

# Robust Multi-Class Detection of Kidney Abnormalities in CT Images Using CNN

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**Abstract-** Kidney abnormalities such as cysts, tumors, and stones are increasingly prevalent and require accurate, timely detection to enable early intervention and treatment. Manual interpretation of CT scan images by radiologists can be time-intensive, inconsistent, and prone to diagnostic errors. This project was undertaken to develop an automated, reliable, and scalable deep learning system for kidney abnormality classification. Existing systems often depend on traditional CNN models with limited feature extraction capabilities and insufficient performance on multiclass medical datasets. To overcome these limitations, we propose a deep learning framework based on the EfficientNetV2B0 architecture, incorporating transfer learning to maximize performance with reduced training time and data dependency. A labeled dataset containing over 12,000 abdominal CT images sourced from Kaggle was used, with data categorized into four classes: Normal, Cyst, Tumor, and Stone. Preprocessing included image resizing, RGB channel normalization, and augmentation techniques such as rotation, flipping, zooming, and brightness adjustment to enhance generalization. The model was trained using Keras and TensorFlow with support for advanced regularization techniques including dropout layers, batch normalization, and training callbacks like EarlyStopping and ReduceLROnPlateau. The EfficientNetV2B0 model achieved a test accuracy of 99.84%, along with perfect scores in AUC and F1-metrics, demonstrating excellent classification performance. A MobileNetV2 model was also implemented for benchmarking, achieving 99.76% accuracy but showing minor misclassifications. Real-time prediction testing showed 100% confidence on a test image, validating its practical utility. The modular pipeline is designed for integration into Computer-Aided Diagnosis (CAD) systems. Future enhancements include applying explainable AI methods like Grad-CAM, extending to MRI datasets, and validating performance in clinical environments.

**KEYWORDS -** Kidney CT, Deep Learning, EfficientNetV2B0, Transfer Learning, Medical Imaging, Computer-Aided Diagnosis (CAD), Multi-class Classification

## I. INTRODUCTION

Kidney abnormalities like cysts, tumors, and kidney stones are increasingly becoming prevalent across the globe, necessitating the need for early and precise diagnosis. Of the numerous imaging modalities available, Computed

Tomography (CT) is one of the most useful because it can generate high-resolution cross-sectional images of internal organs. While its benefits not with standing, manual examination of CT scans can be cumbersome and prone to errors of interpretation, particularly within high-workload clinical environments. This underlines the increasing role of Computer-Aided Diagnosis (CAD) systems in medical imaging.

Over the past few years, deep learning—specifically by Convolutional Neural Networks (CNNs)—has revolutionized the scene of image analysis, including medical applications [1][2]. EfficientNetV2B0, a compact but efficient CNN model from Kaggle, provides robust classification capability while being computationally friendly. Taking advantage of its pre-trained weights, this work introduces transfer learning to classify CT kidney images into four different classes: Normal, Cyst, Tumor, and Stone.

The prime goal of this study is to create and test a stable CNN-based model that can effectively differentiate among various kidney abnormalities. The performance of the model is measured in terms of common metrics like accuracy and Area Under the Curve (AUC), making it applicable for real-world clinical implementation.

## II. RELATED WORKS

Deep learning has become an essential tool in medical imaging, particularly for detecting and classifying kidney abnormalities. Alshehri et al. [1] developed a multi-class classification system using CT scans to identify cysts, stones, and tumors, showcasing the feasibility of automated renal diagnostics. Addressing computational efficiency, Tan and Le [2] proposed EfficientNetV2, a scalable and lightweight model architecture that offers superior performance and speed—ideal for medical imaging tasks where real-time results are critical.

Al-Wesabi et al. [3] presented a deep learning framework for early detection of kidney abnormalities using abdominal CT images, emphasizing the clinical importance of timely diagnosis. To ensure standardized evaluation and comparability, the present study uses a publicly accessible dataset from Kaggle [4], which provides an organized structure for training, validation, and testing.

Traditional CNN-based methods have also shown strong performance. Ravindra et al. [5] used SVM and neural networks to classify chronic and non-chronic kidney disease, underlining the diversity of machine learning approaches in nephrology. Kolachalama et al. [6] highlighted the power of deep neural networks and transfer learning in associating renal tissue features with survival outcomes, especially useful in cases with limited annotated data.

