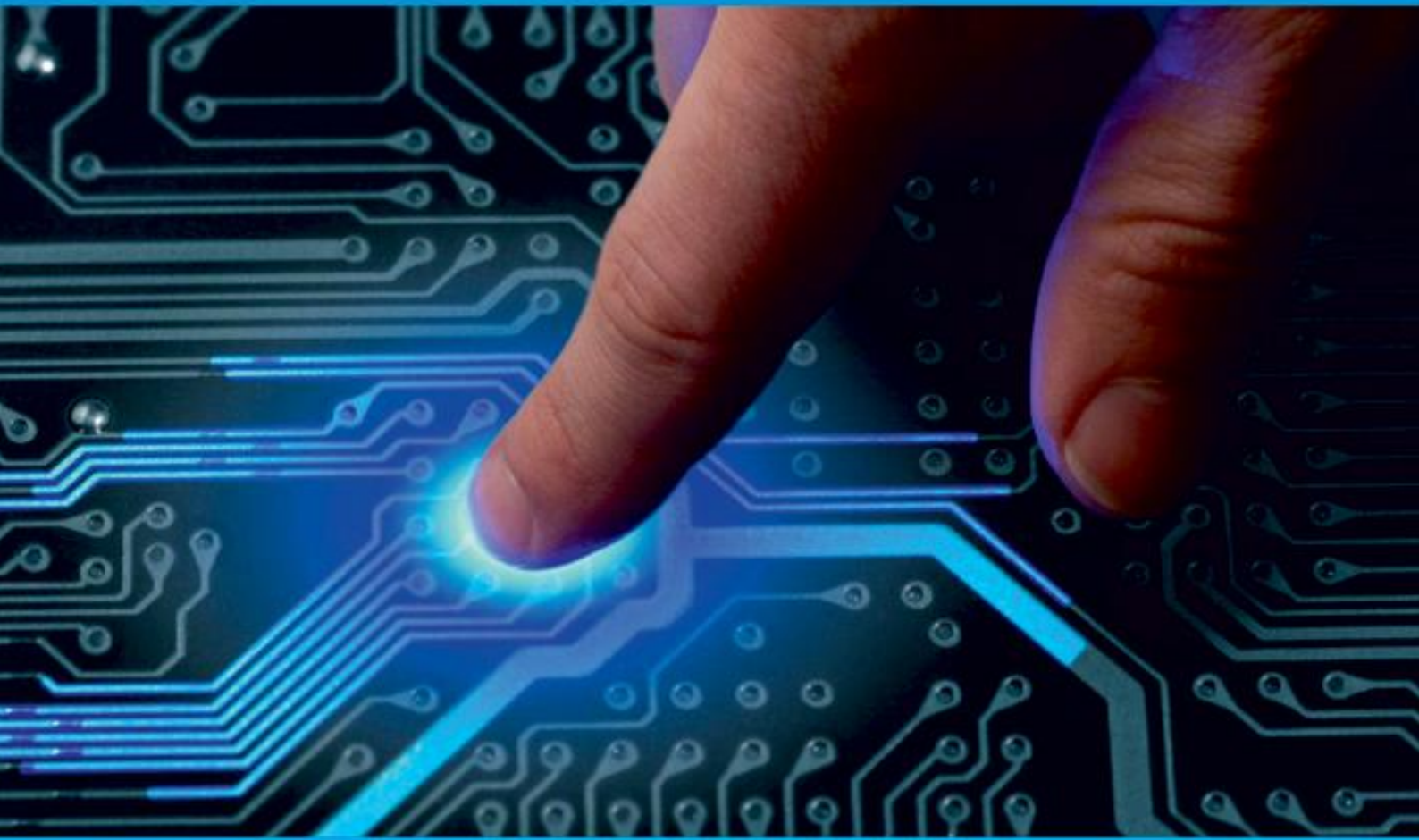




IJIRCCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 2, April 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.379



9940 572 462



6381 907 438



ijircce@gmail.com



www.ijircce.com

Detection of Kidney Stone– A Deep Learning Approach

R. P. Meenaakshi Sundhari¹, M. Mounika², R. Gokilavani³, K. Jothika⁴

Professor, Department of ECE, P. A. College of Engineering and Technology, Pollachi, Coimbatore,
Tamil Nadu, India¹

