (d) zoom_range = 0.2
- (e) horizontal_flip
- (f) brightness_range = (0.5, 1.5))

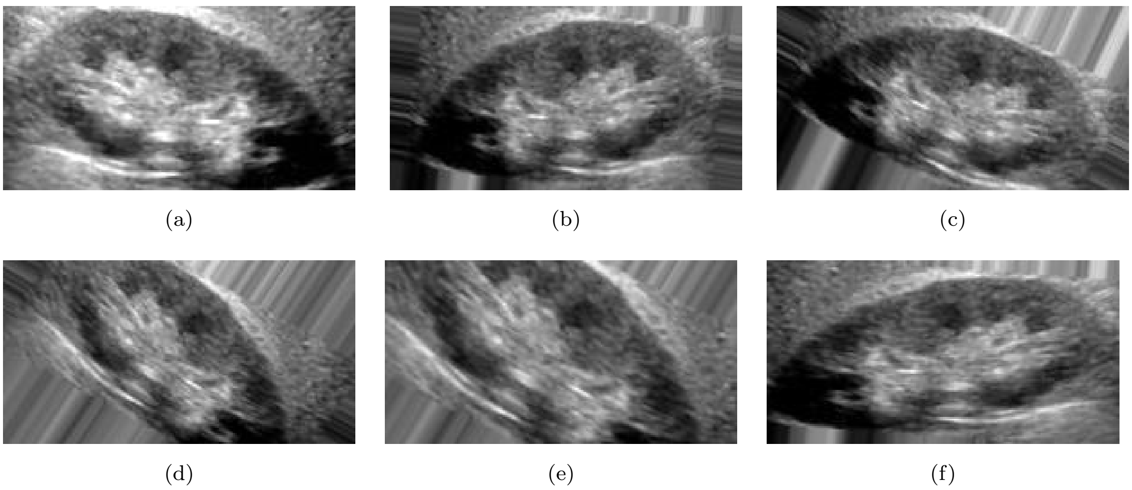


FIGURE 3.1: Augmented Images

3.4 Data-set

- Normal Kidney Images (After Augmentation) = 360
- Abnormal Kidney Images (After Augmentation) = 300

3.5 Pre-processing

The usefulness of ultrasound imaging is degraded by the presence of noise known as speckle. This type of noise is an inherent property of medical ultrasound imaging and because of this noise the image resolution and contrast become reduced, which effects the diagnostic value of this imaging modality . So, speckle noise reduction is an essential pre processing step, whenever ultrasound imaging is used for medical imaging.

3.5.1 De-nosing the Image with Wiener Filter

The Wiener filter is a linear spatial domain filter.To address the multiplicative nature of speckle noise, a homomorphic approach is developed in , which converts the multiplicative noise into additive noise, by taking the logarithm of image and then applies the Wiener filter. Wiener filtering is based on both, global and local statistics and is given by

Formula

$$Y_{ij} = \frac{\sigma_x^2}{\sigma_k^2 + \sigma^2}(K_{uv} - \overline{K}) + \overline{K} \tag{3.1}$$

where Y_{ij} denotes the de-speckled image, $\bar{K}$ is the local mean, σ_k^2 is the local variance, K_{uv} is $(u,v)^{th}$ pixel in the kernel K and σ^2 is the global variance.

(a) (b)

FIGURE 3.2: (a) Normal Image & (b) Filtered Image

3.6 Gray scale conversion

(a) (b)

FIGURE 3.3: Normal to Gray Conversion

3.7 Resizing of images

(a) (b)

FIGURE 3.4: Default size to 224x224

3.8 Weights Normalisation

By re-parameterizing the weights in this way we improve the conditioning of the optimization problem and we speed up convergence of stochastic gradient descent.

img = img/112

3.9 Split Ratio of Training & Testing Images

- Train Images = 70% & Test Images = 30%
- Split Ratio = 0.3

3.10 CNN model

- Normal Kidney images = 360 & Abnormal Kidney Images = 300
- (After Augmentation) Train Images = 462(252+210) & Test Images = 198(108+90) (Split Ratio =0.3)
- Original Image - Gray-scale converted Image
- Gray-scale converted Image - Resizing Image (224x224)
- Resizing Image (224x224) - Wiener Filtered Image
- Wiener Filtered Image - Matrix Array
- Matrix Array - Weights
- Sequential = Convolution layers + Max pooling Layers + Fully Connected layers
- Compile (optimizer='adam', loss='binary_crossentropy'
- Fit Model (Batch-size = 250, epochs=100)
- Save Model(saved_model.h5)

3.11 Convolutional Layers & Connected Layers

Table 3.1: Layers in the Code

Layers	Filters	Kernel Size	Pooling Size	Activation	Regularisation
Conv 1	32	(3,3)		Relu	
Maxpool 1			(2,2)		
Conv 2	64	(3,3)		Relu	
Maxpool 2			(2,2)		
Conv 3	64	(3,3)		Relu	
Maxpool 3			(2,2)		
Flatten	It converts the pooled feature map to a single column				
Dense 1	64			Relu	L2 (0.01)
Dense 2	1			Sigmoid	

3.11.1 Output params image

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 222, 222, 32)      320
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 111, 111, 32)      0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 109, 109, 64)      18496
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 54, 54, 64)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 52, 52, 64)        36928
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 26, 26, 64)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 43264)             0
_________________________________________________________________
dense_2 (Dense)              (None, 64)                2768960
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 65
=================================================================
Total params: 2,824,769
Trainable params: 2,824,769
Non-trainable params: 0
```

3.11.2 Training & Testing Accuracy For 100 Iterations

```
Epoch 100/100
4/4 [==============================] - 20s 5s/step - loss: 0.1721 - accuracy: 0.9843
11/11 [==============================] - 3s 281ms/step - loss: 1.3476 - accuracy: 0.8815
```

Training Accuracy=99% & Testing Accuracy = 89%

3.11.3 Testing Images with Saved Model

