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Research Paper

Kidney Stone Detection Using an EfficientNet-Based Method

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Abstract— This study investigates the application of deep learning methodologies for the accurate and efficient diagnosis and segmentation of kidney stones. Kidney stones, resulting from a complex interplay of environmental and genetic factors, significantly impact human health by reducing quality of life and increasing the risk of various complications. While imaging techniques like magnetic resonance imaging (MRI) and computed tomography (CT) are crucial for diagnosis, they are pose radiation risks to patients. To mitigate these risks and improve diagnostic accuracy, this research explores the potential of SegNet, DeepLabV3+, UNETR, Res U-Net, and EfficientNet-B7, which are the recent deep learning algorithms. The study aims to develop a robust system that can accurately identify different size of kidney stones directly from CT images. This approach has the potential to minimize the need for repeated CT scans, thereby reducing patient exposure to radiation while simultaneously enhancing diagnostic precision and potentially leading to more effective and personalized treatment strategies. The experiments show that the EfficientNet-B7 is the best in kidney stone detection and segmentation task, having higher precision, recall, F1-score, and accuracy values than all other presented existing models. The evaluated deep learning models exhibited robust performance, consistently achieving metrics above 0.85 and frequently surpassing 0.90. EfficientNet-B7 distinguished itself by attaining peak scores across all metrics: 0.93 for Precision, 0.92 for both Recall and F1-Score, and 0.96 for Accuracy, indicating its potential for superior predictive capabilities.

Keywords: Kidney stone detection, Segmentation, Convolutional neural networks, Deep learning

1. Introduction

The human body consists of 3 parts; the thorax, abdomen, and pelvis. Among them, the abdominal region is the largest (Mahadevan et al., 2016). The abdomen region hosts many vital regions such as digestive, endocrine, urinary (Wade and Streitz, 2022). The kidney is one of the important organs in the urinary region. Filtering the blood, balancing the total water and maintaining the circulating pressure in the body are some of the functions performed by the kidneys. A rich blood flow to the kidneys to monitor and regulate multiple organ systems. In addition, the cleaning of metabolic waste products, toxins and drugs in our body are some important functions performed by the kidneys (Tecklenborg et al., 2018) When some minerals in the urinary tract come together to form solid particles then stones occur in kidneys (Khan et al., 2017). The combination of genetic factors and environmental factors such as diet, some medications, hypertension and chronic diseases are effective in the formation of kidney stones (Rao et al., 2011). The relationship between these risk factors and the formation of kidney stones has been shown in previous studies (Silva et al., 2010; Daudon et al., 2012). These stones can cause some problems such as heart diseases (Cheungpasitporn et al., 2014), diabetes (Rule et al., 2011), bone fractures (Taylor et al., 2016) and chronic kidney diseases (Rule et al.,2009). Kidney stones affect an estimated 1% to 15% of the world's population (Romero et al., 2010). Due to affect a large number of people and pose a risk for some diseases, diagnosis and classification of kidney stones is important.

Recently, there are some methods to diagnosis and classify kidney stones (Basiri et al., 2012) such as computed tomography (Kawahara et al., 2016), ultrasonography (McCarthy et al., 2016) and ureterostomy (Castañeda-Argáiz et al., 2016). Choosing an appropriate imaging modality for the diagnosis of stones is associated with reduced stone-free rates, low morbidity, increased survival, shortened recovery time and reduced treatment costs (Imamura et al., 2012). There are differences in the guidelines published by the American Urology Association and the European Urology Association regarding the appropriate imaging method for stone diagnosis. Diagnostic method with CT images provides more precise diagnosis than ultrasound, but in this method, patients are exposed to the negative effects of radiation. The difference in practice and knowledge levels of experts in this field can lead to potential errors in the interpretation of CT images (Manoj et al., 2022). In addition, the cost of performing CT image of the kidneys is about 2 times than of ultrasound in terms of hospitals, insurance companies and patients (Caglayan et al., 2022). Also, there has been an increase in the number of patients with kidney stones recently, so CT images are used more in the diagnosis of kidney stones (Ozbay et al,., 2024) Due to the increasing number of CTs, the workload of healthcare professionals who will evaluate CT images is increasing and the evaluation period is getting longer (Caglayan et al., 2022). For these reasons, it is important to minimize errors when interpreting CT images by healthcare professionals. In this context, deep learning-based methods have been developed to assist healthcare professionals in the interpretation of CT images and to minimize errors (Shen et al., 2017). Therefore, the ability of the deep learning algorithm to learn from data provides a great advantage.

