Kidney Stone Detection Using Deep Learning and Transfer Learning

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***Abstract*— Researchers are now interested in the invention and improvement of diagnostic instruments for medical diagnosis. One of the technologies utilized in medical inspection and diagnosis is deep learning. The utilization of various data mining algorithms on kidney patient data sets is investigated in this study. The purpose of this research is to employ data mining classifiers to predict kidney failure. Back Propagation Convolutional Neural Network is one of the methods utilized for this diagnostic system. The outcomes of the tests show that the Convolutional neural network (CNN) algorithm outperforms than other classification systems. An automated kidney stone classification is implemented using a Convolutional Neural Network (CNN) image and data processing techniques. It is impossible to produce results for large datasets using human inspection and operators. As a result, this research work utilizes the Convolutional Neural Network (CNN) and the ALEXNET algorithm to overcome the challenge.**

Keywords*— *Convolutional neural network (CNN), Artificial Neural Networks (ANN), Computed Tomography (CT), Back-Propagation Network (BPN).

I. INTRODUCTION

Urolithiasis is growing more prevalent. Nearly 1.3 million emergency room visits are considered to be due to urinary stone illness. Despite the presence of a history of urinary stone illness, an unenhanced CT scan allows for a more precise and fast diagnosis. These benefits have expanded the use of CT for supposed urolithiasis, also lengthier turnaround times, increased radiologists' workload, donated to higher imaging volume and lengthier hospital charges [1-3]. The Machine learning algorithms for medicinal image interpretation have completed significant progress thanks to the usage of multiple imaging modalities. The algorithms could also aid in case triage and emergency department workflow improvements (ED). However, two fundamental hurdles must be overcome before deep-learning (DL) algorithms can perform well in medicine. The ability to access huge, well-annotated, and well-balanced datasets is the first. The uniformity of DL models across scanners is the second issue. The classification of COVID-19 diseases using CT scan images were also presented using the deep learning technique [4-7].

When DL algorithms from one scanner are employed in another, the results may not be as good. Variances in picture features generated by differences in acquisition and reconstruction techniques when employing diverse imaging systems account for the lack of generality. Despite significant variances between natural and medical images, previous study has been used a transfer learning with convolutional neural network (CNN) representations pre-trained on a huge set of ordinary images (such as ALEXNET) for biomedical requirements to report the challenge of inadequate and excessive data [8-11]. The models skilled on datasets from the similar imaging sense modality field outstripped out of domain skilled models for medical requests, according to recent studies. Researchers have recently anticipated that incorporating deep learning models for CT scan-related tasks, such as kidney stone detection, would have greater generalization if they were pre-trained on CT images, since transfer learning increases the accuracy when the source and target tasks have comparable characteristics. The generalization is the accurateness of the system qualified with photos from one salesperson and tested on images developed from another salesperson. To our knowledge, no research has been done on the ability of a CNN model that has been pre-trained using medicinal images to manage class inequity or photos from dissimilar sources [12-14].

II. Literature Review

Kidney stones are a big problem that many individuals are dealing with these days. Many people are severely affected by this condition due to a delay in the discovery of kidney stones. Most methods used in the past only detected kidney stones when they were severely affected. Now with the better method called the back propagation network this process will detect the stones in kidneys in early days and it is mostly working on the machine learning algorithms. This technique is broken down into several parts that will aid medical assistance to humans by capturing photos of kidney stones, which will be delivered with high pixels and provide the most accurate location of the stones[15].