```
(224, 224)
(224, 224)
Image name: ab.jpg
 Probs of class 1: [1.]
 Class: [1]
Image name: n.jpg
 Probs of class 1: [1.2600972e-13]
 Class: [0]
```

Chapter 4

URL Generation & API Testing

4.1 Flask

Flask is a lightweight WSGI (Web Server Gateway Interface) web application framework. It is designed to make getting started quick and easy, with the ability to scale up to complex applications.

4.2 Ngrok

Ngrok is a multi-platform tunnelling, reverse proxy software that establishes secure tunnels from a public endpoint such as internet to a locally running network service while capturing all traffic for detailed inspection and replay.

4.3 Flask-Ngrok Platform

- Ngrok is a lightweight tool that creates a secure tunnel on your local machine along with a public URL you can use for browsing your local site.
- Flask is the framework here,once we import Flask, we need to create an instance of the Flask class for our web app.
- We generate Url via Ngrok which is compatible (made via Flask) to run an web application .

4.4 URL Generation Using Flask-Ngrok

We run Flask apps on localhost available over the internet via the Ngrok tool.

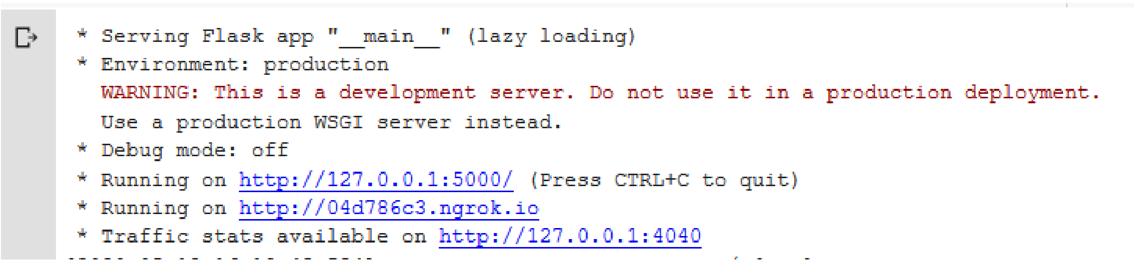
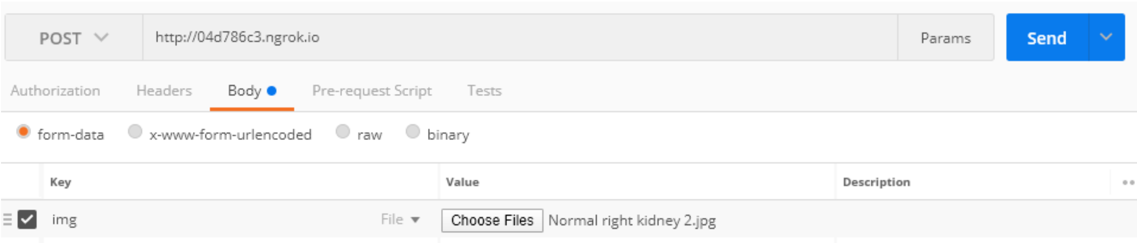
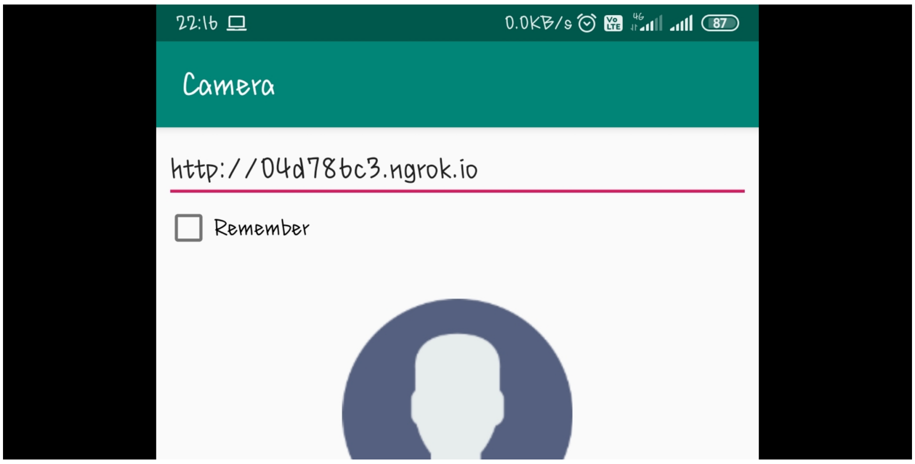


FIGURE 4.1: Server running on Url

4.4.1 Using the generated URL in Postman & Android App



(a)



(b)

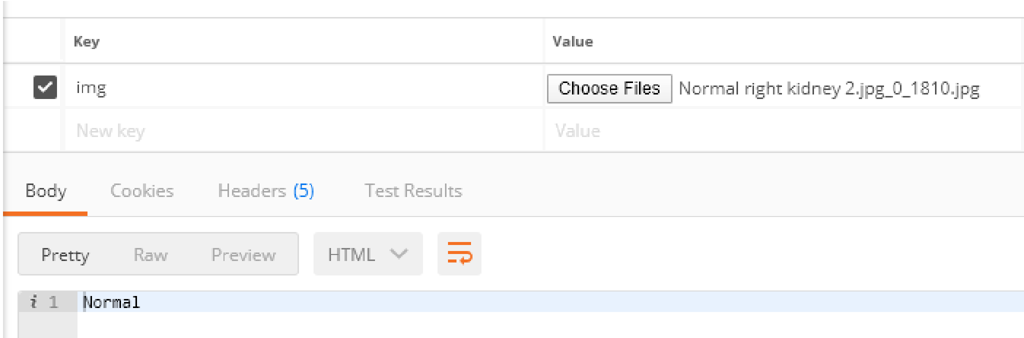
FIGURE 4.2: (a)Url in Postman & (b)Url in App

4.5 API Testing Via Web-services

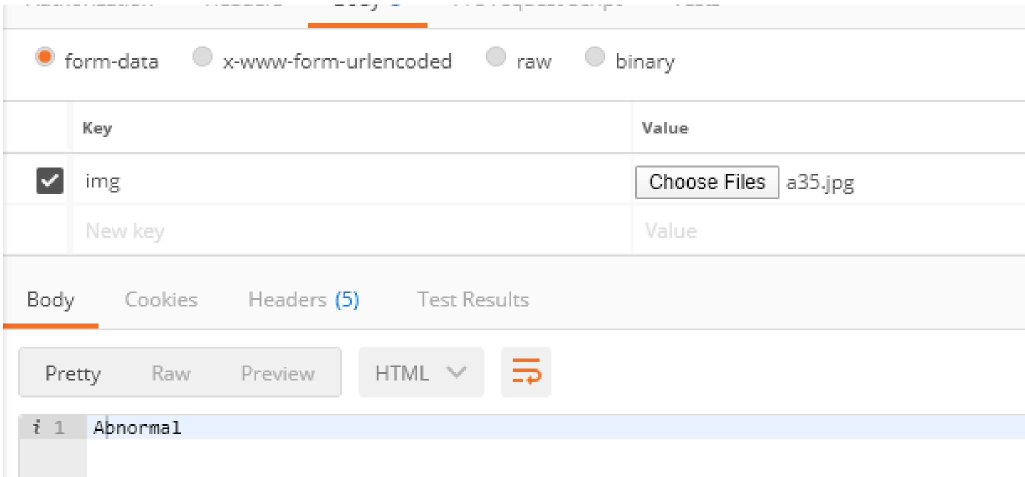
API (application programming interface) testing is a type of software testing that performs verification directly at the API level. It is a part of integration testing that determines whether the API's meet the testers' expectations of functionality, reliability, performance, and security.

Software : **Postman**

Postman is a popular API client that makes it easy for developers to create, share, test and document API's. This is done by allowing users to create and save simple and complex HTTP/s requests, as well as read their responses. The result - more efficient and less tedious work.



(a)



(b)

FIGURE 4.3: (a) Normal Kidney & (b) Abnormal Kidney

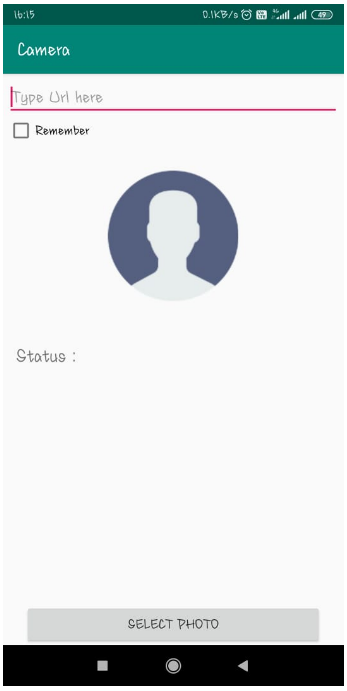
Chapter 5

Android App

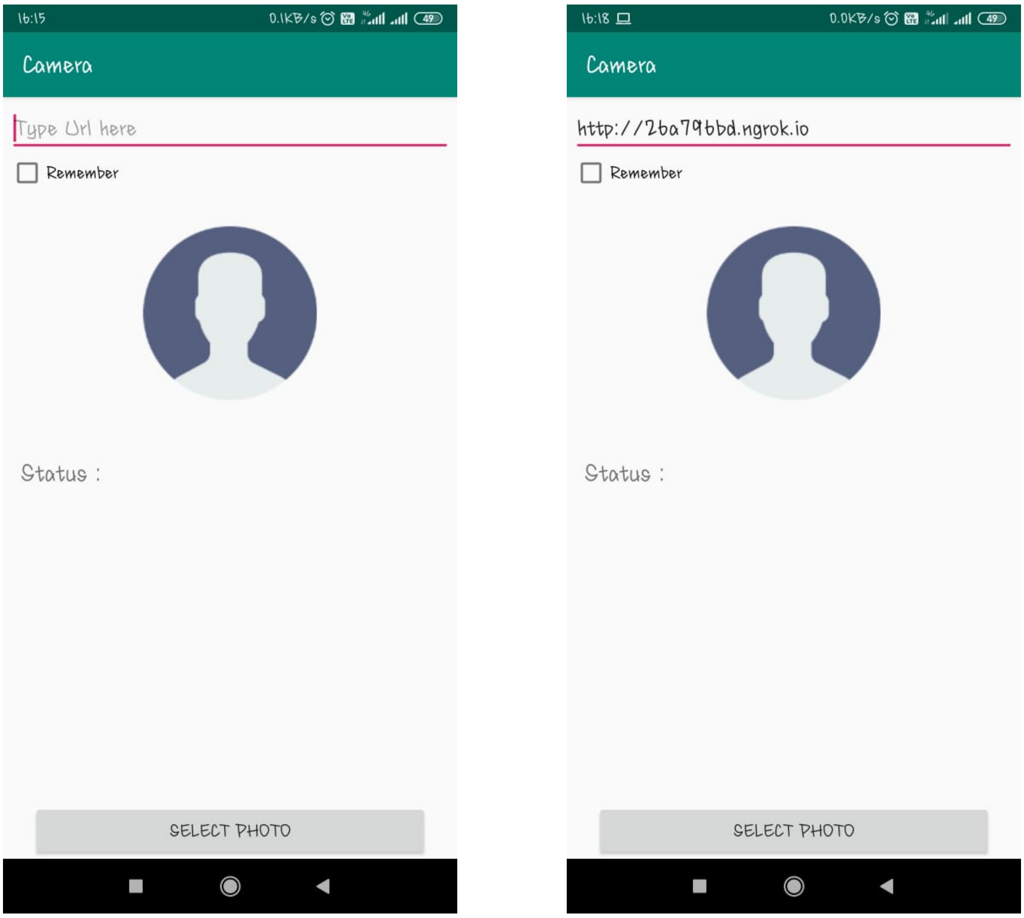
5.1 App Requirements

- **Upload photo** (Button)
- **Url of Saved Model(Python Code)** (Link)
- **Output Status**

.



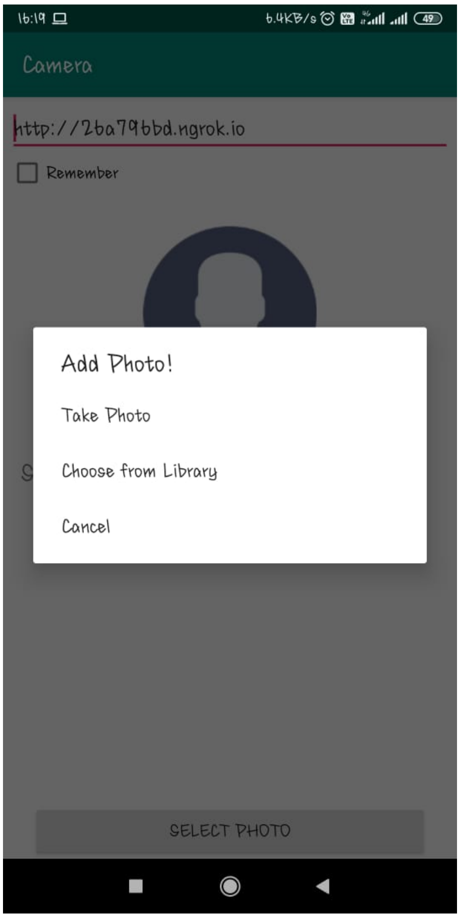
5.2 App Architecture



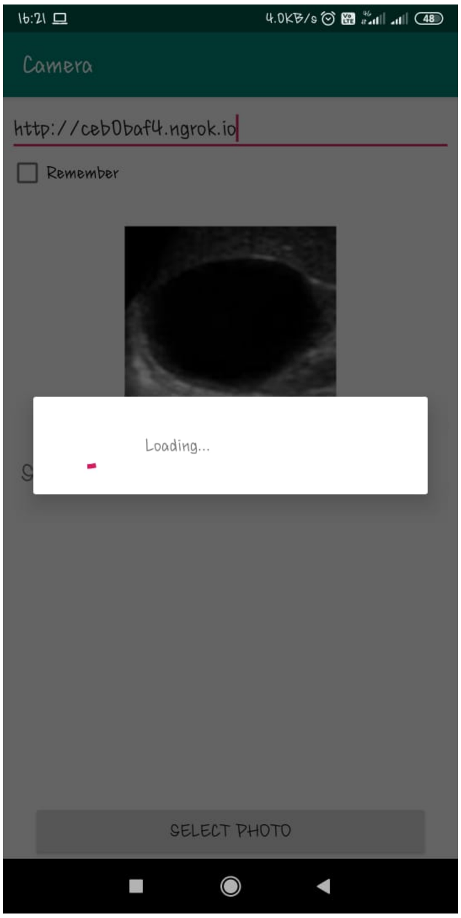
(a) (b)

FIGURE 5.1: (a)Main Frame & (b)Entering Url

5.3 Select the Image & Loading the Image



(a)

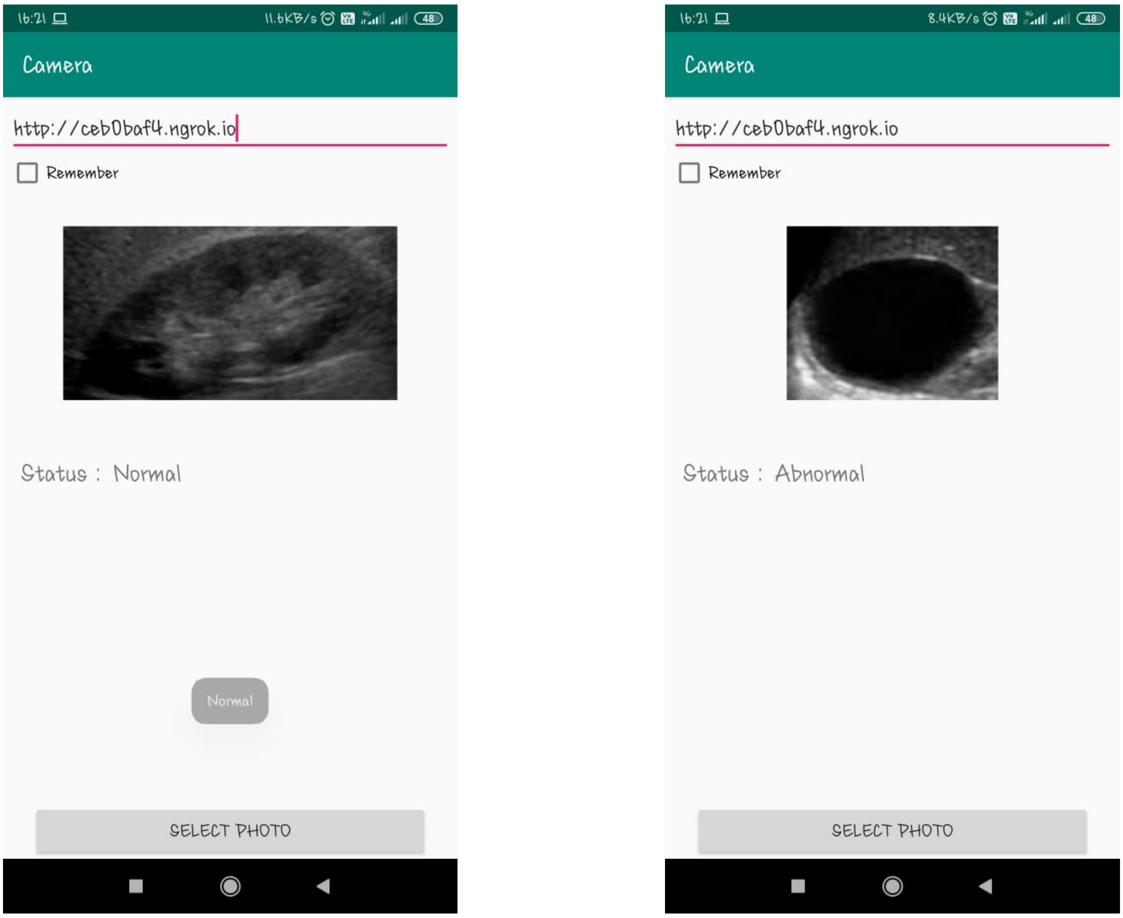


(b)

FIGURE 5.2: (a) Selecting & (b) Loading the image

Chapter 6

Results



(a) (b)

FIGURE 6.1: (a) Normal Kidney & (b) Abnormal Kidney

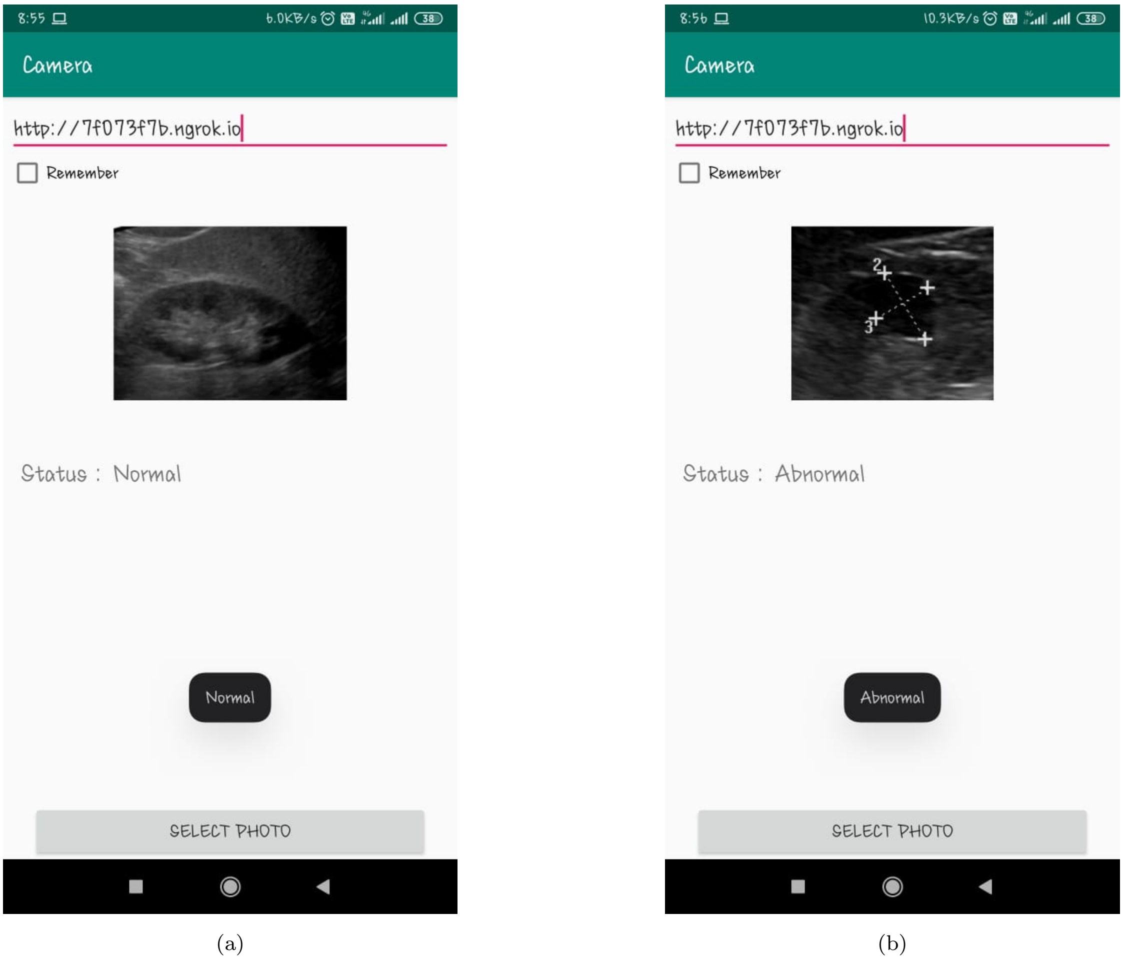
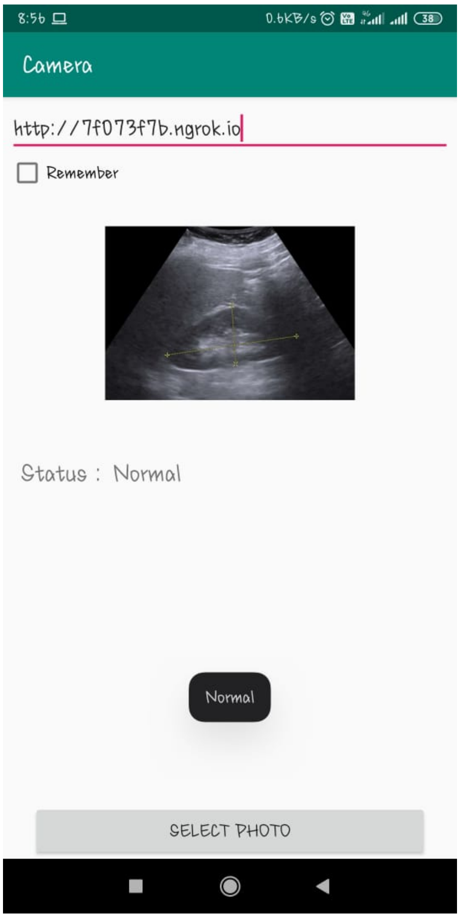
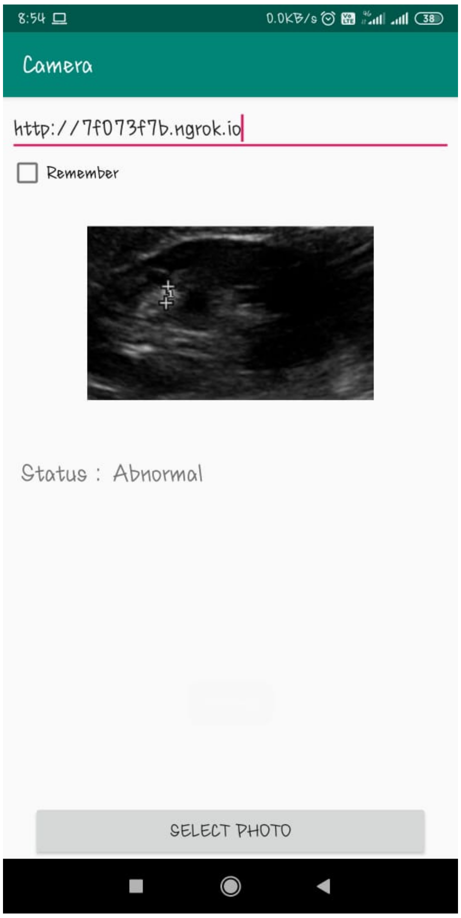


FIGURE 6.2: (a) Normal Kidney & (b) Abnormal Kidney

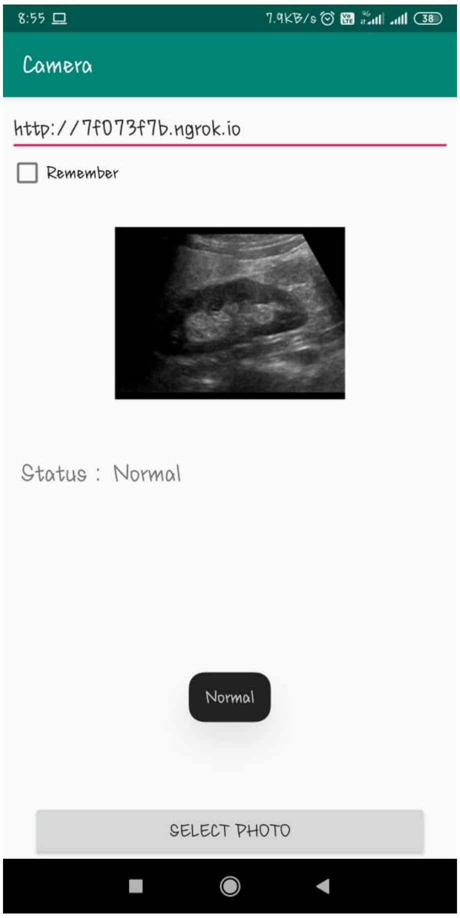


(a)

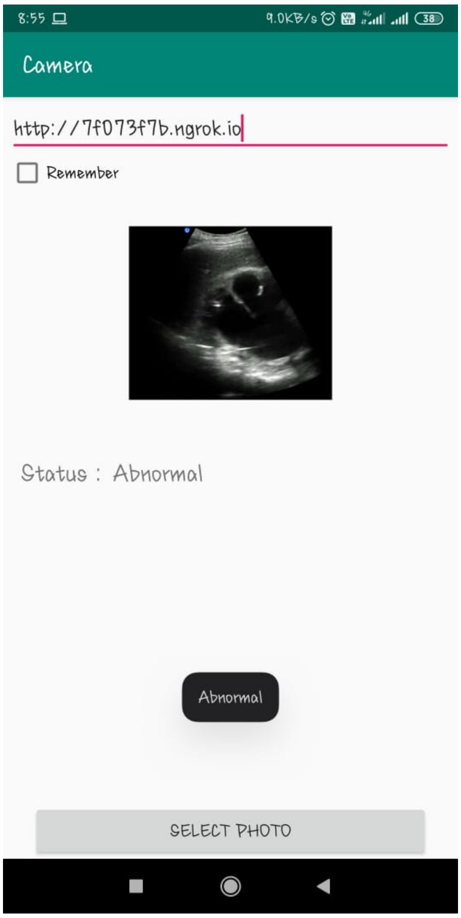


(b)

FIGURE 6.3: (a) Normal Kidney & (b) Abnormal Kidney



(a)



(b)

FIGURE 6.4: (a) Normal Kidney & (b) Abnormal Kidney

