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Deep Learning-Based Renal Stone Detection: A Comprehensive Study and Performance Analysis

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***Abstract* – Early kidney stone detection is essential for the diagnosis and treatment of people who have kidney stones. The objective of this study is to employ deep learning algorithms for renal stone detection, addressing the critical need for early, accurate diagnosis, which can significantly improve patient outcomes and reduce healthcare costs. The paper thoroughly assesses a variety of models, including ResNet, DenseNet, and EfficientNet, for CT images. The limitations of manual identification procedures highlight the urgent need for a more effective automated approach, making this research necessary. Notably, the painstakingly improved DenseNet model achieves a peak accuracy of 0.86, demonstrating its potential superiority. These results convincingly demonstrate the revolutionary power of deep learning, which is poised to revolutionise the detection of renal stones. This fast, trustworthy, and non-invasive method has the potential to advance clinical procedures and significantly improve patient care.**

***Keywords* – CT images, deep learning models, detection, renal stone.**

I. Introduction

Kidney stones, scientifically known as renal stones, are a common health issue that millions of people experience globally. If left untreated, these crystalline formations inside the kidneys can produce excruciating pain and result in catastrophic problems like kidney damage. Radiological imaging techniques like X-rays and CT scans are the mainstay of current procedures for finding these stones. Despite being successful, these methods have disadvantages, including expensive prices and the use of ionising radiation, which raises questions about possible long-term health repercussions. There is a clear need for an improved kidney stone detection method. For quick treatment and the well-being of the patient, rapid and precise stone detection is essential. Furthermore, the cost of using the current diagnostic techniques can be very high for patients and healthcare systems. This study highlights the urgent need for a more practical, affordable, and accurate method of detecting kidney stones.

Deep learning, a branch of artificial intelligence (AI), has become increasingly popular in the detection of kidney stones nowadays. Artificial neural network-based deep learning algorithms provide a viable answer to the drawbacks of traditional diagnostics [1]. These models are able to quickly and accurately diagnose kidney stones by analysing multiple medical imaging sources, such as ultrasound and CT scans. This change could lessen radiation exposure hazards while simultaneously decreasing healthcare expenses and easing patient suffering.

The proposed study provides a comprehensive look at renal stone detection using deep learning using different CNN (Convolutional Neural Network) models, [2] mainly focusing on how deep learning contributes to this progress with performance analysis to come up with the best model to generate better accuracies. The aim of the research is to identify the most suitable deep learning algorithms for renal stone detection using CT scan kidney images. It evaluates the impact of various factors on the accuracy and performance of models for detection.

II. Literature Review

This section reports the literature review of the existing studies, which use deep learning models for renal stone detection. The approaches are analysed and summarised, and this research focuses on solving the challenges in the existing approaches. Artificial neural network, support vector machine, multilayer perceptron with backpropagation methods were used for detection and diagnosis of chronic kidney disease using deep learning-based heterogeneous modified artificial neural network [3], [4]. A deep learning system for automated kidney stone detection and volumetric segmentation on noncontrast CT scans [5], [6] was developed using 3D u-net for kidney segmentation, 13-layer convolutional neural network for stone detection. VGG16 architecture, ResNet-101, Xception_Ir0.001 (CNN model) were used for kidney stone detection [7]–[10]. Self-supervised learning on ImageNet was followed by additional self-supervised learning on unlabelled domain-specific medical images. A novel method called Multi-Instance Contrastive Learning (MICLe) was introduced [11]. Deep transfer learning technique with pre-trained models ResNet-50 and DenseNet-161 were used for automated invasive ductal carcinoma detection using deep transfer learning with whole-slide images [12] of a public histopathology dataset containing

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277 524 image patches. The trends in the prevalence of kidney stones in the United States from 2007 to 2016 [13] were reviewed, and NHANES dataset was created with 28 209 adults. Sentiment analysis of tweets in Malayalam using long short-term memory units and convolutional neural nets [14]–[16] was performed on 12 922 Malayalam tweets. CIFAR-10, CIFAR-100, SVHN, and ImageNet are widely used for renal stone detection. Computer aided detection of ureteral stones in thin slice computed tomography volumes using Convolutional Neural Networks [17] was developed on 465 clinically acquired high-resolution CT volumes of images.

