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# Chronic Kidney Disease Prediction

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***Abstract: Kidney stones play a role in the development of chronic kidney disease. Recurrent kidney stones should be avoided not only because of their immediate clinical manifestations but also because of their long-term predisposition to CKD progression. A lot of people confess to emergency departments with excruciating pain due to kidney stones, which are prevalent ailments around the world. The diagnosis of kidney stone illness involves the use of many imaging modalities. For the entire diagnosis and interpretation of these photos, specialists are required. Systems for computer-aided diagnosis are useful methods that can be utilized as supplemental tools to aid clinicians in their diagnosis. The deep learning (DL) technique, which has lately achieved considerable advancements in the field of artificial intelligence, is offered in this work as a means of automating the detection of kidney stones (containing stones or not) using coronal computed tomography (CT) scans. Different cross-sectional CT images were taken for every individual, resulting in a total of 1453 images. Using CT scans, we have seen that even little kidney stones are accurately detected by our model. This study demonstrates that other difficult urological problems can be addressed using newly popular DL approaches.***
***Keywords: Component, formatting, style, styling, insert (keywords)***

## I. INTRODUCTION

Kidney stones play a role in the development of chronic kidney disease. Recurrent kidney stones should be avoided not only because of their immediate clinical manifestations but also because of their long-term predisposition to CKD progression [1]. Chronic kidney disease (CKD) arises from many heterogeneous disease pathways that alter the function and structure of the kidney irreversibly, over months or years. The diagnosis of CKD rests on establishing a chronic reduction in kidney function and structural kidney damage. Kidney stones lead to chronic kidney disease (CKD) in people with rare hereditary disorders (e.g., primary hyperoxaluria, cystinuria). Kidney stones are a risk factor for CKD, and studies are warranted to assess screening and preventive measures for CKD in stone formers [02].

One of the most prevalent health issues is kidney stone disease, albeit the prevalence varies by country. This rate is said to range between 1 and 20% according to prevalence studies. renal stones can cause renal failure, cause people to stop working because they are so painful, and lower people's quality of life because they impede the urine system. For instance, more than 2 million Americans (USA) apply to the emergency room each year due to renal colic or back discomfort brought on by stones.

Deep learning (DL) techniques have been successfully implemented in many fields nowadays employing physiological inputs and medical imaging.

The deep models have been effectively applied in a variety of applications, including lesion detection, classification, and image segmentation of medical pictures. Accurate and reliable DL models have been created using a variety of medical image types, including magnetic resonance imaging (MRI), computed tomography (CT), and X-rays, to help clinicians diagnose conditions like chronic kidney disease (CKD), cardiac arrhythmia, prostate cancer, brain tumors, skin cancer, and breast cancer. For the automatic detection of kidney and ureteral stones, DL techniques are also used in the field of urology.

In this study, a model was created to reduce physician-induced mistakes and prevent missed stone detection utilizing DL methods and CT images. The majority of stone patients will be treated in the emergency room, and it could be challenging to always get a specialist radiologist. Due to a lack of radiologists, computed tomography reporting periods can occasionally be delayed. When imaging is carried out more quickly than usual, misinterpretation may occur. The examination of kidneys with computer-aided methods for the early and precise diagnosis will also be a significant contribution to the medical field because computed tomography reporting is a time-consuming process.

One of the medical specialties that uses cutting-edge technology for precise diagnosis is urology. In urology surgery, both robots and endourological techniques have been used. Due to the explosion of data, DL has become increasingly prevalent in healthcare applications. Through the use of CT images, we have attempted to apply DL for the automated classification of kidney stone cases in this study. Kidney stones are detectable by the model.

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## II. METHODOLOGY

CNNs are a subtype of neural networks that are particularly good at tasks like classifying and identifying images. CNNs are a variety of multi-layered feed-forward neural networks. CNNs are made up of filters, kernels, or neurons with biases, parameters, and learnable weights. Each filter receives some inputs, conducts convolution, and may then optionally perform non-linearity[41]. A typical CNN architecture is depicted in Figure 1. Convolutional, pooling, Rectified Linear Unit (ReLU), and Fully Connected layers make up CNN's structure.

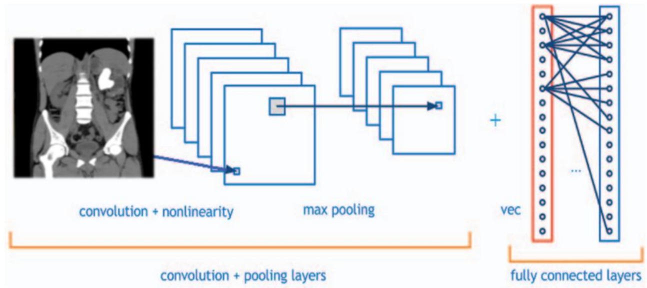


Fig. 1. A traditional Convolutional Neural Networks design.