Chapter 7

Future Scope

7.1 More Data-set

- More Images of Ultrasound Kidney Images both Normal and Abnormal

7.2 More Classifications

- (Cyst,Tumor,Stones) - Gives more clarity of disease to the patient

7.3 Upgrading the Present CNN model

- For Online CNN model we can update the model with more images and generate new url every time

7.4 Offline app

- Deploy the CNN model in the app and Run the app Offline

7.5 Suggest doctors using GPS location

- If the results of the Analysis is Abnormal using the user GPS location it should suggest the doctors or hospitals near by.

Bibliography

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[10] `https://fijisun.com.fj/2017/10/22/kidney-failure-you-can-prevent-it/`

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May 2020

Certi cate We, P SAI PRIDHVI & JEEVAN KUMAR, with Roll No: EDM16B029 & EDM16B040 hereby declare that the material presented in the Project Report titled Kidney Abnormalities Detection Using CNN represents original work carried out by me in the

Department of Electronics and Communication Engineering at the Indian Institute of Information Technology, Design and Manufacturing, Kancheepuram

during the years 2019{2020. Under the Guidance of Dr Priyanaka Kokil. With our signatures, We certify that: We have not manipulated any of the data or results. We have not committed any plagiarism of intellectual property. We have clearly indicated and referenced the contributions of others. We have explicitly acknowledged all collaborative research and discussions. We have understood that any false claim will result in severe disciplinary action. We have understood that the work may be screened for any form of academic misconduct. Date: Student's Signatures In our capacity as supervisor of the above-mentioned work, We certify that the work presented in this Report is carried out under our supervision, and is worthy of consideration for the requirements of B.Tech. Project work. Advisor's Name:Dr Priyanka Kokil Advisor's Signature i

Abstract The chronic kidney disease (CKD)

is fatal disease.

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Thus, it is important to diagnose the kidney diseases at an earlier stage before it cause fatality. This Report proposes an algorithm

and fully functioning APP

for Automatic kidney abnormalities detection Using CNN at an early stage. Kidney abnormalities detection involves two stages: CNN model and Detection

using an Android APP.

The input images used in this work are kidney ultrasound (US) images which are classi ed into two categories such as Normal kidney,

Abnormal kidney.

Acknowledgements I would like to acknowledge and extend my heartfelt gratitude to all those people who have been associated with this project and have helped me with it thus making it a worthwhile experience. I am extremely grateful to Dr.Priyanka Kokil for his timely guidance, motivation, interest shown all through the duration of our project which helped me in expanding my knowledge to achieve the goal. I would also like to thank Mr.Sudharsan sir & Mr.Pratap sir for helping me to complete the project successfully. iii