III. Proposed System

A. Class and Image Count Calculation

A thorough procedure was used to identify the number of unique classes within the sizable training dataset, as well as to calculate the picture counts corresponding to each class.

B. Identification of Minimum and Maximum Image Count Classes

Finding the classes with the highest and lowest image counts in the training dataset was a significant component of the data analysis. The identification of classes with significant differences in picture counts was made possible by this computational technique. Understanding potential class imbalance difficulties, a crucial factor in a larger context of machine learning model training was greatly aided by the astute identification of these extremities.

This comprehensive data analysis served as the foundation, directing subsequent data preprocessing and model development efforts, ensuring that the renal stone detection research remained firmly grounded in a well-informed and carefully analysed dataset.

C. Data Pre-processing

In the research on the identification of renal stones, a number of data pre-processing techniques were carefully used to create a high-quality dataset, enhancing the robustness and dependability of the deep learning model. The following are the steps involved in the critical data preprocessing that has been done:

Data organisation and loading: The data were ordered systematically. In a structured data repository, file paths were meticulously arranged along with their respective class labels. In order to maintain the integrity of class differences, this organisational process was made easier by repeatedly going through various data directories, including those for training, testing, and validation subsets. To facilitate upcoming data management and model training, the resulting DataFrame was further divided into several pieces.

Average height and width calculation: By examining image dimensions, important details about the inherent properties of the dataset were discovered. In particular, the average height and width measurements were calculated using a representative subsample of images, usually consisting of 100 images. This calculated average provided a basic understanding of the most common image proportions in the dataset, which informed the design choices for the input layer of the model.

Image augmentation: Techniques for image augmentation were skilfully used to diversify and increase the dataset, improving its ability to generalise successfully. The original dataset, which only had 1244 images, was greatly expanded to reach a more reliable scale of 4000 images. The dataset was varied by augmentation operations such as image manipulations like rotation, flipping, and zooming, which improved the model's ability to adapt to changing conditions and learn from a wider range of image attributes. Figure 1 shows the result of image augmentation for two sample images.

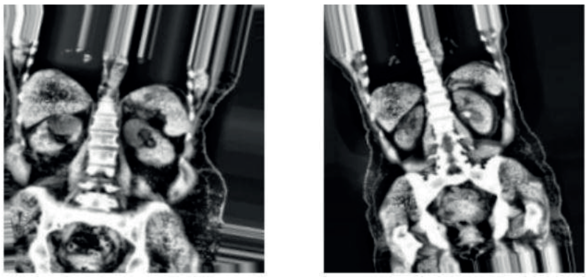

Fig. 1. Result of image augmentation.

Data balancing: It was crucial to minimise class imbalance in the dataset. A fair distribution of 2000 images per class was carefully determined from the 4000 image-supplemented dataset. During model training, this balanced distribution made sure that both classes, designated as Class 1 and Class 0, were fairly represented. To avoid any potential bias or skewed learning outcomes brought on by an unbalanced class distribution, this step was crucial.

IV. Models Used

A. ResNet

The ResNet (Residual Network) model, one of the many employed for renal stone recognition in medical pictures within the field of renal stone identification, is recognised for its effectiveness, even though it might not always achieve the maximum levels of accuracy compared to some other models. The problem of disappearing gradients in deep neural networks is addressed using a novel strategy.

ResNet is conceptually distinguished by the incorporation of residual blocks, where the input and output of a layer are joined together through skip connections or short routes. The network can learn residual functions thanks to this design, which makes it easier to train models that are incredibly deep and specifically suited for the detection of renal stones. The model's parameters (weights and biases) are optimised using backpropagation throughout the training process by minimising a loss function, often cross-entropy. The model's ability to correctly identify renal stones in medical images is improved by computing gradients with respect to the loss.