Deep learning is a method of interoperability of many classifiers based on linear regression and activation functions (Yan and Razmjooy, 2023; Asif et al., 2024; Liu and Ghadimi, 2024). The difference from the traditional statistical linear regression $WTX + b$ is that it contains many artificial neurons instead of one. These neurons are connected to each other in a special way, and this is called a neural network. Each neuron can be considered as a small computing unit. In addition, it contains multiple layers between the input layer and the output, and these layers can contain hundreds of thousands of neurons. These layers between input and output are called hidden layers and neurons in these layers are called hidden neurons. The network consisting of many hidden layers is called deep learning (Chang et al., 2024; Ding et al., 2025)

The use of deep learning-based methods in the field of medical imaging is gradually increasing (Suzuki et al., 2017). Organs or lesions in medical images can be very complex, so a model that can take and process many parameters and learn from data is needed to overcome this complexity. Deep learning-based methods are the closest models to meet these requirements so have been applied in various fields such as segmentation (Alom et al. 2018), classification (Shorfuzzaman et al., 2021), object detection (Rijthoven et al., 2018) in medical image analysis.

In recent years, many studies based on deep learning have been carried out for the diagnosis and classification of kidney stones. In a study using deep learning method, favorable results (accuracy of %74) were obtained despite the limited data set and this showed the potential of CNN in this regard (Torrell-Amado and Serrat-Gual, 2018). Another study showed that a machine learning-based application could help urologists in treatment to kidney stones (Shabaniyan et al., 2019). In an another study, color features and texture features obtained from kidney images and then fed into random forest classifier to classify stones. Although the success rate is low (weighted precision of %63) in this method, the usability of texture and color features has been demonstrated (Serrat et al., 2017). In a study, kidneys were segmented firstly and then the stones were segmented. Later, features obtained from segmented stones were transferred to support vector machine (SVM) to classify kidney stones, yielding 60% sensitivity on an average of two false positives per scan (Liu et al., 2014). An application based on CNN model InceptionV3 was developed to detect kidney stones as well as ureter and bladder stones. The application achieved sensitivity of 0.873 and AUC of 0.964 (Parakh et al., 2019). Researchers developed an application in a study based on deep convolutional neural network by using 625 CT images to detect kidney stones. The results were a sensitivity of 95.9% and AUC of 0.97 (Cui et al., 2020). In another study, researchers developed a 15-layer CNN model also they optimized hyper-parameters of this model. They used 2430 CT images to classify kidney stones. The results were an accuracy of 99% and a classification error with 1.2% (Fitri et al., 2020). In a study, researchers developed a CNN based model. When the average accuracy rates of the 7 radiologists on the images were compared with the CNN based model, more