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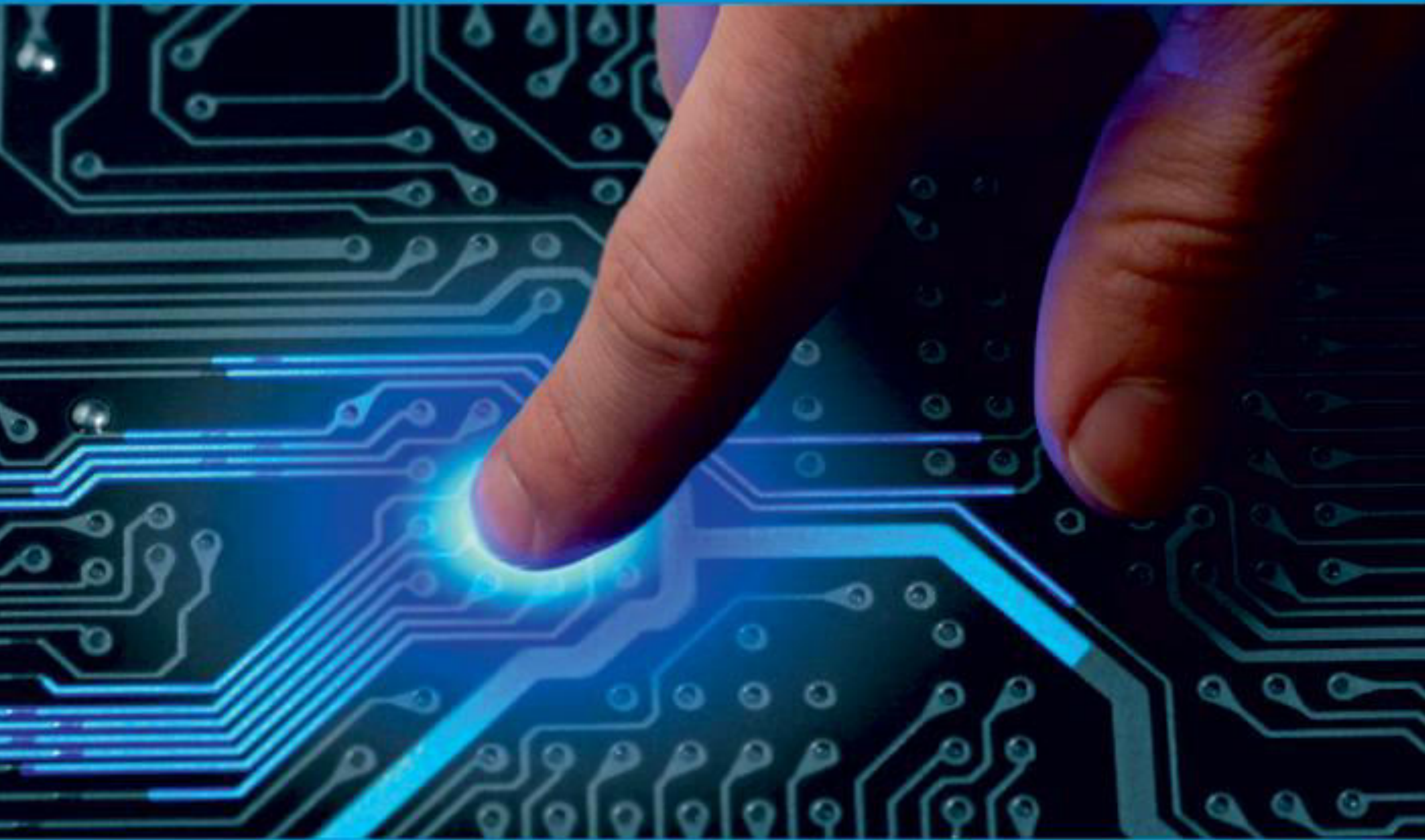

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Kidney Stone Detection using CNN