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Chapter 1. Introduction 3 1.2 Motivation

Statistics of CKD[10] 10%

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of the population worldwide is a ected by chronic kidney disease (CKD), and millions die each year because they do not have access to

a ordable treatment.

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Over 2 million people worldwide currently receive treatment with dialysis or a kidney transplant to stay alive, yet this number may only represent 10% of people who actually need treatment to live.

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More than 80% of all patients who receive treatment for kidney failure are in

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countries with universal access to health care and large elderly populations. It is estimated that number of cases of kidney failure will increase disproportionately in developing countries, such as China and India, where the number of elderly people are increasing. In middle-income countries, treatment with dialysis or kidney transplantation creates a huge nancial burden for the majority of the people who need it. In another 112 countries, many people cannot

a ord

treatment at all, resulting in the death of over 1 million people annually from untreated kidney failure.

Noncommunicable diseases (such as heart disease, diabetes, or kidney disease) have replaced communicable diseases (such as

in uence,

malaria, or AIDs) as the most common causes of premature death worldwide. An estimated 80% of this burden occurs in low- or middle-income countries, and 25% is in people younger than 60 years.

According the 2010 Global Burden of Disease study,it remains among the few growing causes of mortality which made CKD the 13th leading cause of death in 2013; this compared to ranking 27th in 1990, but rose to 18th in 2010.

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Chronic kidney disease can be treated. With early diagnosis and treatment, it's possible to slow or stop the progression of kidney disease.

Chapter 1.

Introduction 4 1.3 What is Chronic Kidney Disease? Chronic kidney disease (

CKD)

is a major Global health issue because of its high risk of end-stage renal disease (ESRD). CKD is decrease in functionality of kidney.The kidneys lter waste and excess uid from the blood. As kidneys fail, waste builds up in the blood.

In the early stages of the disease, most people do not have symptoms. But as CKD gets worse, wastes can build up in your blood and make you unhealthy .Once kidneys fail, dialysis or a kidney transplant is needed to stay alive. This stage of CKD is known as end-stage renal disease (ESRD).[9] 1.4 Types in Kidney Abnormalities Kidney Cysts Kidney

Stones Kidney Cancer(Tumor) 1.5 How is CKD Treated? The best treatment of CKD is early detection, when the disease can be slowed or stopped. However, once kidneys fail, treatment with dialysis or a kidney transplant is needed. 1.6