Computed Tomography (CT) Scan imagination is used to deliver the physical irregularities like stones, contagions and swellings in kidney disease and also produces evidence round the kidney. This work classifies the kidney images using CT according to the process of feature extraction. Algorithms and preprocessing approaches (such as grey-scale conversion) are used to classify kidney pictures as abnormal, produce ROI, and extract features utilizing Sobel filtering and edge detection methods, as well as Cuckoo Search (CS) and Artificial Neural Networks (ANN). Through various stages of image processing, these techniques are utilized to detect kidney stones. The first step is the image pre-processing using filters in which image gets flattened as well as the noise is detached from the image. The Pre-processing includes image augmentation, is used to recover the image. When compared to other imaging like x-ray and ultrasound, CT has less noise. The CS-ANN algorithm operates on the MATLAB platform. When compared to other approaches, the CS-ANN has a zero percent false-acceptance rate[16].

To increase the accuracy and sensitivity of kidney stone detection rate the median filters were used widely in ultrasound pictures. The sample size of 114 was employed with a p-value of 0.8 to improve the accuracy and sensitivity of kidney stone identification with the simulation tool called MATLAB. Affording to the results found, the Median filter has accurateness of 86.4 percent and rank filter has accurateness of 82.3 percent and the sensitivity of median and rank filter is 87.7 percent and 82.5percent respectively. The Median filter has a meaningfully higher accurateness of p=0.018, sensitivity of p= 0.018 as related with the rank filter. The conclusion by the study is the kidney stone detection rate has been enhanced using the Median filter associated with rank filter in relations of accurateness and sensitivity[17].

The BPN with image and data processing methods were employed to implement an automatic kidney stone classification. CT scan and MRI produces a lot of noise and hence leads to inaccuracies. This portrays a separation method for segmenting figured tomography images to perceive the kidney stones in premature stages for IoT applications [18-20].

Individuals today are susceptible to a variety of kidney diseases. The Kidney contaminations are one of the most common ailments among them, with symptoms such as blisters and stones, contamination, tumors, and changes in kidney location and appearance on the rise. The Kidney problems must not be overlooked because kidney failure might put one's life in jeopardy. As a result, early detection and prevention are essential to prevent such renal malformations in patients.

This research examines how kidney defects are discovered and acknowledged. The information can be used to detect and locate kidney infections in the early stages so that appropriate action can be taken to effectively treat them. As a result, it features a recurring application space that includes a PC-assisted discovering framework that aids in recognizing kidney irregularities and determining the likelihood of infection. Furthermore, the CT image features a number of difficulties, including low differentiation, gaussian clamour, spot commotion, various early abnormalities. The higher picture quality is more important than removing associated brightness. To pass this test, appropriate image handling techniques such as pre-planning and ordering tactics were demonstrated. The research work outlines the many ways for detecting and recognizing kidney abnormalities.

III. Algorithms

Using a pre-trained ALEXNET and a convolutional neural network, we propose a kidney stone detection framework based on transfer learning. Transfer learning's primary advantages include resource savings and increased effectiveness while developing new models. Additionally, since the majority of the model will have already been trained, it can assist with model training when only unlabeled datasets are available.

ALEXNET'S TRANSFER LEARNING

Transfer learning in machine learning is a machine-learning strategy that involves reusing a previously learned model on a new task. That is, a computer applies previous task expertise to improve prediction for a new task. The design is made up of eight layers, including five convolutional layers, three fully linked levels, and the softmax layer.

Convolutional Neural Network

Figure 1 displays the convolutional neural network (CNN) architecture, a deep-learning network. CNNs are completely linked networks, and their entire connectivity renders them vulnerable to data overfitting. The Convolutional layers, fully connected layers and max-pooling layers, are the three types of layers in the convolutional neural network (CNN) architecture. CNNs are divided into two sections. The first step is called feature extraction, and it employs convolution and pooling layer groups. The classification using a completely connected layer is the second part. The output is produced by the last portion called SoftMax layer.

Input Layer: This layer is used to give input to our model. The total number of features can be obtained based on the total number of neurons present in the structure. Artificial input neurons constitutes the input layer of a neural network, which provides the initial data into the system for processing by following layers of artificial neurons. The input layer is the first step in the artificial neural network's processing.