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ABSTRACT: Kidney stones are solids formed by minerals in the urine. These stones are formed by a combination of genetic and environmental factors. This is not only because of obesity but also because of certain foods, some medications, and inadequate drinking water. Kidney stones affect different race, culture, and geographic groups. Many ways are used to diagnose this kidney stone like a blood test, urine test and scanning. Scans are also divided into CT (Computed Tomography) scans, ultrasound scans, and Doppler scans. Today in this field of automation automatic diagnostics of kidney stones proves advantageous. In a scanning centre where only a technician is available, this method can help in producing better and accurate results. Also even if a doctor is present results with presence of kidney stones can be prioritized over others for diagnosis and treatment. Here we have built a CNN (Convolutional Neural Network) consisting of alternating convolutional and maximum pooling layers for detection of kidney stones.
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KEYWORDS: Kidney stones, CNN, convolutional neural network, CT, Computed Tomography, maximum pooling.

I. INTRODUCTION

Health is Wealth. Good health means a balanced and healthy physical and mental state of an individual. This balance can be achieved with healthy organs and mindset. Kidney is one such vital organ of human body. Kidney removes wastes and extra fluid from our body and also removes acid that is produced by the cells of our body and maintain a healthy balance of water, salts, and minerals in our blood. Any disruption in kidney can cause severe health issues such as stone formation. Urinary stones and kidney stones, collectively known as kidney stones, are debilitating diseases and are a common cause of emergency visits. Here we have used a CNN for automated diagnosis of kidney stones. A convolutional neural network (CNN) is a neural network with one or more convolutional layers and is primarily used for image processing, classification, segmentation, and other autocorrelation data. Here, we built our own sequential CNN from scratch. Sequential models, also known as machine learning models, determine the type of data to input or output. One of the most common algorithms for sequential data consists of iterations of consonants, audio clips, images, and so on. Recurrent neural networks (RNNs) are used to model sequential events. Here, a CT-scanned image of the kidney was used as the input image. The reason for using a sequential model is that you don't necessarily have to map the output to one or more inputs. Each layer can have multiple exits. This may or may not require layer release. The topology should be non-linear. Therefore, we used 15 layers of alternating folding, maximum bunching, and high density layers. These are briefly discussed in the following sections.

II. RELATED WORK

Malathy Chidambaranathan [1] in this article has proposed Backpropagation network (BPN) with image and data processing techniques which is used to implement automated kidney stone classification. The author states that it makes it impossible for human testing and operators to obtain large amounts of data results. CT scans and MRIs generate a lot of noise and are therefore inaccurate. Artificial intelligence techniques with neural network techniques have shown to be of great importance in this area. In this project, features are extracted by GLCM and classified by BPN. This project uses Fuzzy C Mean (FCM) clustering algorithm, a segmentation method for segmenting computed tomographic images to detect kidney stones at an early stage.

Anushri Parakh [2] states in this project that it is HIPAA compliant. In a retrospective clinical study approved by the Institutional Review Board, 535 adults with suspected urinary stones in abdominal and pelvic CT scans were considered without enhancement. When tested using data from the same or different section-level scanners, GrayNet's pre trained model showed higher classification accuracy than ImageNet's pre trained model or a randomly initialized model. At the patient level, the AUC for stone detection ranged from 0.92 to 0.95, depending on the model. The

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accuracy of GrayNet SB (95%) was higher than that of ImageNet SB (91%) and Random SB (88%). For stones larger than 5 mm, all models worked similarly (false negatives: 4 out of 35). For stones smaller than 5 mm, the number of false negatives for GrayNet-SB, ImageNet-SB, and Random-SB was one-seventeenth, 3 out of 17 and 5 out of 17, respectively. GrayNet-SB identified stones in all 22 test cases with obstructive uropathy. CNN's cascade model can detect urinary stones with high accuracy on unenhanced CT scans (AUC, 0.954). You can improve CNN performance and generalization across scanners by using transfer learning on your dataset enhanced with annotated medical images.

[3] Author, M Mua'ad and his team used image processing techniques to identify kidney stones. The purpose of this work is to implement image analysis classification techniques for the detection and classification of kidney stones. The proposed framework consists of four parts. These are (1) Image pre processing (2) Kidney segmentation using K-means clustering to determine the affected area (3) Feature extraction (4) Disease classification. Texture features are extracted using the Gray Level Co-Occurrence Matrix (GLCM) statistical features, and classification is performed using a Support Vector Machine (SVM).

