Detection and Classification of Kidney Diseases Using CT Scanned Image

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ABSTRACT

Prediction and Classification on the basis of a dataset has been revolutionised with the advancement in Deep Learning and Machine Learning. These technologies are being employed by different industries and are benefited by predicting the future trends and hence taking appropriate action beforehand. The proposed work aims towards predicting and classifying different kidney diseases with the help of CT scanned images. With the increase in bad lifestyle, pollution, and exposure to different types of radiation, the majority of the population is suffering from kidney diseases in one form or another. Oftentimes, these diseases are getting diagnosed very late leading to severe and irreversible damage. Hence, this research is based on employing Deep Learning algorithms such as CNN(Convolutional neural network) to predict and diagnose kidney diseases. Moreover, the SMOTE(Synthetic Minority Over-sampling Technique) class is used for tackling imbalanced datasets. Supervised classification techniques are utilised for the classification. It aims to increase the accuracy of the diagnosis and help doctors to take appropriate measures at the correct time.

KEYWORD
CNN, SMOTE, Image Classification, Kidney Diseases, Deep Learning.

I. INTRODUCTION

Kidney is a two bean-shaped organ located in the lower back. Being a part of the Urinary System, they play a vital role in maintaining the overall health of the body. They filter waste products and excess fluids from the blood, regulate blood pressure, and help to produce red blood cells. But in the modern era, Kidney disease also known as Renal Disease is getting common. It can be caused by a variety of factors including diabetes, high blood pressure, genetic disorders, infections, bad lifestyle and fooding habits. These diseases lead to further complications that hamper the lifestyle of a person as well as overall health. Amongst all Kidney diseases the proposed work mainly focuses on the these three types of Kidney disorders :

Kidney stones - These are hard deposits formed in the kidneys from minerals and salts. They have the potential to induce discomfort, nausea, and blood in the urine. Kidney stones are classified into four types: calcium stones, struvite stones, uric acid stones, and cystine stones. Treatment for kidney stones may involve drugs to assist the stone pass or surgical treatments to remove the stone, depending on the size and location of the stone.

Kidney cysts - Kidney cysts are fluid-filled sacs that can form within the kidneys. They are usually non-cancerous and do not produce symptoms. However, if a cyst grows in size or starts pressing on adjacent organs, it can cause pain or discomfort. If kidney cysts create issues, they may need to be surgically removed or drained.

Kidney Tumour - Kidney tumours are abnormal growths that can develop in the kidneys. They might be benign (non-cancerous) or malignant (cancerous). Blood in the urine, abdominal discomfort, and a lump or mass in the abdomen are all symptoms of kidney tumour. Treatment for kidney tumours may include surgery to remove the tumour, chemotherapy, or radiation therapy.

There are various models to classify images based on different characteristics such as Random Forest, KNN(K-Nearest Neighbour), and CNN. In this project, Deep Learning concepts and image classification is used for predicting amongst Kidney Stone, Cysts and Tumour. Computed Tomography (CT) scanned images are used as the Dataset. In most cases the dataset is unbalanced and for that SMOTE algorithm is employed to balance the dataset so that algorithm gives unbiased results. The balanced data is then pushed to (Convolutional Neural Network) CNN algorithm where the images are preprocessed to reduce the size without reducing the characteristic. Afterwards, Convolution, Max-pooling, Min-pooling and Striding layers are applied to form an image matrix resulting in flattening of the dataset. The flattened dataset is then converted into a neural network. Finally the dense layer adds the fully connected image to the neural network.

II. RELATED WORK

[1] explored methods for the detection of chronic Kidney disease. Adaptive Hybridized Deep Convolutional Neural Network (AHDCNN) was used to categorise different CKD. Different features are determined from the noise free data and fed into the classifier. Proposed approach is based on the method for deeper learning and ROIs given by radiologists.