### *A. Convolutional Layer*

The convolutional layer, which does the majority of the computational work, is the core element of a convolutional network. The primary objective of the Convolution layer is to identify characteristics in the incoming data, which is a picture. Convolution learns visual attributes from tiny squares of input images, preserving the spatial relationship between pixels. By using a group of teachable neurons, the input image is distorted. The output image is produced using a feature map or activation map, and the input data for the feature maps are the feature maps for the subsequent convolutional layer.

### *B. Pooling Layer*

Each activation map's dimensionality is decreased but the most crucial data is retained in the pooling layer. There are a number of non-overlapping rectangles created from the supplied photographs. Each zone is down-sampled using a non-linear operation, such as average or maximum. This layer, which is typically sandwiched between convolutional layers, enables higher generalization, faster convergence, robustness, and resistance to distortion and translation.

### *C. Rectified Linear Unit Layer*

A non-linear process called a "Rectified linear unit" contains devices that use rectifiers. Each pixel is impacted because it is an element-wise operation, and the feature map's negative values are all changed to zero. The rectifier is defined as f(x)=max(0,x) in the literature on neural networks. so we'll use that definition to understand how the Rectified Linear Unit functions..

### *D. Fully Connected Layer*

Every filter in the layer before it is connected to every filter in the layer after it, which is known as a fully connected layer (FCL). High-level features of the input image are represented in the output from the convolutional, pooling, and ReLU layers. utilizing these characteristics to classify the input image according to the training dataset is the aim of using the FCL. The final pooling layer, or FCL, is thought of as the layer that feeds the characteristics to the Softmax activation function classifier. The Fully Connected Layer's output probabilities add up to one. Softmax is used as the activation function to ensure this. A vector of arbitrary real-valued scores is squashed by the Softmax function into a set of numbers between 0 and 1 with a sum of 1.

## III. THE PROPOSED ALGORITHM

Fig. 2 presents the block diagram of the suggested CNN recognition algorithm. The following steps are where the algorithm is mostly executed:

1) Change the input photos' dimensions to 256x256x2.
2) Create an eight-layer CNN structure, using convolutional, max pooling, convolutional, convolutional, and layers that use convolutions as appropriate.
3) The Softmax classifier should be used for classification after all features have been extracted.

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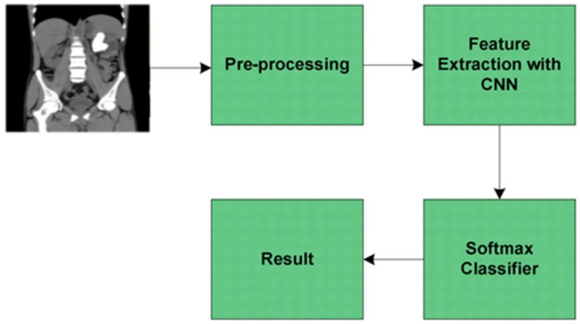



Fig. 2. The proposed algorithm's block diagram.

The proposed CNN's feature extraction block's organizational structure is shown in Fig. 3.

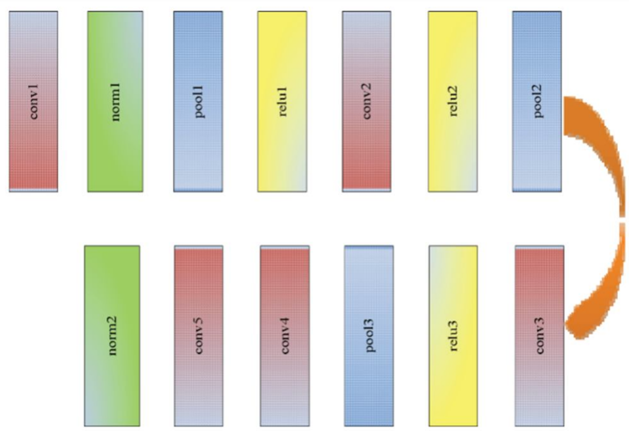
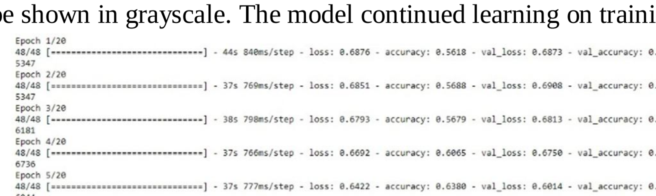



Fig. 3. The suggested CNN's feature extraction block's organisational structure

## IV. EXPERIMENTAL RESULTS

The collection of datasets of kidneys is around 1,799 images and they are divided into training and testing sets. The images in the database are exposed to the pre-processing stage where the re-sizing task is carried out to maintain the uniform dimension among the images. After pre-processing, each image's dimensions were modified to 256x256. Of the 1453 C T images, 80% were used for training, 10% for validation, and 10% for testing during the model's training phase.