III. PROPOSED METHOD

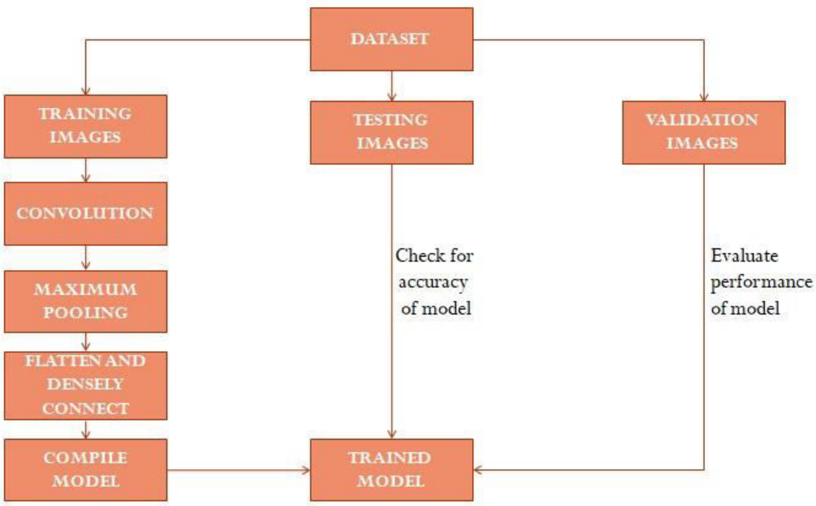

Fig.1.Methodology

A. *Dataset:* We have collected a total of 6,500 images of abdominal part of human and also human kidney. Each image is of 256x256 pixels in size. We have given 2 as channel value since images are in greyscale. Then we have split dataset into 32 batches. Number of samples passed to network at once is called batch size. Each batch consists of 202 images selected in random. We can increase the accuracy of model by increasing the number of epochs. A single pass over entire training set to network is called Epochs. We also keep a dataset prefetched in pipeline of our network to improve time efficiency of our model. Then we have set it to autotune the model which means it tracks time spent in each operation so that it can be fed into optimization algorithm. Then we have randomly flipped and rotated the images. These images are then matched with original dataset using 'map.lambda' function.

B. *Training Images:* A machine needs the basic information to be provided to it. This basic input, or the experience in the paradigm of machine learning, is given in the form of training images. Training data is the past information on a specific task. In context of our project, training data will have a set of C.T. scanned images of abdominal part of human and also human kidney both with and without stones along with a tag. Training images are so important because it helps us organize unstructured images, recognize and classify

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elements of images, validate our machine learning model and provides key input for algorithm used in our model. A total of 80% of images in each batch i.e., 161 images are used for training.

C. *Convolution:* Convolutional layer is the first layer of a C.N.N. (Convolutional Neural Network). Convolutional layer is the core building block of a C.N.N. and it is where the majority of computation occurs. Input parameters given to this layer are input data, a filter or feature map and an activation function. Let's assume that the input will be a greyscale image, which is made up of a matrix of pixels in 2D. This means that the input will have two dimensions, height and width which correspond to a BW (black and white) colours in an image. We also have a feature detector which is also called a kernel or a filter, which will stride across different parts of the image, checking if the feature is present. This process is known as a convolution. The filter is then applied to an area of the image and a dot product is calculated between the input pixels and the filter. This dot product is then fed into an output array. Activation function used here is ReLU (Rectified Linear Unit) which gives an output of 1 if feature is present or 0 if feature is not present.