[2] explored Lesion detection using CT images. Morphological cascade convolutional neural network (RCNN) was employed which gives highly precise and robust detection of kidney lesions. A six layer FPN is modified to generate different size feature maps for overall location and classification. However their model has shown low precision when there are several complicated goals such as polycystic kidney.

[3] explored the idea of recognizing kidney stones from CT scan pictures. Firstly enhancement of input image is done by histogram equalisation approach and for better visibility, Embossing technique is employed. Lastly, the convolution kernel and SVM image is classified. Obtained 98.71% accuracy on the basis of TP, TN, FP, FN parameters.

[4] explored a smartphone based implementation(in the form of application(APP)) of kidney abnormalities(stones and cysts) detection using ultrasound images. For the detection of kidney abnormality Viola Jones algorithm, texture feature extraction and SVM classifier is used. The result of the proposed algorithm gives the accuracy of 90.91% in detection of the abnormalities.

[5] explored the classification of the Kidney disease using Ultrasound(US) image, namely into four classes : Normal, Cyst, Calculi and Tumour. Model used is Probabilistic Neural Network(PNN). Equal number of data is used for training and testing of the data which results in the accuracy of 92.99%, Sensitivity of 88.04% and Specificity of 97.33% is obtained. Drawback of the model is that an equal amount of data is used for training and testing, which can be improved by increasing the number of samples for training work.

[6] explored the classification of the Kidney tumour and pining out the tumour regions by processing the Computer Tomography(CT) scan images. They have used K-means segmentation and K-means clustering technique which gives the accuracy of 91.2 and dice coefficient of 87.7. Further improvement can be done by using new segmentation techniques.

[7] explored the detection of kidney stones via Magnetic Resonance Image(MRI) with the help of Neural Network. Feature extraction has been done by Principal Component Analysis (PCA) and Back Propagation Network (BPN). By using this model they are able to detect the stone and also the stone region is separated from the image.

[8] explored the idea of detection of Chronic Kidney Disease (CKD) from Computed Tomography(CT) scan image and blood samples. They proposed four various units: photo edge, virtual assistant, book reader and prediction respectively. K-Nearest Neighbors Algorithm is used for classification of CKD and non-CKD.

[9] explored the ACF algorithm for kidney identification. It is difficult to discover stones especially for the kidney because those present in other organs close to the abdomen have the same severity. To improve the quality of this work, kidney stone calculation utilising a weighted coefficient can be used.

[10] explored a highly efficient and accurate CKD diagnosis model based on 1D CNN. MissForest Imputation is used for handling missing data. In addition Isolation Forest a memory efficient technique is employed to deal with anomalies. However, the model is yet to be trained for a large dataset.

[11] explored the 1-D CNN-SVM algorithm to extract features directly from the raw signals which successfully classifies the data with accuracy of 98.04%. It is a simple yet highly accurate model. A high correlation of 0.9898 and 0.9799 is obtained when tested against proposed sensing methods and urea estimation. Further improvement is possible using Deep learning techniques.

III. PROPOSED METHOD

The research paper proposes a deep learning model that classifies the type of Kidney disease using Computed Tomography (CT) scanned images. It takes CT scanned images as input, balances out the imbalanced data with the help of SMOTE algorithm and applies some deep learning algorithm to give an output. In addition, it classifies the image into kidney Stones, Cyst, Tumour or Normal.

1. Workflow

The workflow of the proposed work is explained in Fig- 1. Firstly data(imbalanced) is collected from Kaggle and then with the help of SMOTE class it is balanced. Afterwards, pre-processing of the data is done to reduce the size of the image. The dataset is then fed to the model(CNN) for training and tested. At last the model is giving the result after classification.