Detection Method Medical image classi cation plays an essential role in clinical treatment. However, the traditional method has shown less performance. Moreover, by traditional methods, much time is needed to be spent on extracting and selecting classi cation features. The deep neural network is an emerging machine learning method that has proven its high E ciency for di erent classi cations.The convolutional neural network dominates with the best results on varying image classi cations.

Chapter 1. Introduction 5 1.7

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CNN A Convolutional Neural Network (CNN) is a class of deep neural networks, most commonly applied to analyzing visual imagery.

Convolutional neural networks have been one of the most in uential innovations in the eld of computer vision. It indicates that the network employs a mathematical operation called convolution. It is a specialized kind of linear operation. 1.7.1

Convolutional Layers

The convolutional

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layer is the core building block of a CNN. The layer's parameters consist of a set of learnable lters (or kernels), which have a small receptive eld, but extend through the full depth of the input

volume. 1.7.2 Max

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pooling The Pooling layer is responsible for reducing the spatial size of the

Convolved Feature. This is to decrease the computational power required to process the data through dimensionality reduction. 1.7.3 Kernel size CNN are basically a stack of layers which are de ned by the action of a number of lters on the input. Those lters are usually called kernels.

Chapter 1. Introduction 6 1.7.4

Pooling size It reduces the spatial size of the convoluted features in Pooling layers. 1.7.5 Activation Activation functions are mathematical equations that determine the output of a neural network. The function is attached to each neuron in the network, and determines whether it should be activated or not. Functions : 'sigmoid', 'relu', 'tanh' 1.7.6

Weights Each neuron in a neural network computes an output value by applying a speci c function to the input. The function that is applied to the input values is determined by a vector of weights and a bias. 1.7.7

Dense layer A linear operation in which every input is connected to every output by a weight. Generally followed by a non-linear activation function. 1.7.8 L2 Regularisation In L2 regularization, regularization term is the sum of square of all feature weights as shown above in the equation. L2 regularization forces the weights to be small but does not make them zero and does non sparse solution. 1.7.9 Flatten Flattening transforms a two-dimensional matrix of features into a vector that can be fed into a fully connected neural network classi er.

Chapter 1. Introduction 7 1.7.10

Dropout Dropout is a technique used to prevent a model from over tting. Dropout works by randomly setting the outgoing edges of hidden units (neurons that make up hidden layers) to 0 at each update of the training phase. 1.8 Compilation & Saving Model 1.8.1 Compile Render the model of weights for a required no of classi cations. 1.8.1.1 Optimizer Optimizers are algorithms or methods used to change the attributes of your neural network such as weights and learning rate in order to reduce the losses. Optimizers : 'adam', 'rmsprop', 'SGD' 1.8.1.2 Loss function A loss function is used to optimize the parameter values in a neural network model. Loss functions : 'binary cross-entropy', 'sparse categorical cross-entropy' 1.8.1.3 Fit the model Batch size -