successful results were obtained by the CNN based model as 93% vs. 86% (Jendeberg et al., 2021). In another study, researchers developed a model based on multi-feature fusion CNN to classify normal and abnormal kidneys. They used 3722 abdominal images. The result was accuracy of 94.67% (Wu and Yi, 2020). Asif et al. (2024) introduced two novel ensemble models for enhancing kidney stone detection in CT images. The first, StackedEnsembleNet, employs a hierarchical deep learning architecture. This architecture strategically combines the predictive outputs of four pre-trained convolutional neural networks: InceptionV3, InceptionResNetV2, MobileNet, and Xception, creating a robust and accurate ensemble for identifying kidney stones within medical imaging data. Yan and Razmjooy (2023) presented a novel computer-aided diagnosis system for kidney stone detection within CT images. Their approach uniquely integrates deep learning techniques with a metaheuristic optimization inspired by the coronavirus herd immunity principle. This innovative framework leverages a fractional-order variant of the herd immunity enhancer to dynamically customize a Deep Belief Network (DBN). This tailored DBN architecture aims to deliver a highly efficient and reliable diagnostic system for accurately identifying kidney stones in medical imaging data. Liu and Ghadimi (2024) introduced a novel CNN-based approach for diagnosing kidney stones within CT images. Recognizing the significant challenges posed by data imbalance and variability in medical imaging protocols, which often hinder the generalization capabilities of deep learning models, this research incorporates a three-pronged preprocessing strategy. This strategy aims to enhance the quality and quantity of raw CT images, thereby creating a more robust and reliable dataset for training effective CNN models for kidney stone detection. Chang et al. (2024) investigated the potential of a novel predictive system for chronic kidney disease risk assessment. The system leverages biosensor technology to measure uric acid concentrations within kidney stones and integrates these measurements with an artificial neural network (ANN) for sophisticated risk prediction. Ding et al. (2025) introduced a novel automated methodology for enhanced kidney stone detection. This approach integrates the powerful features of AlexNet, a renowned convolutional neural network, with the efficient learning capabilities of Extreme Learning Machines (ELM). Subsequently, the performance of this integrated network is further optimized through a refined version of the Firebug Swarm Optimization algorithm. This innovative combination aims to significantly improve the accuracy and efficiency of kidney stone detection. Ozbay et al. (2024) introduced a novel Masked Autoencoder (MAE) for Kidney Tumor Detection (KTD). This approach excels in scenarios with limited labeled data by effectively leveraging self-supervised learning (SSL) techniques. Specifically, we incorporate self-distillation (SD) into the MAE framework, enabling the model to learn robust representations through self-supervision. The SD loss is calculated on both the decoder outputs and the latent representations of the encoder, resulting in a powerful SSLSD-KTD model that demonstrates significant improvements in KTD performance.