Convolutional layer*:* Convolutional layers perform a convolution on the input before forwarding the output to the next layer. The pixels in a convolution's receptive area are all converted to a single value. The convolutional layer's final output is a vector.

Batch normalization layer: Batch normalization is a network layer that enables each layer to learn more independently from the others. It's used to normalize the output of the previous layers. Standardizes the inputs to a layer for each mini-batch. This stabilizes the learning process and reduces the number of training epochs required to build deep networks dramatically.

Max Pooling is a convolution method in which the Kernel collects the maximum value from the area it convolves. Max Pooling basically means that we will only forward the most relevant information.

Layer ReLu*:* It is a function of activation.

Softmax layer**:** This layer is usually the final output layer of a multi-class classification neural network. It's usually used to fit neural network output between zero and one. A fully connected layer connects every node in the preceding layer.

Fully-Connected Layer: *I*n a fully-connected layer, each node is connected to all nodes in the previous layer.

Output Layer: It is a completely linked layer that straightens and delivers the input from the other layers in order to change the output into the appropriate number of classes by the system. In a neural network model, the output layer is the layer that immediately produces a prediction. An output layer is present in all closed loop control neural network architectures.

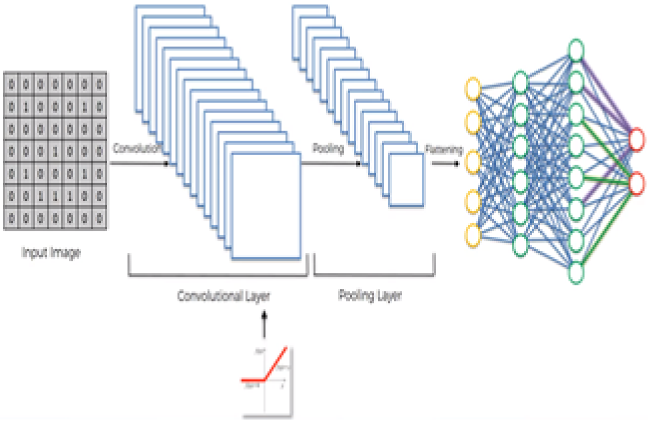

Fig.1. Architecture of Convolutional Neural Networks

IV. PROPOSED WORK

In this work, we recommend a system that employs two strategies to improve performance and accuracy: ALEXNET and convolutional neural networks. The project's workflow is depicted in Figure 2.

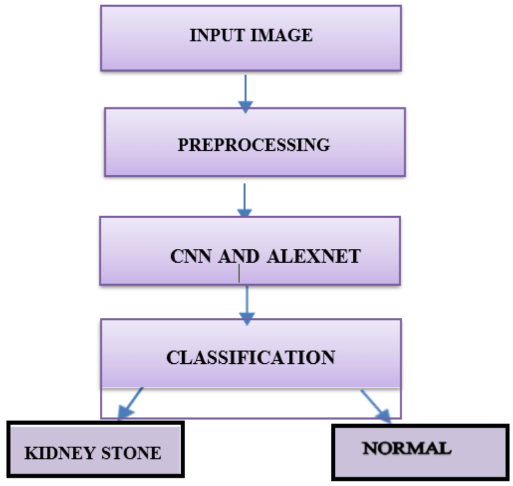

Fig. 2. Workflow of the Proposed System

A. ***MODULE 1:***

B. This is where we give the system the collected dataset as input.

C. ***MODULE 2****:*

Pre-processing is used to improve image data by removing undesired distortions and boosting specific visual features that are relevant for further processing and analysis. An undesired distortion also be removed by testing out various activation, loss, and optimizer procedures. Further by Changing the unit, layers numbers and the batch size the undesired distortions would be reduced significantly.

The visual features of performance metrics of images would be boosted by the following techniques. They are as follows: adding more number of layers, increasing the Epochs, changing the image size and also using transfer learning technique.