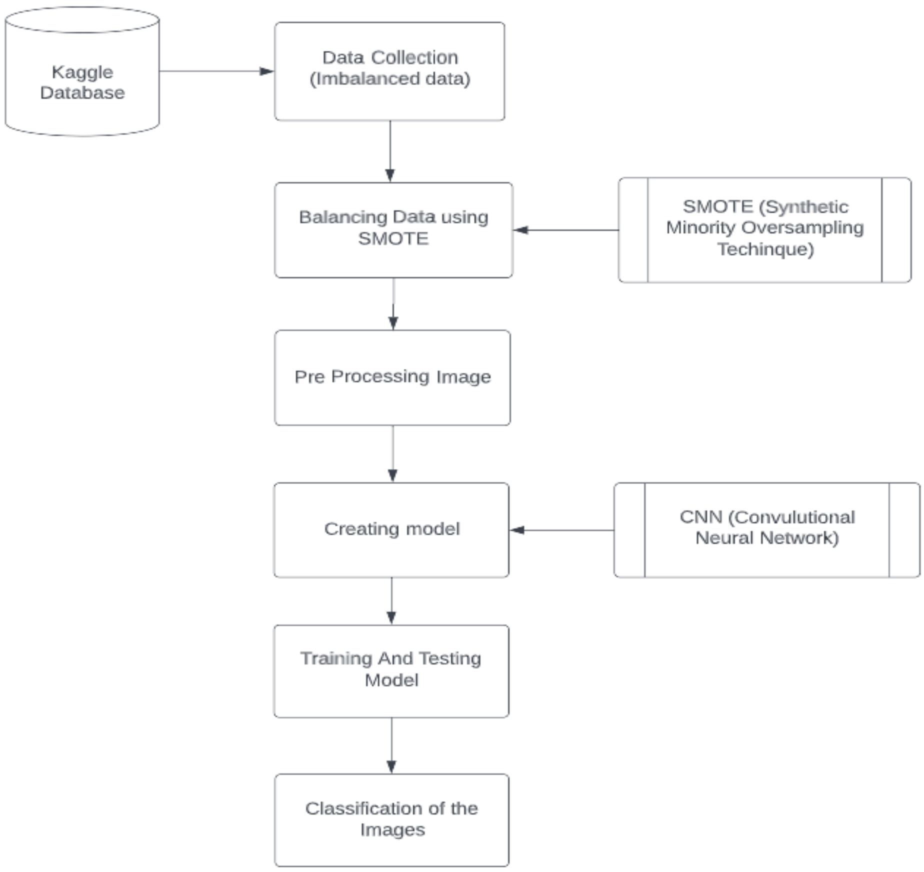

Fig. 1: Flow Diagram

2. Dataset

The dataset is taken from Kaggle.com having the CT Scanned Image of Kidney Stone, Kidney Tumour, Kidney Cyst and Normal Kidney. The data is imbalanced which is show in Fig- 2.