This study was conducted to use this advantage of deep learning in the diagnosis of kidney stones. The following parts of our work consist of:

- In the second part, material and method with dataset, have been explained.
- In the third part, experimental analysis and performance results have been exposed.
- In the last part, the study is concluded.

2. Material and Method

2.1. Dataset

In this study, 5034 kidney computer tomography (CT) images were used. Of these images, 2578 have kidney stones and 2456 do not have kidney stones. The entire dataset used in this study is in Digital Imaging and Communications in Medicine (DICOM) format and they are all 256x256 in size. These CT images are taken from the Ministry of Health of the Republic of Turkey. Non-commercial use of this dataset is allowed, so there is no obstacle to using this dataset in our study. For the training and testing of the classification model, 80% of the data was added to the training set, and the remaining 20% was added to the testing set. Therefore, 4028 CT images were used in the training set and the remaining 1006 in the test set. Figure 1 presents the number of kidney CT images in training and test set. Figure 2 shows some CT images from dataset for without kidney stones and with kidney stones.

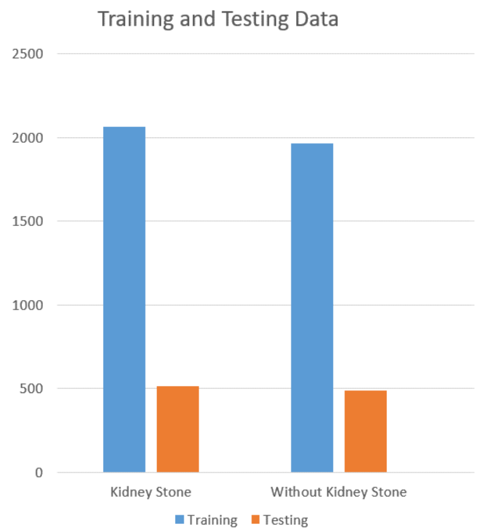
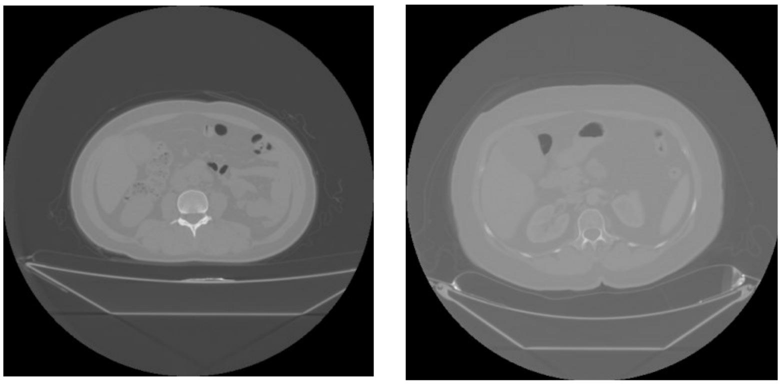
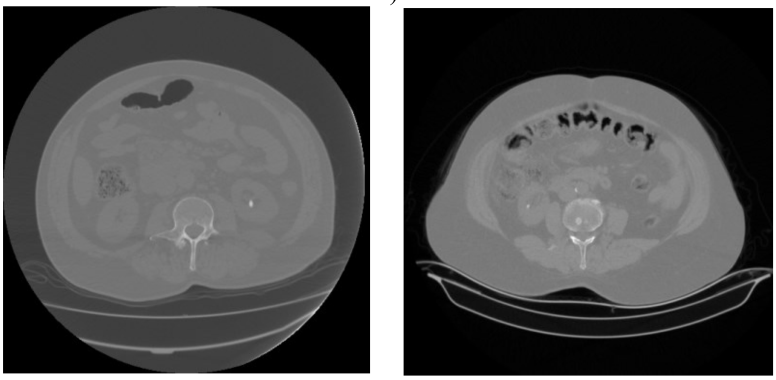


Figure 1. Number of kidney CT images in training and test set



a)



b)

Figure 2. Some CT images from dataset for a) without kidney stones b) with kidney stones

2.2. EfficentNet-B7 Method

In this study, EfficentNet-B7 was used for the diagnosis and classification of kidney stones. EfficientNet is based on CNN architecture and it has 8 different versions from B0 to B7 (Tan and Le, 2019). In CNN architecture, model scaling is often used to increase accuracy. While scaling the model, one of the three dimensions of the network is usually changed. These dimensions are width, depth and image resolution. Although it was possible to make changes to multiple dimensions at the same time, doing so was not preferred as it required more manual adjustments and reduced accuracy. EfficientNet was developed based on the idea that balancing width, depth and image resolution are not changed separately, but in the same way by using a constant coefficient. By this way, compound scaling can be performed. The compound scaling method is the key point in the EfficientNet-x architecture as shown in Figure 3.