B. EfficientNet

In the pursuit of accurate renal stone diagnosis, EfficientNet, a well-known convolutional neural network (CNN) architecture famous for its effectiveness and efficiency, was used. Despite being highly regarded for its capacity to establish a compromise between model size and performance, this model may not always reach the best level of accuracy when compared to other models used to identify renal stones. The conceptual brilliance of EfficientNet is based on its capacity to provide astounding accuracy while yet being computationally effective. This is accomplished by scaling depth (*d*), width (*w*), and resolution (*r*) uniformly using the compound scaling formula: $d = \alpha^{\phi}$, $w = \beta^{\phi}$, $r = \gamma^{\phi}$ where the model's architecture is dynamically adjusted by the α, β, γ, and ϕ. By doing this procedure, it is possible to optimise feature extraction at various scales, which is essential for identifying the minute details of renal stone images.

C. DenseNet

The DenseNet (Densely Connected Convolutional Network) architecture, known for its proficiency in image classification, was used in the pursuit of greater accuracy in renal stone detection. This is especially true in the complex field of renal stone detection. With a dense connectivity pattern, DenseNet stands out. This method encourages strong feature propagation, enabling the network to understand complex image properties necessary for accurate renal stone detection. Each layer receives input not only from its predecessor but also from all preceding levels.

D. DenseNet with Hyper-parameter Tuning

DenseNet (Densely Connected Convolutional Network) was successfully used to improve the diagnosis of renal stones through careful fine-tuning of critical hyperparameters. Hyper-parameter optimisation was used to adapt this complex model, known for its image classification abilities, for the challenging task of renal stone detection. DenseNet stands out due to its distinct connectivity patterns that allow each layer to accept input from preceding layers. Because of the robust feature sharing that is made possible by this architectural feature, it is possible to capture complicated image properties for renal stone diagnosis with high accuracy.

To improve model performance, the optimisation method involves meticulous hyper-parameter adjustments:

Learning Rate Adjustment:

The formula $\alpha_{\text{new}} = \alpha_{\text{old}} \times \text{decay}^{(\text{epoch/decay\_step})}$ was used to systematically modify the learning rate (α). In order to achieve the best convergence without overshooting, this formula managed the decrease in learning rate over epochs.

Batch Size Modification:

The batch size (B) was optimised using the formula $B_{\text{new}} = B_{\text{old}} \times S_{\text{new}}/S_{\text{old}}$. This tactical adjustment ensured effective training while preserving computational resources.

Layer Configuration Optimisation:

A crucial step in the tuning process was choosing the right number of layers (L). Although it was not predicated on a formula, it involved iterative testing to increase the network ability to detect features of kidney stones. Figure 2 shows the images from negative and positive class.

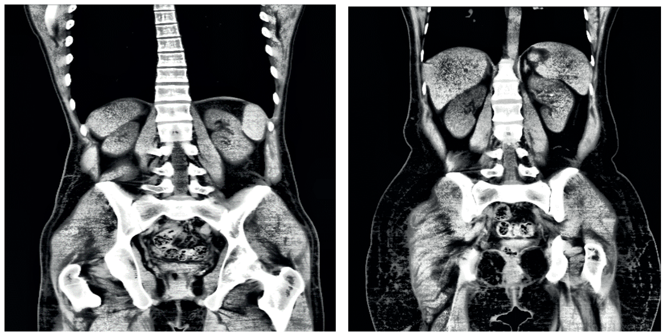

Fig. 2. Left image: Negative class; Right image: Positive class.

Algorithm:
Input:
- Training and validation datasets;
- Model architecture (e.g., ResNet, EfficientNet, DenseNet, DenseNet Hypertuned);
- Hyper-parameters: batch size, number of epochs, learning rate, weight decay, dropout rate;
- Image dimensions (input size);
- Number of classes (output size).

Output:
- Trained model for renal stone detection.