It is a number of samples processed before the model is updated Epoch (Iterations) - the number of complete passes through the training data-set. 1.8.2

Saving Model An H5 le is a data le saved in the Hierarchical Data Format (HDF).It is a le format to store structured data.Keras saves models in this format as it can easily store the weights and model con guration in a single le.

Chapter 2

Objectives Collecting as much as Data set Images possible for Training CNN Model. Increasing Data set Images by Augmentation Technique. Removing Speckle Noise from Ultrasound Medical Images. Training a CNN model E ectively for high training & testing accuracy's. URL generating via Flask. API testing URL via Postman. Creating interface between android app and ask URL (Tunnel) via Ngrok. API testing URL via Designed Android APP. Results. Analysis of results of Ultrasound kidney image in the APP shows us

the requirement of doctor. 8

Chapter 3 Methodology 3.1 Algorithm 3.2 Data-set Normal Kidney Images = 60 Abnormal Kidney Images = 50 9

Chapter 2. Methodology 10 3.3 Augmentation Image data augmentation is a technique that can be used to arti cially expand the size of a training data-set by creating modi ed versions of images in the data-set. There are 6(including the original) modi ed versions of images. (a) Original Image (b) rotation range = 40, (c) shear range = 0.2 (d) zoom range = 0.2 (e) horizontal ip (f) brightness range = (0.5, 1.5)) (a) (b) (c) (d) (e) (f) Figure 3.1: Augmented Images

Chapter 2. Methodology 11 3.4 Data-set Normal Kidney Images (After Augmentation) = 360 Abnormal Kidney Images (After Augmentation) = 300 3.5 Pre-processing

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The usefulness of ultrasound imaging is degraded by the presence of noise known as speckle.

This type of noise is an inherent property of medical ultrasound imaging and because of this noise the image resolution and contrast become reduced, which e ects the diagnostic value of this imaging modality . So, speckle noise reduction is an essential pre processing step, whenever ultrasound imaging is used for medical imaging. 3.5.1 De-nosing the Image with Wiener Filter The Wiener lter is a linear spatial domain lter.To address the multiplicative nature of speckle noise, a homomorphic approach is developed in , which converts the multiplicative noise into additive noise, by taking the logarithm of image and then applies the Wiener lter. Wiener ltering is based on both, global and local statistics and is given by Formula Y ij = 2 x 2 k + 2 (K uv * K) + K (3.1) where Y ij denotes the de-speckled image, K is the local mean, 2 k is the local variance, K uv is (u;v) th pixel in the kernel K and 2 is the global variance. (a) (b) Figure 3.2: (a) Normal Image & (b) Filtered Image

Chapter 2. Methodology 12 3.6 Gray scale conversion (a) (b) Figure 3.3: Normal to Gray Conversion 3.7 Resizing of images (a) (b) Figure 3.4: Default size to 224x224 3.8 Weights Normalisation By re-parameterizing the weights in this way we improve the conditioning of the optimization problem and we speed up convergence of stochastic gradient descent.