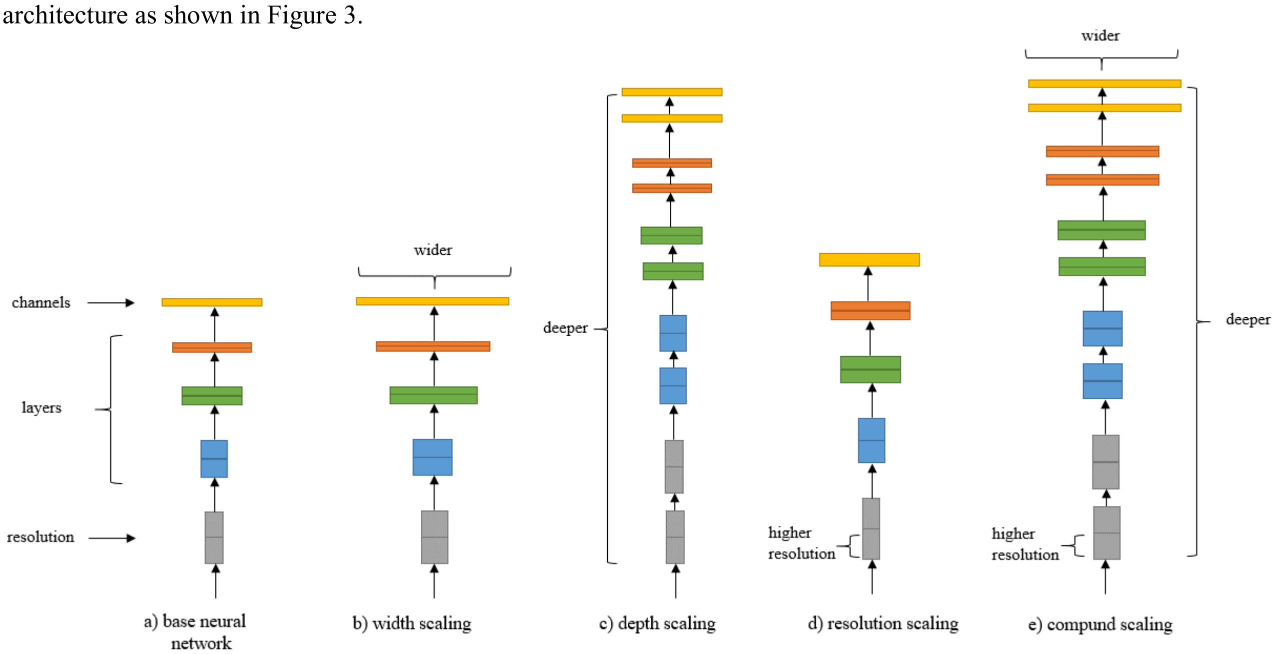


Figure 3. Architecture of EfficientNet-Bx (Seyfi et al., 2024)

The parameters used in model scaling are shown below. The φ parameter in the equation is a compound coefficient used to evenly scale network uniformly by controlling the Floating Point Operations (FLOPs).

$$\begin{aligned} depth: d &= \alpha\, \Phi \\ width: w &= \beta\, \Phi \\ resolution: r &= \gamma\, \Phi \\ s.t. \alpha \cdot \beta 2 \cdot \gamma 2 &\approx 2 \\ \alpha \geq 1, \beta \geq 1, \gamma &\geq 1 \end{aligned} \tag{1}$$

The parameters α, β, and γ are used to distribute the depth, width, and image resolution respectively. As equation 1 shows, doubling the depth of network will double the FLOPS, while doubling the width of network or resolution will quadruple the FLOPS because the FLOPs are proportional with parameters d, w^2, r^2. In the EfficientNet architecture, $\alpha \cdot \beta^2 \cdot \gamma^2$ constrained approximately by 2 so for each φ the total FLOPs increase approximately by 2^{φ}.

EfficientNet-B7 is the scaled version of the EfficientNet-B0 architecture. From EfficientNet B0 to EfficientNetB7, the depth, width, resolution and model size increase thereby increasing the accuracy. In this way, Efficient-NetB7 is the best performing model among the EfficientNet models. In comparison with other models; Efficient-NetB7 achieved higher accuracy on ImageNet than previous state-of-art CNN models and is 8.4 times smaller and 6.1 times faster than the best CNN model. The archtiecture of EfficientNet-B7 has been shown in Figure 4. The resolution of the input image is 600x600, the depth value is 3.1 and the width value is 2.