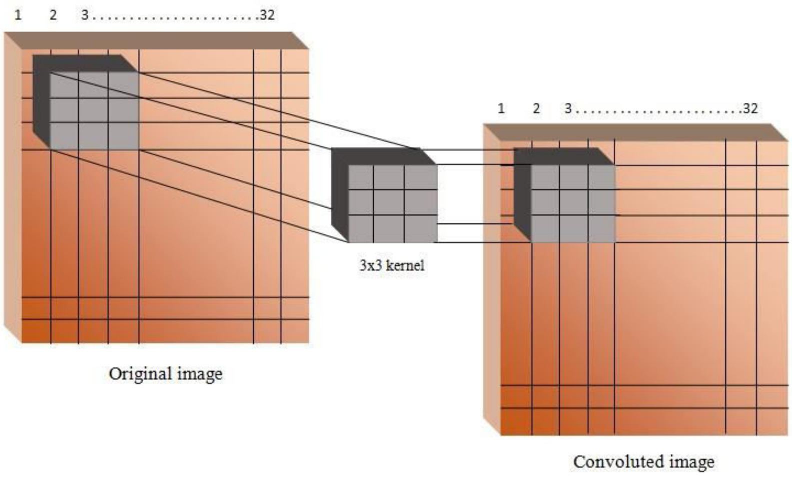

Fig.2.Convolution

D. *Maximum pooling:* Pooling layer is also called down sampling layer. The pooling layer is also called down sampling layer. It conducts dimensionality reduction and reduces the number of input parameters. Similar to the convolution layer, the pooling operation sweeps the filter across the input, the difference being that this filter has no weights. Instead, the kernel applies an aggregate function to the value of the received field and fills the output array. With maximum pooling, the filter moves across the input, selecting the pixel with the maximum value and sending it to the output array.

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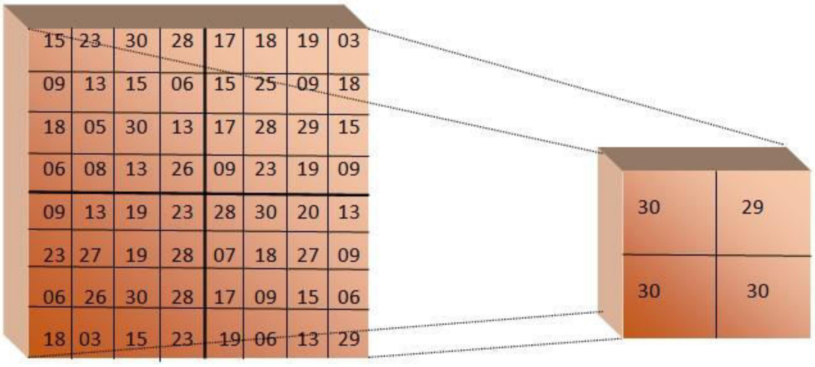

Fig.3.Maximum Pooling

E. *Flatten and densely connect:* Flatten layer can be assumed as array of selected image pixel values which you will provide as an input to CNN layers. It is basically applied after the pooling layers. To visualize it there is a toolkit called keract which we have used in Keras in Python. Flattening is converting the data into a 1dimensional array for inputting it to the next layer. We flatten the output of the convolutional layers to create a single long feature vector.

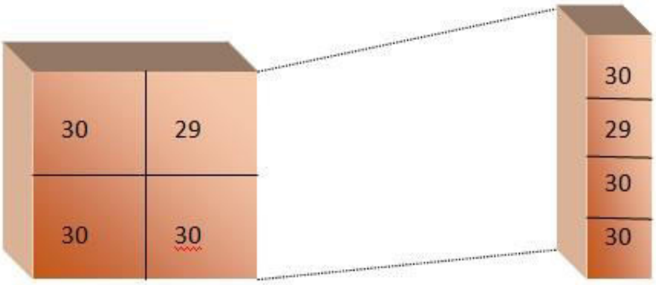

Fig.4.Flattenning into 1D

Densely connected layer is also called Fully Connected Layer. This is because it is this layer which fully connects previous convolutional and maximum pooling layers to output. This layer undertakes the task of classifying based on features extracted from images by the previous layer. This layer uses a soft max function which gives a probability from 0 to 1 i.e., relative probability of stone being present or not.