UG Scholars, Department of ECE P. A. College of Engineering and Technology, Pollachi, Coimbatore,
Tamil Nadu, India^{2,3,4}

ABSTRACT: Renal stone disease is a highly serious and potentially lethal ailment that is still present in modern times. If stone diseases are left untreated in their early stages, kidney damage will eventually result. Diabetes mellitus, hypertension, glomerulonephritis, and other illnesses are the most frequent causes of kidney failure. Diagnosing renal illness as soon as possible is crucial since kidney disease can be devastating. An early detection system for kidney illnesses was classified using a back propagation network. The proposed approach leverages convolutional neural networks (CNNs) using ResNet50 as the foundation for deep learning techniques. The pre-trained classifier images from the dataset are compared with the kidney pics. The Kaggle website provided the data. Utilizing CNN layers yields optimal outcomes in terms of precise classification.

KEYWORDS: Convolutional Neural Network (CNN), Deep Learning, Kidney Stone, ResNet50.

I. INTRODUCTION

The development of stones is one of the most common conditions affecting the kidneys and bladder. A urinary stone can cause discomfort in the lower abdomen and large amounts of hematuria. Consequently, in order to treat individuals before their condition worsens, early detection is necessary. Urinary stones can be detected in the lower body by pelvic x-ray imaging since most of them are solid and visible with this type of imaging. Although abdominal x-ray scans, which are not commonly used for stone detection, are less expensive and particle-intensive than CT scanning, the most popular medical imaging modality for this reason. However, identifying urinary stones in a standard radiation image is a difficult task since stones and other anatomic structures are projected in a 2D image in this modality. Deep learning has been effectively employed in many medical imaging applications, leading to notable gains over conventional feature creation techniques. On the other hand, deep learning performance frequently depends on the volume of training data. Medical image databases are limited compared to other fields due to the high cost of data collection, data protection issues, and the difficulties associated with picture classification, which calls for expertise. In addition, class disparity is a common issue in medical fields where the number of normal samples greatly exceeds that of those with lesions.

II. PREVIOUS METHOD

However, the employment of AI-based technologies, such as collecting features and deep neural networks, The most widely used approach for training neural network models is the back propagation network. It is used to process the picture and data in order to execute a computerized renal stone categorization. Human inspection is the standard approach for medical resonance renal image categorization and stone identification. This approach is inaccurate because it is not feasible to manage enormous amounts of information. Due to operator negligence, magnetic resonance (MR) pictures may have noise. This results in serious mistakes in image processing demonstrates immense potential in this field for collecting the area that is important using the back propagating network approach. The Back Propagation Network was employed in this study to identify kidney stones. Performance of the BPN algorithm was evaluated as a function of training efficiency and grouping precision. When compared to other neural network-based classification approaches, the Back Propagation Network performs better.

III. PROPOSED METHOD

In the proposed study, we use a convolutional neural network with a Resnet architecture to identify kidney stones.