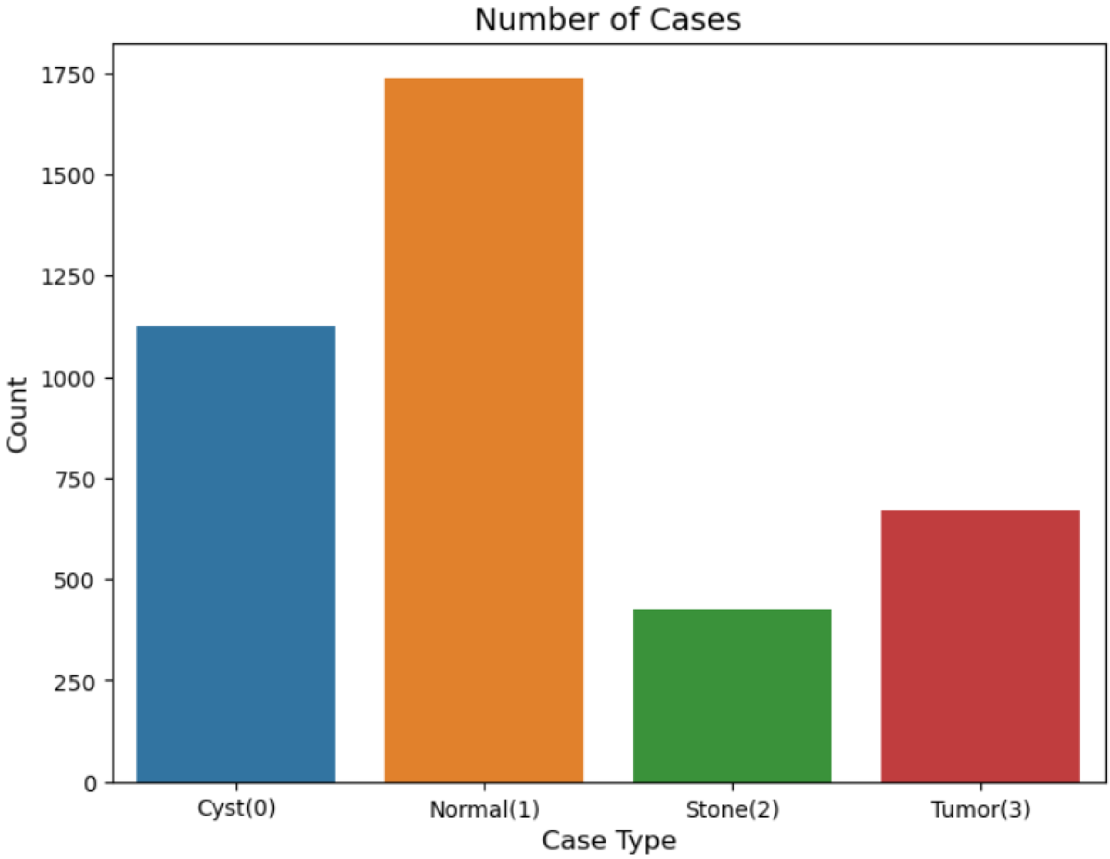

Fig. 2: Imbalanced Dataset

These are the four types of CT Scanned Image that are fed to the CNN.

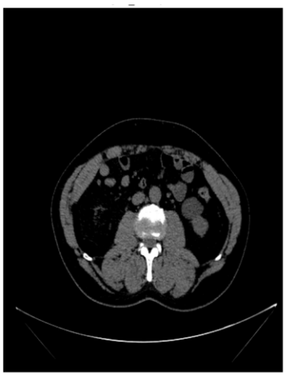

Fig. 3: Cyst

Fig. 4: Normal

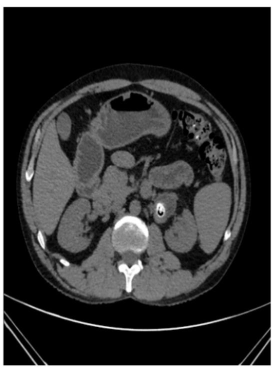

Fig. 5: Stone

Fig. 6: Tumor

3. Algorithm for Classification

Input : CT Scanned Image
Output : Classification
Process :
Step 1 : Converting the Imbalanced data to Balanced data using SMOTE.
Step 2 : Preprocessing the images -
 2.1. Resizing the image
 2.2. Normalization of the image
Step 3 : Creating the CNN model
 3.1. Applying Convolution Layer(2 times)
 3.2. Applying Max-Pooling Layer(2 times)
 3.3. Flattening
 3.4. Densing
Step 4 : Training the mode
Step 5 : Testing the model

IV. IMPLEMENTATION

1. Convolution Neural Network(CNN)

Convolutional Neural Network is a deep learning Neural architecture that learns directly from data. It is widely used for image classification and image recognition. Moreover, it is employed to classify audio, time-series and signal data. The pre-processing done by CNN relates to the working of neurons and hence it almost emulates the human brain. It has many layers with which it classifies the image. The layers are Convolutional layer, Padding, Max pooling, Average pooling, Stride, and at last Densing.