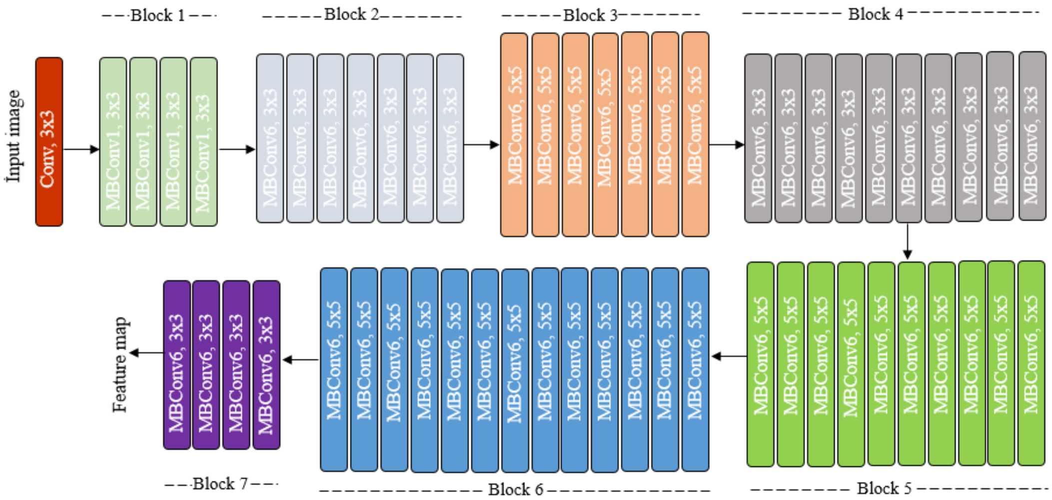


Figure 4. The architecture of EfficientNet-B7 (Dharaneswar and Kumar, 2025)

The EfficientNet-B7 architecture is composed of blocks that have Mobile Inverted Bottleneck Convolution (MBConv) modules.

3. Experimental Analysis

The experimental evaluation of the methods, alongside a selection of comparative models, was carried out on a Windows 10 workstation equipped with an Intel Core i7-8700 processor, 16 GB of RAM, and an Nvidia GeForce 4GB graphics card. All models were implemented using Python 3.8, leveraging the Keras and TensorFlow libraries for network training and execution. The different learning methods which are EfficientNet-B7 (Tan and Le, 2019), SegNet (Badrinarayanan et al., 2017), DeepLabV3+(Chen et al., 2018), UNETR (Hatamizadeh et al., 2022), and Res U-Net (Zhang et al. ,2018), have been compared in this study. The metrics Recall (R_e), F1-Score (F_1), Precision (P_r), and Accuracy (A_{cc}) are used to measure model performance as given in Table 1. The performance metrics have been shown in Eqs.(2) to (5).

$$P_r = \frac{TP}{TP+FP} \tag{2}$$

$$R_e = \frac{TP}{TP+FN} \tag{3}$$

$$F_1 = 2.\frac{P_r x R_e}{P_r + R_e} \tag{4}$$

$$A_{cc} = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

where TP, TN, FP and FN are true positive, true negative, false positive, and false negative, respectively.

Table 1. The performance comparison results

Model	Precision ($PREC$)	Recall	F1-Score	Accuracy (Acc)
SegNet (Badrinarayanan et al., 2017)	0.92	0.85	0.88	0.95
DeepLabV3+(Chen et al., 2018)	0.88	0.90	0.89	0.94
UNETR (Hatamizadeh et al., 2022)	0.91	0.88	0.89	0.95
Res U-Net(Zhang et al. ,2018)	0.90	0.87	0.88	0.94
EfficientNet-B7 (Tan and Le, 2019)	0.93	0.92	0.92	0.96