After model training was finished, test performance values were obtained using 145 images that weren't used in the deep model's training. By modifying the batch size, learning rate, and image size, for example, we ran various tests. For 40 epochs, the model kept learning from the training set of data. This can detect an image with two classes that are kidney stone is present and a kidney stone is absent and the result will be shown in grayscale. The model continued learning on training data for 40 epochs.



```
Epoch 1/20
48/48 [==============================] - 44s 840ms/step - loss: 0.6876 - accuracy: 0.5618 - val_loss: 0.6873 - val_accuracy: 0.
5347
Epoch 2/20
48/48 [==============================] - 37s 769ms/step - loss: 0.6851 - accuracy: 0.5688 - val_loss: 0.6908 - val_accuracy: 0.
5347
Epoch 3/20
48/48 [==============================] - 38s 798ms/step - loss: 0.6793 - accuracy: 0.5679 - val_loss: 0.6813 - val_accuracy: 0.
6181
Epoch 4/20
48/48 [==============================] - 37s 766ms/step - loss: 0.6692 - accuracy: 0.6065 - val_loss: 0.6750 - val_accuracy: 0.
6736
Epoch 5/20
48/48 [==============================] - 37s 777ms/step - loss: 0.6422 - accuracy: 0.6380 - val_loss: 0.6014 - val_accuracy: 0.
6944
```

Fig. 4. Results of 1-5 epoch.

```
Epoch 16/20
48/48 [==============================] - 37s 767ms/step - loss: 1.0371e-04 - accuracy: 1.0000 - val_loss: 0.0797 - val_accurac
y: 0.9861
Epoch 17/20
48/48 [==============================] - 36s 760ms/step - loss: 8.3653e-05 - accuracy: 1.0000 - val_loss: 0.0801 - val_accurac
y: 0.9861
Epoch 18/20
48/48 [==============================] - 37s 774ms/step - loss: 7.0892e-05 - accuracy: 1.0000 - val_loss: 0.0804 - val_accurac
y: 0.9861
Epoch 19/20
48/48 [==============================] - 36s 757ms/step - loss: 6.0686e-05 - accuracy: 1.0000 - val_loss: 0.0803 - val_accurac
y: 0.9861
Epoch 20/20
48/48 [==============================] - 36s 758ms/step - loss: 5.2714e-05 - accuracy: 1.0000 - val_loss: 0.0801 - val_accurac
y: 0.9861
```

Fig. 5. Results of 16-20 epoch.

```
In [94]: # this gives us the accuracy after each epoch
         history.history["accuracy"]

Out[94]: [0.5617879033088684,
          0.5687993168830872,
          0.5679228901863098,
          0.6064855456352234,
          0.6380367875099182,
          0.697633683681488,
          0.8124452233314514,
          0.9219982624053955,
          0.9631901979446411,
          0.9851008057594299,
          0.9912357330322266,
          1.0,
          1.0,
          1.0,
          1.0,
          1.0,
          1.0,
          1.0,
          1.0,
          1.0]
```

Fig. 6. Accuracy progression during training.

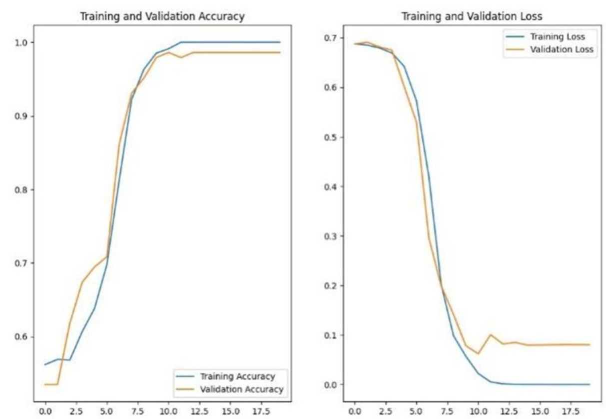



Fig. 7. Accuracy Chart and Loss Chart


Fig. 8. Image predicted vs Actual label with accuracy

## V. CONCLUSION

In this study, a DL model is suggested for the use of CT images in the detection of kidney stone cases. Using data from 433 subjects, the suggested deep model has produced an accuracy rate of 99.40%. The use of the CNN algorithm on CT scans has proved to be an effective tool in predicting the presence of kidney stones in patients. By analyzing the patterns and structures of the kidney and surrounding tissues, the algorithm can accurately identify the presence of kidney stones. The accuracy of the prediction is reflected in the confidence rate provided by the algorithm. This has the potential to significantly improve the diagnostic process, allowing for early detection and treatment of kidney stones, which can prevent complications and improve patient outcomes. Further research and development of this technology could lead to even more accurate and efficient diagnosis of kidney stones, ultimately benefiting patients and healthcare providers alike.