MODULE 3:

Input Layers: This layer is used to give input to our model. The total number of features can be obtained based on the total number of neurons present in the structure. Artificial input neurons constitutes the input layer of a neural network, which provides the initial data into the system for processing by following layers of artificial neurons.

Hidden Layer**:** The input layer sends data to the hidden layer, which processes it. The hidden layer receives the input from the input layer. There could be a lot of hidden layers based on the model and data quantity. The number of neurons in each hidden layer might vary, however they are usually more than the number of features.

Though the number of neurons in each buried layer varies, it is usually greater than the number of features. The network is also called as a nonlinear network because the output from each layer is formed by matrix multiplication of the previous layer's output such that layer's learnable weights, addition of learnable biases, and then activation function.

MODULE 4: According to the labelled training set, classification algorithms try to identify the category of a new observation among a set of categories. The categorization accuracy varies depending on the task, anatomical anatomy, tissue preparation, and characteristics.

V. EXPERIMENTAL RESULTS AND ANALYSIS

The suggested system is evaluated using the Kaggle Stone dataset. We have used a dataset of 50 samples for CNN and 150 samples for ALEXNET, IN which half of the images were trained and tested for kidney stones and the other half were trained and checked for normal using both algorithms. The image is resized for ALEXNET to 227 by 227 by 3, and for CNN to 256 by 256 by 3. MATLAB R2018a is used to implement the system and its recognition steps. This Project proposes to spot the Stone from CT scanned medical images using multi clustering model and morphological process. The segmentation refers to the process of partitioning a digital image into multiple segments. The Kidney CT is taken and its noises are removed using filters. The morphological process was used to smoothen the Stone region from the noisy background. CNN algorithm gives more accuracy than the machine learning.

Figures 3 and 4 show the identification of kidney stones using Alexnet and CNN, respectively. The graph of kidney stone detection shows that the process was carried out for the time period of 8 minutes 45 seconds with a accuracy of 69.39% using CNN whereas in ALEXNET technique, the process was completed within a time slot of 1min 17seconds with a validation accuracy of 96%.

The contrast between existing and anticipated work is shown in Table 1.

TABLE 1 . COMPARISON BETWEEN THE PROPOSED WORK AND OTHER RELATED WORKS

S.NO	YEAR	TITLE OF REFERENCES	ALGORITHM	IMPORTANCE	DATA SET	ACCURACY
1.	2012	Diagnosis of Kidney Stone Disease Artificial Neural Network for	LVQ, RBF and feedforward architecture with back propagation algorithm	Early detection of kidney stones and best model of diagnosis.	Real set data collected from different medical laboratories	92%
2.	2019	Urinary Stone Detection in CT Images Using DCNN	Deep Convolutional Neural Networks	CT scan and kidney stone detection	Random s1 ,s2 database	95%
3.	2019	Chronic Kidney Disease (CKD) Prediction using CNN	Mathematical concepts and	Support Vector Machine, Random Forest, XGBoost, Logistic Regression, Neural networks, Naive Bayes Classifier	Not Specified	90%
4.	2020	Kidney Stone Detection from ultrasound images by using Canny edge detection and CNN classification	Central Neural Networks	Pre -processing , noise filtering and segmentation	collected images from Google	70-85%
5.	2020	Artificial Neural Network for kidney Stone Detection	Cuckoo Search Algorithm	generate ROI, using of sobel filtering and edge detection method	Real set data collected from Hospitals in the form of DICOM	94.61%
6.	2021	Early detection of Kidney Stones in Ultrasound Images Using Median Filter and Rank Filter	Median filtering algorithm is proposed	median filter and rank filter	Not Specified	82.2%
7.	2021	Improving the accuracy of predicting disease	clustering Neural Network S	Noise filter, SOM cluster	Kaggle Database	93%