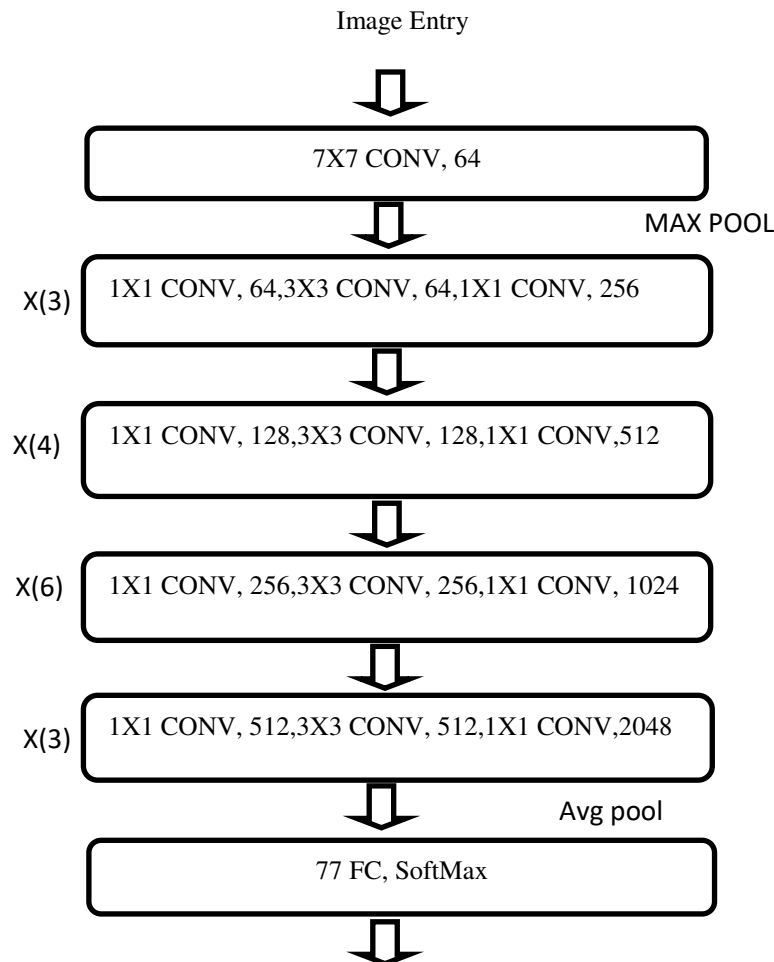
A. Dataset

The largest dataset available to the study group is therefore typically obtained by academics using Kaggle. The Kaggle repository is where the data was found. MPEG or JPEG format is used for the data. However, they are in JPEG format and have been divided into two files for training and testing in this study.

The most helpful datasets for assessing the kidney stone are those that contain pictures of real network configurations. It also takes a lot of time to turn the unlabeled network traces into a labelled dataset. Because of this, researchers typically use a variable scale of signal intensities in various pictures. Preprocessing functions are activities that are typically necessary prior to the major data analysis and information extraction, and are often classified as radiometric or geometric adjustments. The kidney photos are scaled at a certain range *processing*.

B. Classification

Both organized and unstructured data can be classified. Data can be categorized via classification into a predetermined number of groups. The primary goal of a classification challenge is to identify the class or category to which a new data set belongs. Categorization is a technique of supervised learning in machine learning and statistics where a software programmer learns from the input given to it and then applies This capacity to organize newly acquired data. This type of data may contain multi-class or bi-class information (e.g., identifying if the person is male or female).



C. Skip Connections in ResNet50

There are two methods in which these skip links function. To address the issue of vanishing gradients, they start by creating an alternative route for the gradient to follow. They also make it possible for the model to identify a distinct value. This ensures that the top tiers of the model perform equally well to the bottom ones. All things considered, the leftover blocks greatly facilitate the layers' learning of identity functions. Consequently, ResNet50 lowers error % while improving the appearance of deep neural networks with more neural layers. In other words, skip connections allow networks to be trained that are significantly more sophisticated than was previously conceivable by combining the outputs of earlier layers with the outcomes of later layers.