Architecture Diagram

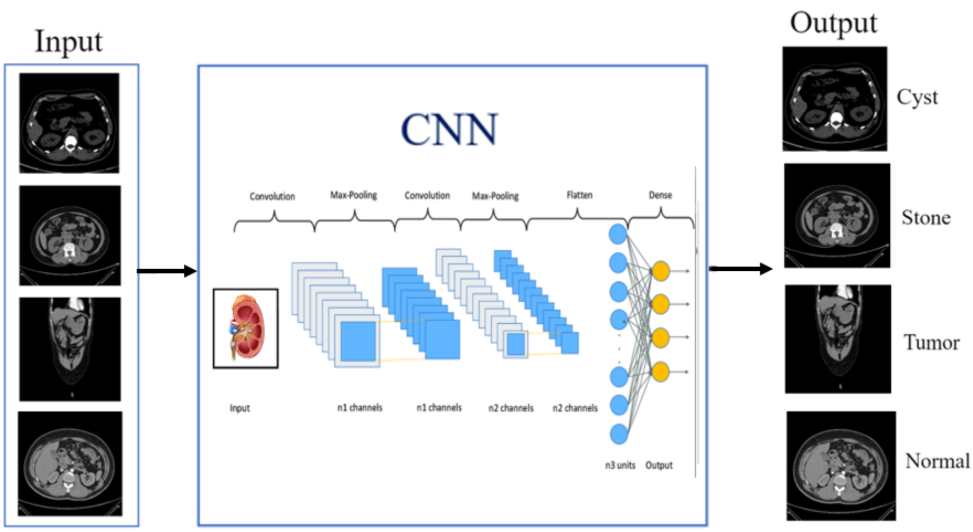

Fig. 7: Architecture Diagram

Multiple layers such as Convolution, Max-Pooling and Densing layers are applied to break down to pick up specify features of the image. Afterward, the image is flattened and lastly formed into Neural Network as given in the Fig - 7.

Convolutional Layer - It is the first layer to pull-out features from an input picture. It retains the link between pixels by learning visual properties using tiny squares of input data. It is a mathematical process which requires two inputs: an image matrix and a kernel or filter.

Image Dimension - $h \times w \times d$ (1)

Filter Dimension - $f_h \times f_w \times d$ (2)

Output Dimension - $(h - f_h + 1) \times (w - f_w + 1) \times 1$ (3)

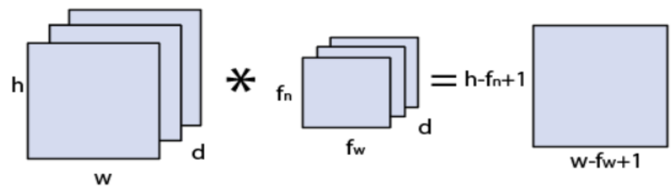

Fig. 8: Convolution process

Strides - The amount of pixels shifted over by the input matrix is referred to as the Stride. If strides equals 1 then we jump the filter 1 pixel at a time. Similarly, if it is 2 then we jump the filter 2 pixels at a time.

Padding - It is an extra layer that can be added to an image's border. If the image is shrunk and we apply a neural network with a large number of layers, the resulting filtered image will be small. The corner pixel will only be covered once but the central pixel will be covered multiple times. Because of that the output is reduced and details of the image's corner is lost. Hence we need an extra layer at the border of the image to cover up the characteristic of the corner.

Pooling Layer - This layer picks up the important and major feature of a particular zone in the image matrix and then down samples the whole image. Max pooling picks up the maximum value while Average pooling picks up the average value of the particular area in the image matrix. Since the most important character is picked up, the image is automatically downsampled.

Fully Connected Layer - This layer computes the class scores using the information from the layer above and returns a 1-D array with the same size as the number of classes.