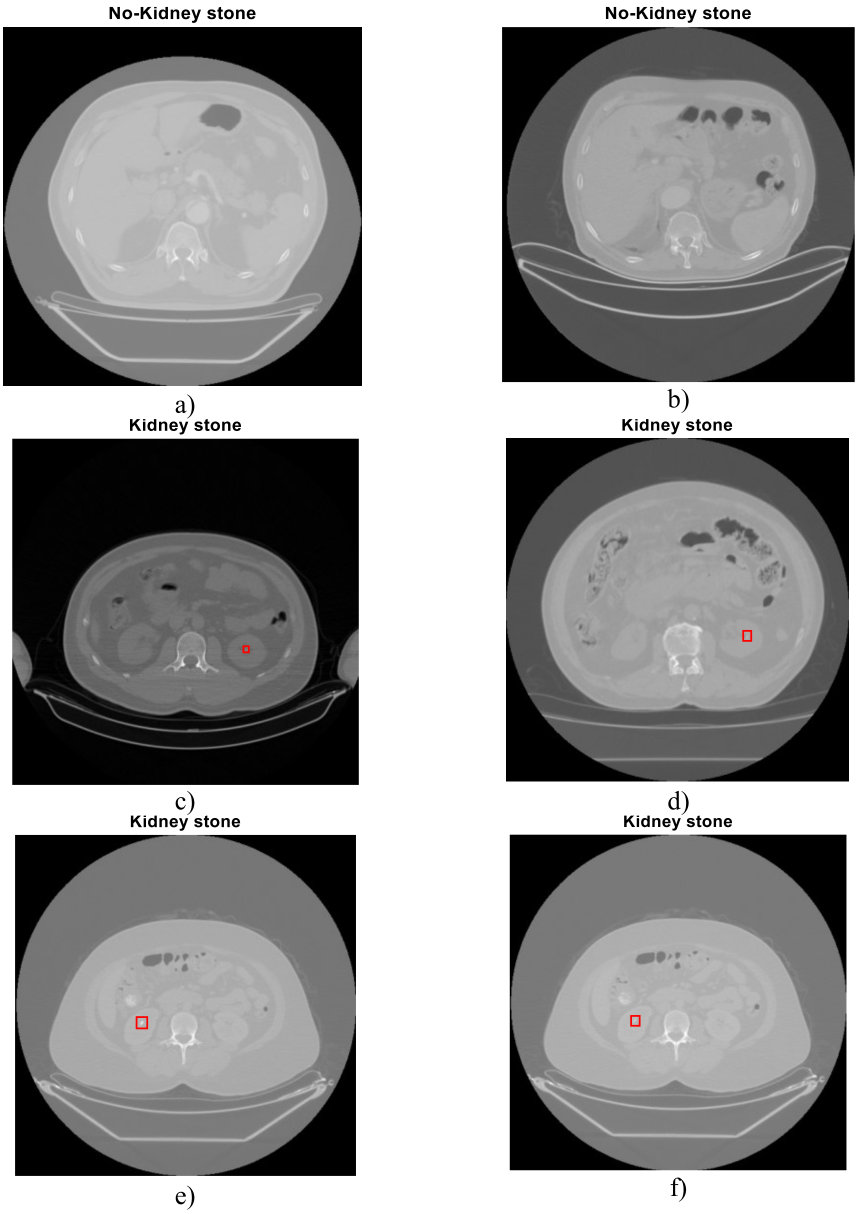
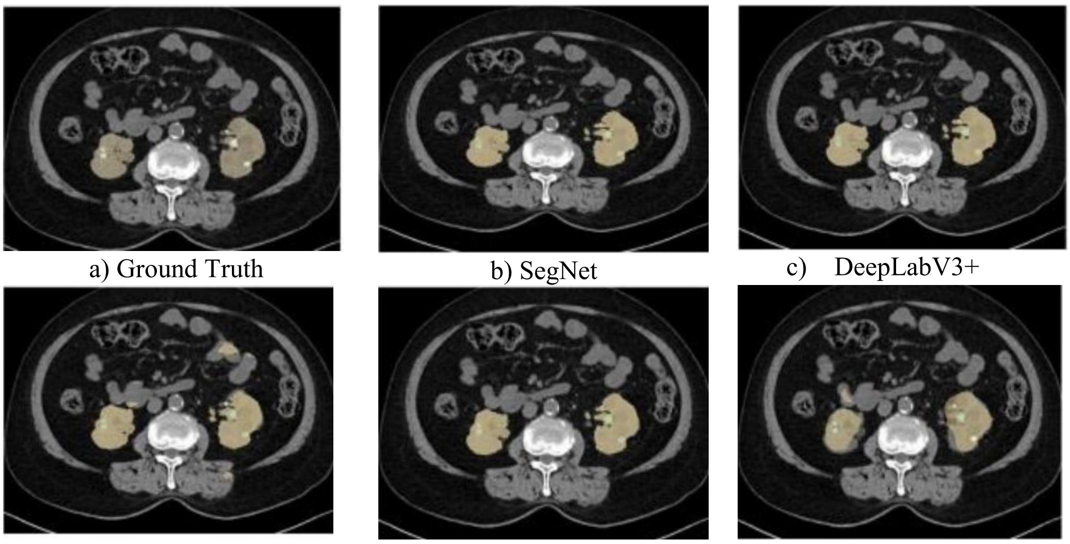