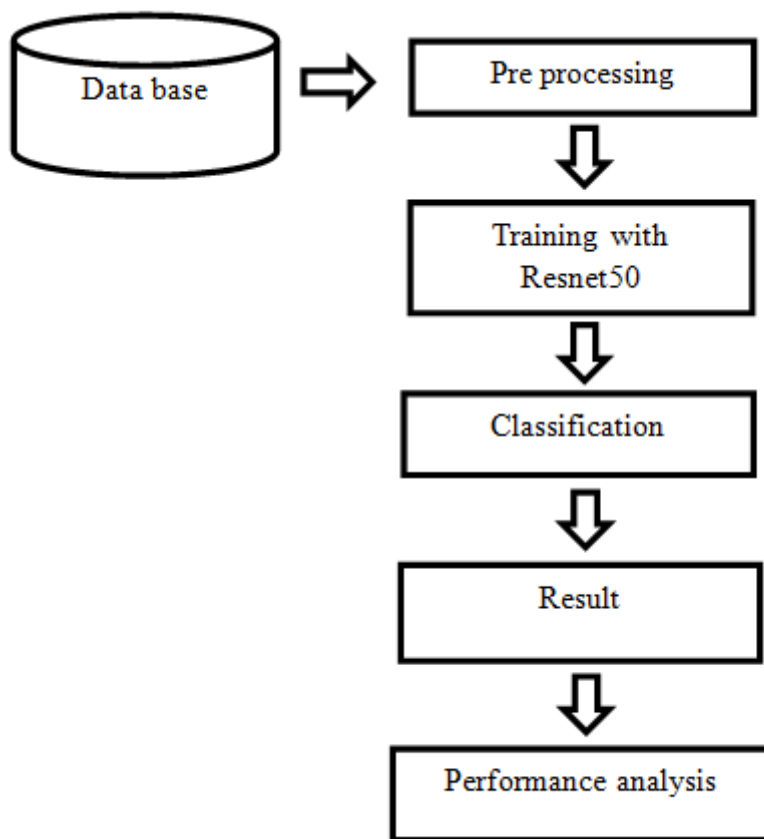


Fig 2. Proposed system block diagram

D. A Resnet50 vs. BPN comparison

BPN is a conventional neural network architecture that uses backpropagation, a technique for modifying the network weights based on the difference between the expected and actual output, for training. A hidden layer, a data layer, and an exit layer are the three layers. Although gradients fading in very deep networks may be a problem for BPN, it can be used in many different applications. In contrast, the ResNet50 architecture is a more complex and modern design that uses residual connections to address the problem of vanishing gradients. It is trained using the supervised learning technique of random gradient descent and has 50 layers. Regarding picture classification tasks, particularly those that call for a large number.

E. Classification

The process of categorizing images according to their visual content is called image classification. This crucial machine vision problem has various practical applications, such as face detection, object recognition, and medical imaging. Two deep learning techniques, Convolutional Neural Networks (CNNs) and ResNet50, have shown remarkable performance on several test datasets. After being trained using directed learning, these algorithms adjust the variables to lessen the difference between the expected and actual results. Even though image classification is a difficult problem, recent advances in deep learning. These algorithms adjust the variables to lessen the difference between the expected and

actual results. Even though image classification is a difficult problem, recent advances in deep learning have produced appreciable gains in efficiency, making it a crucial component of many systems for computer vision. The input image is shown in Figure 2. The picture is preprocessed before being trained with the ResNet50 architecture. Figure 3 shows the preprocessed picture. In preprocessing the image will be resized. Figure 4 depicts the image of training phase. Table 1 depicts the performance metrics of the CNN parameters.

IV. RESULTS AND DISCUSSION

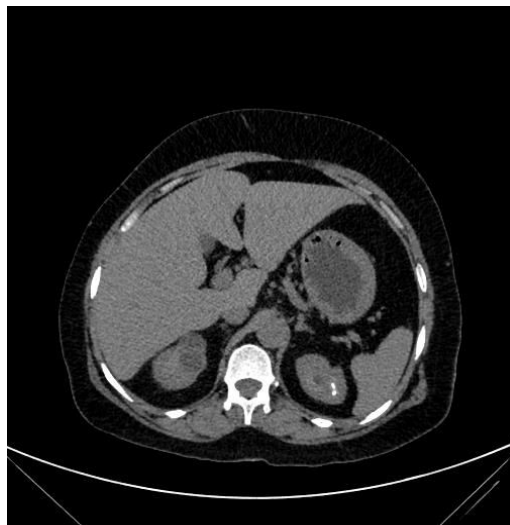


Fig 2. Input Picture



Fig 3. Resized Picture

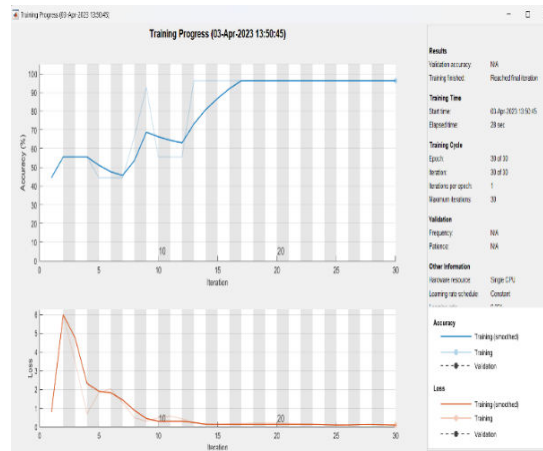


Fig 4. Training Phase

Table 1. Performance metrics

SL. No	PARAMETERS	PERFORMANCE METRICS
1.	Accuracy	95.9
2.	Error rate	0.04
3.	Sensitivity	95.5
4.	Specificity	96.3
5.	Precision	96.2
6.	FPR	0.03
7.	F1 Score	95.9
8.	MCC	91.8
9.	Kappa	91.8