2. Process

The image data is taken and then it is converted into a data frame. After that the images are labelled corresponding to its type:-

Cysts -> [0] (Cyst image is labelled as 0)
Normal -> [1] (Normal Kidney image is labelled as 1)
Stone -> [2] (Kidney Stone image is labelled as 2)
Tumor -> [3] (Kidney Tumor image is labelled as 3)

SMOTE

The dataset available is imbalanced. In any classification and prediction model an imbalanced dataset is a major problem as the model is trained with the imbalanced dataset and hence the classification of diseases will be in the favour of the majority class of the dataset available. One of the ways to deal with this problem is oversampling the minority class of the data by just duplicating the minority class sample available and balancing the dataset. This approach of dealing with imbalanced data is known as SMOTE (Synthetic Minority Oversampling Technique).

After applying the SMOTE algorithm the dataset is balanced shown in Fig- 9.

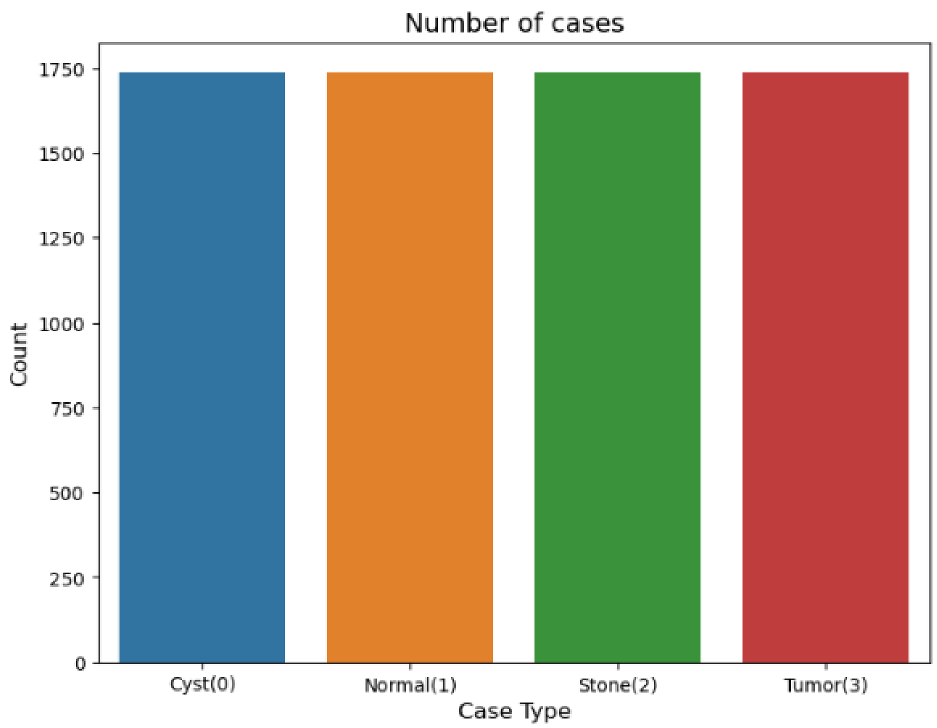

Fig. 9: Balanced Dataset

Preprocessing of Data

The raw data is processed to make it suitable for algorithms. This includes, but is not limited to, colour-correction, scaling, orientation, resizing, etc.

Model Summary

For the image classification CNN(Convolutional Neural Network) is used. We have used 3 Convolution layers, 2 Max-Pooling, 1 Flattening and then Densing as shown in the Fig- 10.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 28)        784

 max_pooling2d (MaxPooling2D  (None, 13, 13, 28)       0
 )

 conv2d_1 (Conv2D)           (None, 11, 11, 64)        16192

 max_pooling2d_1 (MaxPooling  (None, 5, 5, 64)         0
 2D)