Algorithm:
1. Initialise the specified base model architecture with pre-trained ImageNet weights.
2. Configure the top layers for task-specific fine-tuning (e.g., image classification):
   - add a Global Average Pooling layer to reduce spatial dimensions;
   - add a Dense layer with the number of output units equal to the number of classes;
   - optionally, add a Dropout layer for regularisation.
3. Compile the model:
   - use categorical cross-entropy loss for classification tasks;
   - employ the Adam optimizer with the specified learning rate;
   - optionally, apply weight decay to the optimizer to prevent overfitting.
4. Create data generators for training and validation, enabling efficient batch-wise data loading and pre-processing.
5. Implement callback mechanisms:
   - use EarlyStopping to monitor validation loss and enable early termination if convergence stalls;
   - optionally, employ ModelCheckpoint to save the best model weights during training.
6. Initiate model training:
   - use the ‘fit’ function with the training data generator;
   - configure batch size, number of training epochs, and validation data;
   - incorporate defined callbacks for monitoring and control.
7. Upon training completion, the model is finely tuned for the target classification task.

V. Experimental Results and Discussion

In the study, DenseNet consistently outperformed ResNet and EfficientNet in terms of accuracy for detecting kidney stones. This accuracy disparity is mostly caused by DenseNet distinctive architectural layout. DenseNet performs better than ResNet, which has a 0.52 accuracy score. ResNet architectural traits can be used to explain this disparity. ResNet residual connections make deep networks possible, but given its reduced accuracy, it is possible that they cannot accurately capture the complex patterns found in medical imagery. This indicates that ResNet finds it difficult to extract the information required to discriminate between different forms of renal stones. In contrast, DenseNet (conventional) and DenseNet (hypertuned) greatly outperformed ResNet, with accuracies of 0.81 and 0.86, respectively. The important aspect in this case is the densely connected architecture of DenseNet. As a result of the architecture support for feature reuse and effective gradient flow across the network, DenseNet is better able to recognise subtle patterns, which improves accuracy.

Furthermore, DenseNet constant macro and weighted average precision, recall, and F1-scores, which are shown across both conventional and hyper-parameter tuned variations, reveal its strong performance across a variety of evaluation criteria. DenseNet consistently maintains good performance for jobs involving renal stone identification. In the final analysis, DenseNet densely linked architecture, which excels at catching complex patterns in medical images, is primarily responsible for its greater accuracy. ResNet, on the other hand, may not be suited for this particular task given its lesser precision. According to the presented accuracy scores, the findings highlight the critical significance that neural network architecture plays in producing accurate results in medical picture categorisation tasks.

VI. Performance Measures

Table I shows the comparison of various deep learning models and their parameters.

TABLE I
PERFORMANCE MEASURES

Parameters	ResNet	DenseNet	EfficientNet	DenseNet (Hypertuned)
Accuracy	0.52	0.81	0.80	0.86
Macro avg precision	0.26	0.86	0.82	0.81
Macro avg recall	0.50	0.86	0.80	0.81
Macro avg F1-score	0.34	0.86	0.80	0.81
Macro avg support	346	346	346	346
Weighted avg precision	0.27	0.87	0.82	0.81
Weighted avg recall	0.52	0.86	0.80	0.81
Weighted avg F1-score	0.35	0.86	0.80	0.81
Weighted avg support	346	346	346	346

VII. Conclusion

In the realm of medical imaging, precise renal stone detection is essential for improving patient care and diagnostic accuracy. The research aimed to identify the most effective deep learning models, including DenseNet, EfficientNet, and ResNet. DenseNet emerged as the superior model, achieving an exceptional accuracy of 0.86, surpassing expectations, and thereby proving its ability to capture intricate patterns in medical images of CT scans. The objective of the research extended beyond accuracy, aiming to advance renal stone detection and provide innovative solutions to the medical community. Looking ahead, there is potential in fine-tuning parameters and integrating real-time clinical data for continuous improvement. This research lays the foundation for a future where swift and reliable renal stone diagnosis enhances patient care. In conclusion, DenseNet stands as the ideal model for renal stone detection, significantly improving patient care and seamlessly integrating diagnosis into medical practice.

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