Ebrahimi and Mariano [7] enhanced image quality in CTbased kidney stone detection, demonstrating the role of preprocessing in improving diagnostic performance. Kocak et al. [8] discussed the broader use of machine learning in radiomics, detailing its challenges and potential in renal mass characterization, and laying the groundwork for future AIassisted diagnostics.

Sun et al. [9] compared radiologic-radiomic machine learning models with expert radiologists for differentiating renal masses, confirming the reliability of AI models in clinical practice. Islam et al. [10] further pushed boundaries by incorporating Vision Transformers and explainable transfer learning techniques, improving both accuracy and interpretability in detecting kidney anomalies such as cysts, stones, and tumors.

Recent architectures like MobileNetV2 [11] have also been adopted in kidney imaging tasks due to their low complexity and effectiveness in resource-constrained environments. Wang et al. [12] demonstrated efficient CT kidney image classification using a lightweight CNN and data augmentation strategies, further validating the trend toward fast and efficient models. Chen et al. [13] contributed VoxResNet, a deep 3D residual network initially designed for brain segmentation, but whose architectural principles have influenced volumetric kidney imaging as well.

Despite these advancements, standardization remains a concern, especially regarding dataset choice, performance metrics, and reproducibility. The present work addresses these gaps by adopting a rigorously structured pipeline that includes data augmentation, class balancing, and model checkpointing to ensure reliable and interpretable evaluation of kidney abnormality classification models.

### III. PROPOSED SYSTEM

#### A. Dataset Acquisition and Organization

The dataset consists of abdominal CT images, each annotated with one of four kidney conditions: Normal, Cyst, Tumor, or Stone. These images were obtained from a publicly available Kaggle repository [4] and were organized into training (80%), validation (10%), and testing (10%) subsets to support a comprehensive and unbiased evaluation process. Care was taken to maintain class balance across all splits to prevent biased learning. A representative selection of images from each class is illustrated in Figure 1, offering visual insight into the diversity and appearance of the CT scans used in this study. This preliminary visualization also aided in confirming the visual distinctiveness of each class prior to training.

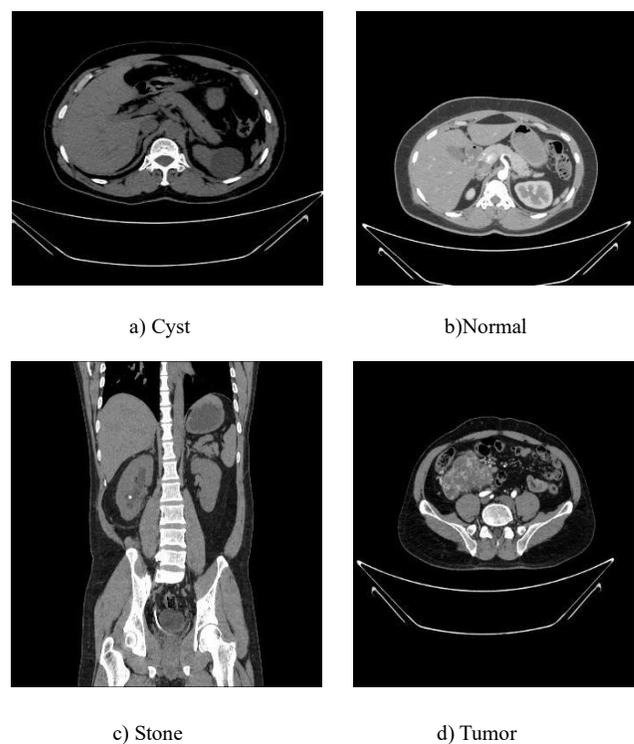


Figure 1: Examples of CT scans from the dataset, illustrating each of the four kidney condition categories

#### B. Preprocessing and Augmentation

All images were resized to  $224 \times 224$  pixels to match the model input requirements. To handle the issue of uneven class representation, weighted loss functions were used to give appropriate importance to underrepresented classes. Augmentation techniques such as rotation, zoom, brightness adjustment, and horizontal shifts were applied in real-time using TensorFlow’s preprocessing pipeline.