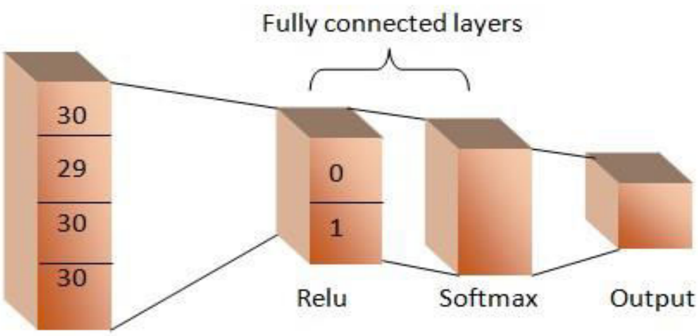

Fig.5. Fully connecting layers to a single output

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F. *Compile model:* C.N.N. which have built is then compiled to obtain desired output. Here we have used Adam algorithm as our optimizer. This algorithm is also called Adaptive moment estimation. Adam optimization is an extension of stochastic gradient descent and can be used in place of traditional stochastic gradient descent to update network weights more efficiently. Stochastic gradient descent maintains a single learning rate for all weight updates, and the learning rate does not change during training. The learning rate is maintained for each network weight (parameter) and is adjusted individually as the learning is deployed with the Adam algorithm.

G. *Trained model:* Now we fit our compiled model. We call fit() function, which takes 3 parameters: batch_size, epochs and verbose. It trains the model by dividing the data into batches specified in batch_size and iterating over the entire dataset for a specified number of epochs. We train your model for a fixed number of epochs. Verbose chooses how to display the output of the neural network during training. If you set verbose = 0, nothing will be displayed. With verbose = 1, the output looks like this: Epoch 1/200.

H. *Testing images:* In which category the machine should put an image of unknown category is called a testing image. Once you have built a machine learning model using training images, you need to test it. In this case, the AI platform uses test images to check the accuracy of the model and adjust or optimize the model for better results. Here we have taken 10% of images in each batch for testing purpose which is 21 images.

I. *Validation images:* The model we have built needs to be evaluated on a regular basis in order to be trained, which is the purpose of the validation image. You can determine how accurate the model is by calculating the loss that the model will generate at any point in the validation image. That is the purpose of training. The collection of instances used to fine tune the classifier's hyper parameters is called a validation image set.

J. *Architecture of CNN:* We have used 12 layers of alternating convolution and maximum pooling layers. Then 13th layer is Flattening layer. As a last step we have used two densely connected layers which uses a ReLU and a softmax function.

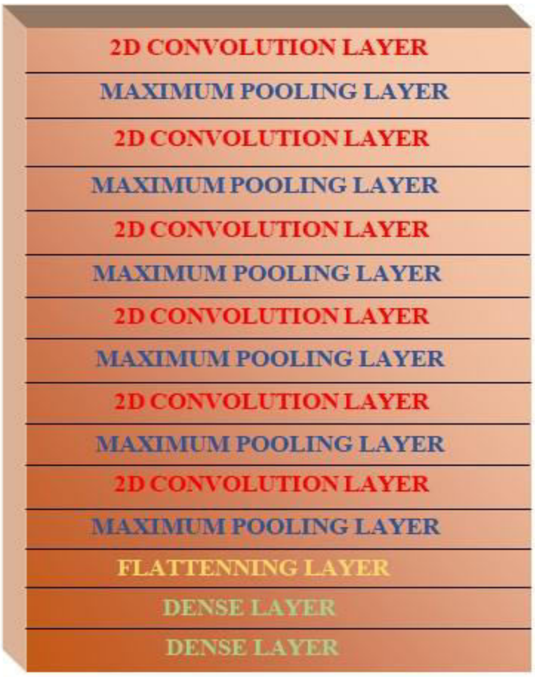

Fig.6. Architecture of CNN

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An overview of all layers describing number of filters used, size of filter and activation functions employed is given in following table:

Layer number	LAYER	NUMBER OF FILTERS	ACTIVATION FUNCTION	SIZE OF KERNEL	POOL SIZE
1.	Convo2D	32	relu	3x3	-
2.	MaxPooling		-	-	2x2
3.	Convo2D	64	relu	3x3	-
4.	MaxPooling		-	-	2x2
5.	Convo2D	64	relu	3x3	-
6.	MaxPooling		-	-	2x2
7.	Convo2D	64	relu	3x3	-
8.	MaxPooling		-	-	2x2
9.	Convo2D	64	relu	3x3	-
10.	MaxPooling		-	-	2x2
11.	Convo2D	64	relu	3x3	-
12.	MaxPooling		-	-	2x2
13.	Flatten		-	-	-
14.	Dense	64	relu	-	-
15.	Dense		softmax	-	-