 flatten (Flatten)           (None, 1600)              0

 dense (Dense)               (None, 4)                 6404

=================================================================
Total params: 23,380
Trainable params: 23,380
Non-trainable params: 0
_________________________________________________________________
```

Fig. 10: Model Summary

Relu Activation Function - If it receives negative value then it gives 0 as output and if it receives positive value then it gives the same value as output. It is a simple activation function and hence takes very little processing time.

$$\text{ReLU formula is : } f(x) = \max(0,x) \tag{4}$$

Softmax Activation Function - It accepts a vector of input, normalizes it and then provides the probability distribution depending upon the input provided. Vector values can be negative, positive or zero but after applying activation function all the values will be in the interval of (0 ,1). The proposed work is having 4 classes and for all the classes probability is calculated.

$$S(y)_i = \frac{exp(y_i)}{\sum_{j=1}^{n} exp(y_i)} \tag{5}$$

Training

The training is done up to 5 Epoch considering that the model should not get overfit. As shown in Fig. 5 the accuracy of the model is increasing with the number of Epochs. Firstly the accuracy is very less and loss is high. With the following epochs the accuracy is increasing steadily and the loss is decreasing.

```
Epoch 1/5
196/196 [==============================] - 3s 12ms/step - loss: 0.5685 - accuracy: 0.7815 - val_loss: 0.0752 - val_accuracy: 0.
9899
Epoch 2/5
196/196 [==============================] - 2s 11ms/step - loss: 0.0367 - accuracy: 0.9957 - val_loss: 0.0102 - val_accuracy: 0.
9986
Epoch 3/5
196/196 [==============================] - 2s 11ms/step - loss: 0.0080 - accuracy: 0.9992 - val_loss: 0.0041 - val_accuracy: 1.
0000
Epoch 4/5
196/196 [==============================] - 2s 11ms/step - loss: 0.0047 - accuracy: 0.9994 - val_loss: 0.0033 - val_accuracy: 1.
0000
Epoch 5/5
196/196 [==============================] - 2s 11ms/step - loss: 0.0175 - accuracy: 0.9944 - val_loss: 0.0167 - val_accuracy: 0.
9986
```

Fig. 11: Training Model

V. RESULT AND DISCUSSION

1. Training Loss Curve

It shows the change in loss over subsequent number of epochs. This graph helps to analyse the performance of the model and diagnose whether the model is getting overfit or underfit. Considering the proposed training model the following Fig. 12 shows the Training Loss Curve.

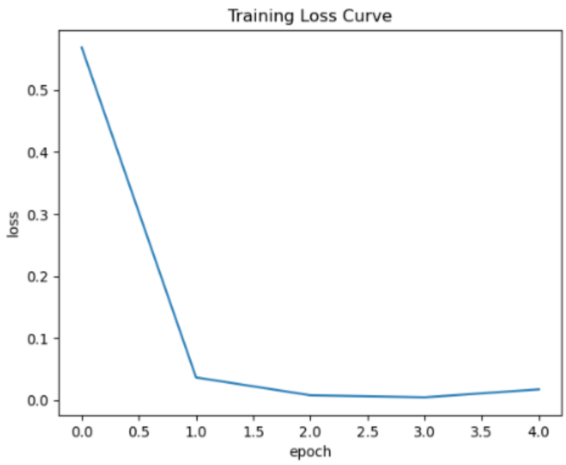

Fig. 12: loss vs epoch

2. Training Accuracy Curve

It shows the change accuracy with the increasing number of epochs. With this graph we can easily analyse accuracy of the model and diagnose how accuracy is varying. Considering the above Training Model the following Fig. 13 shows the Training Accuracy Curve.

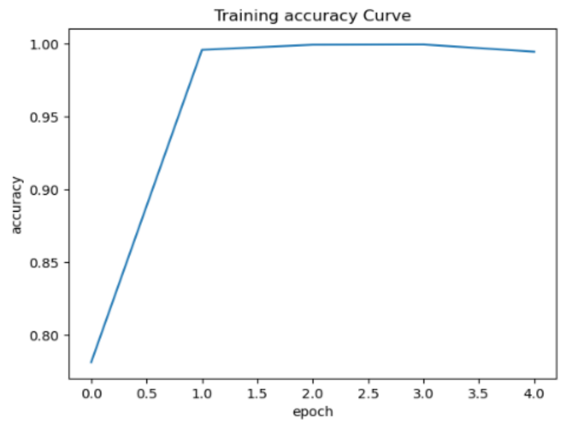

Fig. 13: accuracy vs epoch

3. Confusion Matrix

It is a matrix that contains the information about the performance of the algorithm. Each row represents the actual class of the data(image) and each column constitute the predicted class of the data(image).

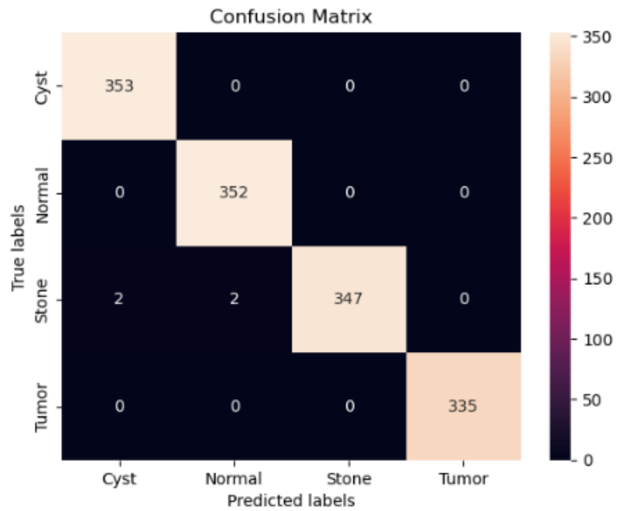

Fig. 14: Confusion Matrix

4. F1 Score

This metric integrates the precision and recall of the classes. It helps to differentiate between the classes with respect to their score. Harmonic mean is used to calculate the score.

The F1 score of the model is:- 0.997.