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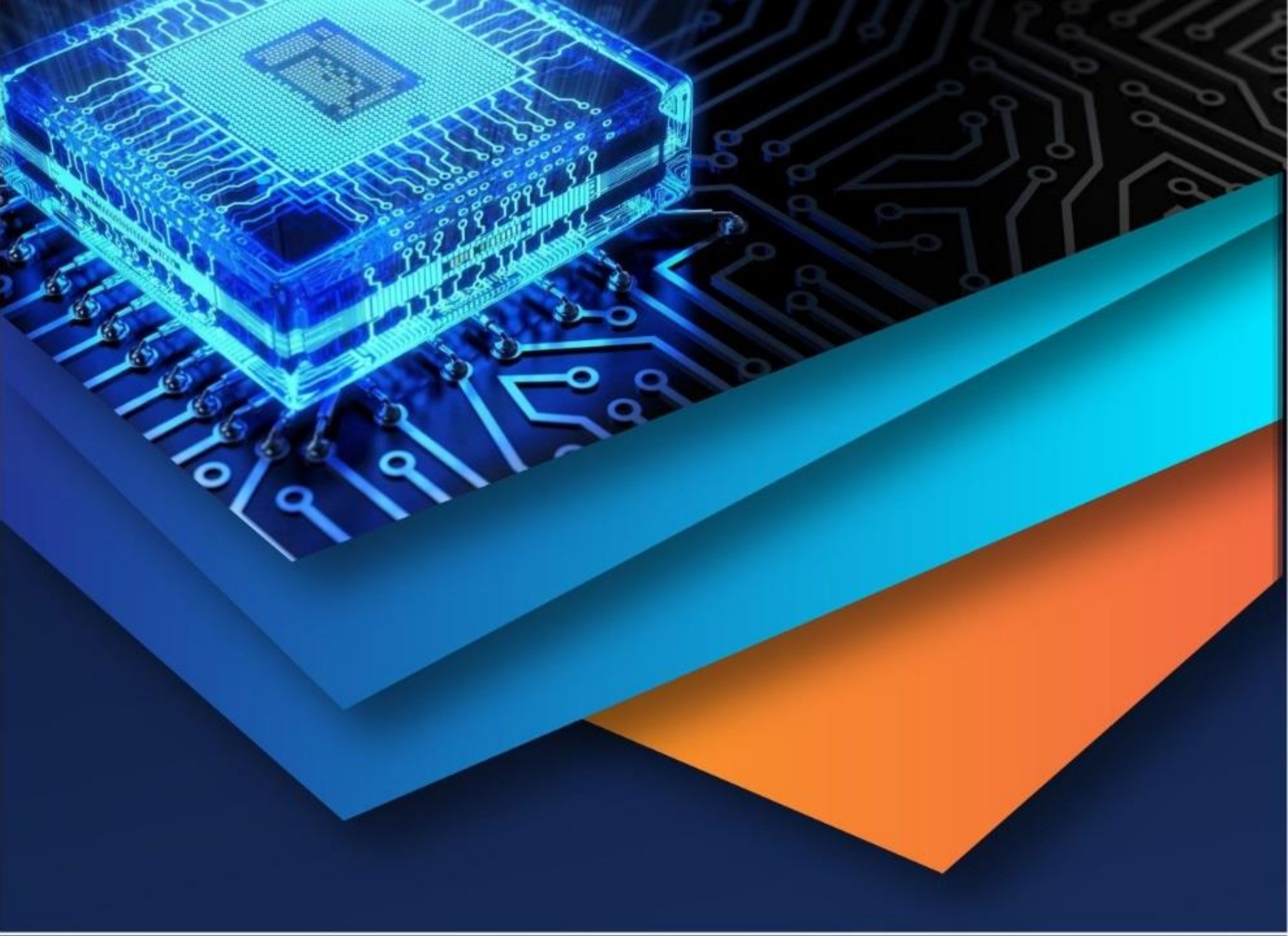


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