img = img/112 3.9 Split Ratio of Training & Testing Images Train Images = 70% & Test Images = 30% Split Ratio = 0.3

Chapter 2. Methodology 13 3.10 CNN model Normal Kidney images = 360 & Abnormal Kidney Images = 300 (After Augmentation) Train Images = 462(252+210) & Test Images = 198(108+90) (Split Ratio =0.3) Original Image - Gray-scale converted Image Gray-scale converted Image - Resizing Image (224x224) Resizing Image (224x224) - Wiener Filtered Image Wiener Filtered Image - Matrix Array Matrix Array - Weights Sequential = Convolution layers + Max pooling Layers + Fully Connected layers Compile (optimizer='adam', loss='binary crossentropy' Fit Model (Batch-size = 250, epochs=100) Save Model(saved model.h5) 3.11

Convolutional Layers & Connected Layers Table 3.1: Layers in the Code Layers Filters Kernel Size Pooling Size Activation Regularisation Conv 1 32 (3,3) Relu Maxpool 1 (2,2) Conv 2 64 (3,3) Relu Maxpool 2 (2,2) Conv 3 64 (3,3) Relu Maxpool 3 (2,2) Flatten It converts the pooled feature map to a single column Dense 1 64 Relu L2 (0.01) Dense 2 1 Sigmoid

Chapter 2. Methodology 14 3.11.1 Output params image 3.11.2 Training & Testing Accuracy For 100 Iterations

Training Accuracy=99% & Testing Accuracy = 89% 3.11.3 Testing Images with Saved Model

Chapter 4 URL Generation & API Testing 4.1 Flask Flask is a lightweight WSGI (Web Server Gateway Interface) web application framework. It is designed to make getting started quick and easy, with the ability to scale up to complex applications. 4.2 Ngrok Ngrok is a multi-platform tunnelling, reverse proxy software that establishes secure tunnels from a public endpoint such as internet to a locally running network service while capturing all tra c for detailed inspection and replay. 4.3 Flask-Ngrok Platform Ngrok is a lightweight tool that creates a secure tunnel on your local machine along with a public URL you can use for browsing your local site. Flask is the framework here,once we import Flask, we need to create an instance of the Flask class for our web app. We generate Url via Ngrok which is compatible (made via Flask) to run an web application . 15

Chapter 4. URL Generation & API Testing 16 4.4 URL Generation Using Flask-Ngrok We run Flask apps on localhost available over the internet via the Ngrok tool. Figure 4.1: Server running on Url 4.4.1 Using the generated URL in Postman & Android App (a) (b) Figure 4.2: (a) Url in Postman & (b)Url in App

Chapter 4. URL Generation & API Testing 17 4.5 API Testing Via Web-services API (application programming interface) testing is a type of software testing that performs veri cation directly at the API level. It is a part of integration testing that determines whether the API's meet the testers' expectations of functionality, reliability, performance, and security. Software : Postman Postman is a popular API client that makes it easy for developers to create, share, test and document API's. This is done by allowing users to create and save simple and complex HTTP/s requests, as well as read their responses. The result - more e cient and less tedious work. (a) (b) Figure 4.3: (a) Normal Kidney & (b) Abnormal Kidney