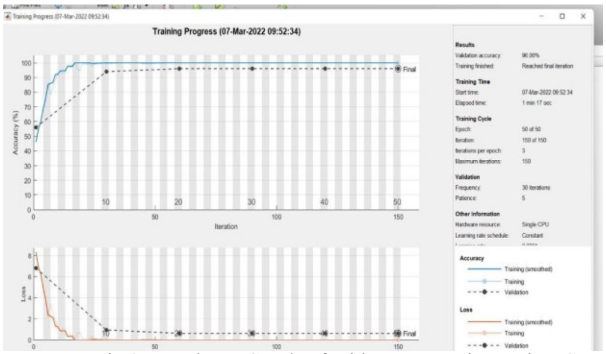

Fig.3. Resultant Graph of Kidney Detection Using CNN

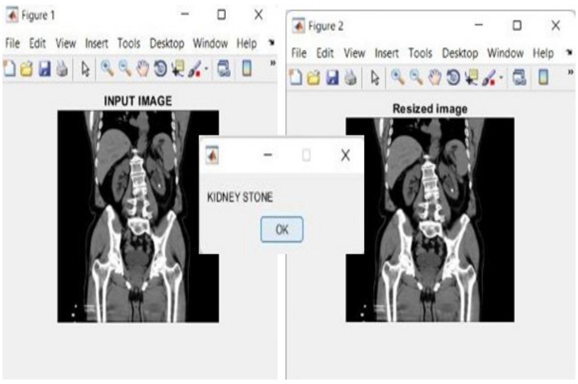

Fig.4. Resultant Graph of Kidney Detection Using ALEXNET

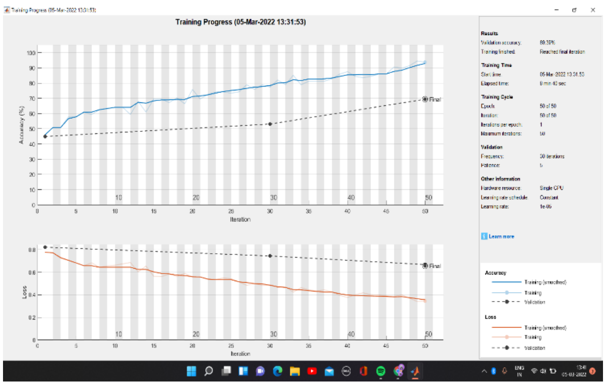

Fig. 5. Detection of a Kidney Stone image

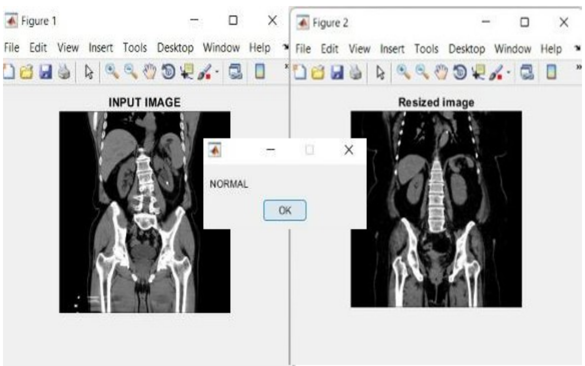

Fig. 6. Detection of a Normal Kidney image

V. FINAL DETECTION RESULTS

The figure 5 and 6 clearly gives the difference between a normal Kidney and the Kidney with stone. Likewise we can able to notice the stone present in the kidney and for the further treatment.

VI. CONCLUSION

This paper was examined and deployed to detect whether a kidney stone is present or not using pretrained ALEXNET and CNN. On a public dataset, the suggested technique was tested on both ALEXNET and CNN. CNN achieved a maximum accuracy of 69 percent, whereas ALEXNET achieved a maximum accuracy of 96 percent. The results of the experiments demonstrate that ALEXNET is more accurate and has a faster prediction rate(1 min 17 sec) than CNN(8 min 45 sec). This experiment gives us a sliver of evidence that can ensure greater recognition in a short period of time. With more time and more thorough research, the proposed system would be improved in the future.

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