Fig.7. Overview of all layers of CNN

IV. PSEUDO CODE

Step 1: Divide dataset into training, testing and validation images.
Step 2: Apply convolution on training images.
Step 3: Apply maximum pooling on convoluted images.
Step 4: Flatten the images.
Step 5: Use densely connected layers to connect previous layers to output.
Step 6: Compile model to obtain trained model.
Step 7: Now check for accuracy of model on testing images.
Step 8: Validate performance of model using validation images.
Step 9: End.

V. SIMULATION RESULTS

CNN model is trained with different cross sectional C.T. scan images of kidney containing stones and also without stones. We can evaluate the performance of model using parameters such as size of the stone detected, it's shape and ability in detecting presence or absence of stone in kidney. The accuracy results in the identification of stones showed that the deep CNN model is 87% and can greatly impact the efficient identification of stones in kidney. Our proposed model is trained using images of normal as well kidney with stones which establishes a Convolutional Neural Network and this model is saved. The saved model will run on the driver code in order to compare the trained images with the new test images from partitioned dataset. This model can be integrated with a scanning machine which gives result on site i.e, it predicts if stone is present in kidney or not along with scanning of kidney. This saves time, automates the process of medical diagnosis and reduces burden of doctors. Overview of accuracy achieved with different sets of dataset.

Dataset	Accuracy achieved
Training images	84.87%
Testing images	90.62%
Validation images	87.19%

Fig.8. Accuracy achieved

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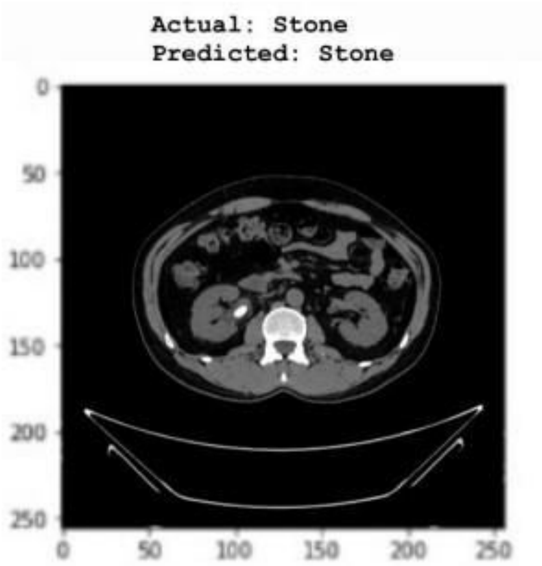

Fig.9.Kidney with stone

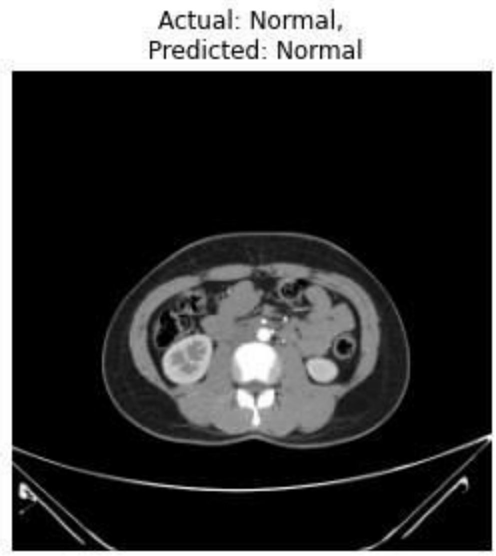

Fig.10. Kidney without stone

Fig.11.Stone detected in human kidney
in a abdominal CT scanned image

Fig 12. Healthy human kidney
in a abdominal CT scanned image

VI. Conclusion and Future Work

Kidney stone is a serious problem which can cause severe health issues if neglected. It is estimated that 1 in 10 people will **suffer from** kidney **stones** at some point in their lives. **Therefore,** this **issue needs an** early and **accurate** detection. With regard to this problem, our proposed system is developed which will detect the presence of stones in human kidney and gives result accordingly.

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