```
In [59]: print("F1 Score is :",f1_score(y_test,b,average='micro'))

F1 Score is : 0.9971243709561467
```

Fig. 15: F1 Score

Tumour image is given to the model for predicting and the output is shown in the Fig. 16. The model is showing correct output.

```
In [220]: a = model.predict(pic1)

1/1 [==============================] - 0s 22ms/step

In [221]: if a.argmax() == 0 :
              print("The detected disease is \"Cyst\"")
          elif a.argmax() == 1 :
              print("Kidney is \"Normal\" ")
          elif a.argmax() == 2:
              print("The detected disease is \"Stone\"")
          else:
              print("The detected disease is \"Tumor\"")

The detected disease is "Tumor"
```

Fig. 16: Tumor Case

Normal image is given to the model for predicting and the output is shown in the Fig. 17. The model is showing correct output.

```
In [189]: a = model.predict(pic1)

1/1 [==============================] - 0s 42ms/step

In [190]: if a.argmax() == 0 :
              print("The detected disease is \"Cyst\"")
          elif a.argmax() == 1 :
              print("Kidney is \"Normal\" ")
          elif a.argmax() == 2:
              print("The detected disease is \"Stone\"")
          else:
              print("The detected disease is \"Tumor\"")

Kidney is "Normal"
```

Fig. 17: Normal Case

VI. CONCLUSION

The identification and categorization of kidney diseases using the CNN algorithm has produced encouraging results. The system was able to categorise the majority of the training photos despite having a very limited dataset for training. This study reveals how CNN algorithms might be used to automate the detection of kidney illness, which would increase the speed and precision of the diagnostic procedure. Additionally, the algorithm's capability to discriminate between Stone, Cyst, and Tumour underlines its potential for assisting in the selection of treatments and tracking the development of diseases. However, further research is needed to validate these findings and to evaluate the use of CNN algorithms in a clinical setting. Additionally, it would be worthwhile to investigate the use of other deep learning techniques in combination with CNNs to potentially further improve the performance of the algorithm.

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