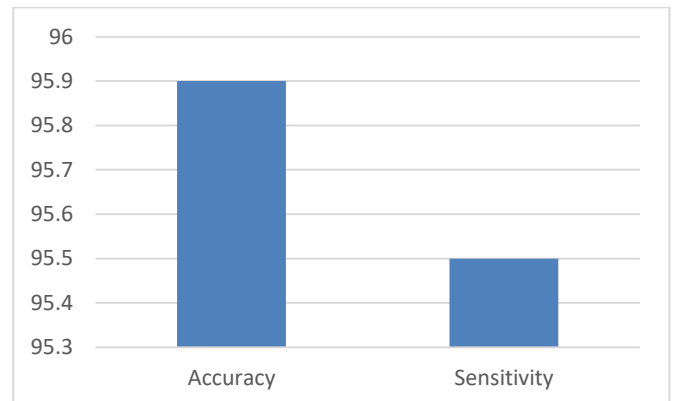


Fig 5. Performance metrics bar chart

V. CONCLUSION

A model was created in the proposed study to help identify kidney stone disease. In order to discern between images of kidney stones that are normal and those that are pathological, the model suggests using a convolutional neural network to extract feature information from photos. Several open and private data sets are used to test the proposed method. The proposed method performs better than the latest method. On the Kaggle data set, the suggested model has a 95.9% accuracy rate. The ResNet50 design offers faster categorization than other neural network-based classification techniques. Finding the kidney stone is a time- and labor-saving benefit of this treatment.

REFERENCES

[1]Linta Antony, Sami Azam (Sep 2021)“A Comprehensive Unsupervised FrameworkforChronic Kidney Disease Prediction”.

[2] Kadir Yildirim, Pinar Gundogan Bozdog, Muhammed Talo, Ozal Yildirim, Murat Karabatak and U Rajendra Acharya (2021) "Deep learning model for automated kidney stone detection using coronal CT images".

[3] E. M. Senan, M. H. Al-Adhaileh, F. W. Alsaade, T. H. H. Aldhyani, A. A. Alqarni, N. Alsharif, M. I. Uddin, A. H. Alahmadi, M. E. Jadhav, and M. Y. Alzahrani (Jun 2021) “Diagnosis of chronic kidney disease using effective classification algorithms and recursive feature elimination techniques”.

- [4] Yingpu Cui, Zhaonan Sun, Shuai Ma, Weipeng Liu, Xiangpeng Wang, Xiaodong Zhang, et al., (2021) "Automatic detection and scoring of kidney stones on noncontrast images using stone nephrolithometry: combined deep learning and thresholding methods".
- [5] Cui, Y., Sun, Z., Ma, S., Liu, W., Wang, X., Zhang, X., Wang, X. (2021) "Automatic Detection and Scoring of Kidney Stones on Noncontrast CT Images Using S.T.O.N.E. Nephrolithometry".
- [6] Yildirim, K., Bozdag, P.G., Talo, M., Yildirim, O., Karabatak, M., Acharya, U.R. (2021) "Deep learning model for automated kidney stone detection using coronal CT images".
- [7] Nithya, A., Appathurai, A., Venkatadri, N., Ramji, D.R., Anna Palagan, C. (2020) "kidney disease detection and segmentation using artificial neural network and multi-kernel kmeans clustering for ultrasound images".
- [8] M.Akshaya, R.Nithusaa(Dec 2020) "Kidney stone Detection Using Neural Networks".
- [9] S. Y. Yashfi, M. A. Islam, Pritilata, N. Sakib, T. Islam, M. Shahbaaz, and S. S. Pantho, (Jul 2020) "Risk prediction of chronic kidney disease using machine learning algorithms".



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



SJIF Scientific Journal Impact Factor



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

 9940 572 462  6381 907 438  ijircce@gmail.com



www.ijircce.com

Scan to save the contact details