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Chapter X. Chapter Title Here 23 (a) (b) Figure 6.3: (a) Normal Kidney & (b) Abnormal Kidney

Chapter

X. Chapter Title Here 24 (a) (b) Figure 6.4: (a) Normal Kidney & (b) Abnormal Kidney

Chapter 7 Future Scope 7.1 More Data-set More Images of Ultrasound Kidney Images both Normal and Abnormal 7.2 More Classi cations (Cyst,Tumor,Stones) - Gives more clarity of disease to the patient 7.3 Upgrading the Present CNN model For Online CNN model we can update the model with more images and generate new url every time 7.4 O ine app Deploy the CNN model in the app and Run the app O ine 7.5 Suggest doctors using GPS location If the results of the Analysis is Abnormal using the user GPS location it should suggest the doctors or hospitals near by. 25

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Over two million people worldwide currently receive treatment with dialysis or a kidney transplant to stay alive, yet this number may only represent 10 per cent of people who actually need treatment to live. Of the two million people who receive treatment for kidney failure, the majority are treated in	

8	96%
countries with universal access to health care and large elderly populations. It is estimated that number of cases of kidney failure will increase disproportionately in developing countries, such as China and India, where the number of elderly people are increasing. In middle-income countries, treatment with dialysis or kidney transplantation creates a huge nancial burden for the	

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Chapter 1.

Introduction 4 1.3 What is Chronic Kidney Disease? Chronic kidney disease (

10: https://www.kidney.org/kidneydisease/global-facts-about-kidney-disease	74%

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Thus, it is important to diagnose the kidney diseases at an earlier stage before it cause fatality. This paper proposes an algorithm for automatic kidney abnormalities detec- tion and classification at an early stage. Kidney abnormalities detection involves two stages: feature extraction and detection.

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pooling The Pooling layer is responsible for reducing the spatial size of the

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Pooling Layer The pooling or downsampling layer is responsible for reducing the spacial size of the

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CNN A Convolutional Neural Network (CNN) is a class of deep neural networks, most commonly applied to analyzing visual imagery.	CNN) A convolutional neural network (CNN) is a type of artificial neural networks, proposed by Yann Le Cun in 1988, most commonly applied to analyzing visual imagery[1].

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pooling The Pooling layer is responsible for reducing the spatial size of the	

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Pooling The pooling or downsampling layer is responsible for reducing the spacial size of the	