Figure 5. The detection results a) and b) without kidney stones c) and d) with left-kidney stones e) and f) with right-kidney stones

Table 1 presents a performance comparison of various deep learning models for a specific task, likely image segmentation, based on four key metrics: Precision, Recall, F1-Score, and Accuracy. Across the board, the models demonstrate strong performance, with all metrics generally exceeding 0.85 and often reaching above 0.90. Notably, the EfficientNet-B7 model stands out, achieving the highest scores in Precision (0.93), Recall (0.92), F1-Score (0.92), and Accuracy (0.96), suggesting superior overall performance. SegNet and UNETR also exhibit competitive results, with both achieving an accuracy of 0.95 and balanced precision and recall scores. DeepLabV3+ and Res U-Net, while still performing admirably, show slightly lower scores compared to the top performers, particularly in precision for DeepLabV3+ and a more balanced but slightly lower performance for Res U-Net. So, the data indicates that EfficientNet-B7 is the most effective model among those compared, demonstrating the best balance and highest overall predictive power for the task at hand. However, the other models provide viable alternatives with strong performance profiles.



a) Ground Truth b) SegNet c) DeepLabV3+
d) UNETR e) Res U-Net f) EfficientNet-B7

Figure 6. The 2D visual analysis samples of independently trained models based on kidney and stone segmentation

The performance analysis in Figure 6 shows the effectiveness of the proposed model in the detection of kidney stones when compared to SegNet, DeepLabV3+, UNETR, and Res U-Net. The segmentation results provided by these models were observed when compared to ground truth. Although SegNet provided effective results in some cases despite its simpler structure, it was insufficient in detailed segmentations. DeepLabV3+, with its more complex structure, showed better performance by clearly detecting object edges. UNETR and Res U-Net models provided high accuracy rates thanks to their well-established structures and powerful feature extraction mechanisms. As a result, the performance of the proposed model shows that it is in strong competition with Res U-Net and DeepLabV3+ in particular. These models provide satisfactory results in terms of segmentation quality and offer more effective use for clinical applications. When supported by numerical results, each of these models has different advantages for certain scenarios. Supporting the obtained results with a detailed statistical analysis will further reveal the potential effects of these models in clinical applications.

4. Conclusion

In this study, a deep learning-based method is proposed for kidney stone detection, which is an important problem in the medical imaging field. In particular, the model developed based on the EfficientNetB7 architecture achieved higher accuracy, sensitivity and precision values compared to other popular segmentation models such as SegNet, DeepLabV3+, UNETR and Res U-Net when evaluated on various metrics. The obtained results show that the EfficientNetB7 architecture provides the extraction of more complex and detailed features in the kidney stone detection problem. The fact that the model can successfully detect kidney stones of different sizes and has low false positive rates offers significant advantages for clinical applications. The findings of this study reveal that EfficientNetB7 is a potential tool in the field of medical imaging, especially in challenging tasks such as kidney stone detection. In particular, the value of 0.96 in the Accuracy metric shows that the model performs with a much higher overall accuracy than other models. These results reveal that EfficientNet B7 is quite successful in both detailed object detection tasks and produces more reliable results compared to other models.

In future studies, testing the generalizability of the model on different datasets and training the model with a dataset containing larger and more diverse kidney stone samples may contribute to further improving the obtained results. Additionally, studies can be conducted on topics such as optimizing the model for real-time applications and integrating it into a medical imaging system that can be used in clinical environments.

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