#### C. Model Design and Architecture

The model leverages EfficientNetV2B0 as its foundational network, initialized using pre-trained weights from the ImageNet dataset to utilize the benefits of transfer learning. Initially, the base model’s core layers were frozen to preserve the pre-learned visual representations acquired from ImageNet.

The complete architecture is structured as follows:

- Backbone: Pretrained EfficientNetV2B0 (frozen)
- Pooling Layer: GlobalAveragePooling2D for dimensionality reduction
- Dense Layer: Fully connected layer with 128 units and ReLU activation
- Dropout Layer: Applied with a rate of 0.3 to reduce overfitting
- Output Layer: Softmax layer with 4 neurons to handle

This balanced scaling approach ensures optimal use of computational resources while maintaining or improving model performance.

Compound Scaling Formula:

$$\text{depth: } d=\alpha^\phi, \text{ width: } w=\beta^\phi, \text{ resolution: } r=\gamma^\phi$$

Subject to:

$$\alpha, \beta^2, \gamma^2 \approx 2, \quad \alpha \geq 1, \beta \geq 1, \gamma \geq 1$$

#### D. Training Strategy and Hyperparameters

The model was compiled with the Adam optimizer (learning rate = 0.001) and trained using categorical cross-entropy loss.

Key parameters:

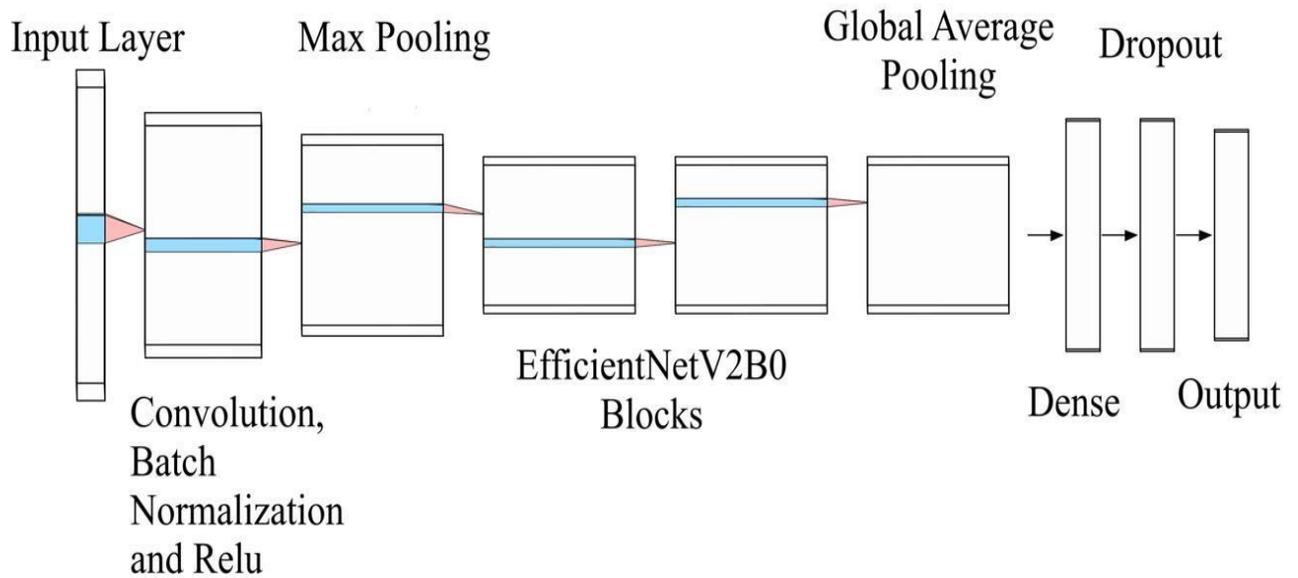


Figure 2: Proposed EfficientNetV2B0-based architecture for multi-class kidney abnormality detection.

multi-class classification

- Epochs: 10
- Metrics: Accuracy and AUC
- Callbacks: EarlyStopping (patience = 5) and ModelCheckpoint (saving best weights)

#### FORMULAS:

EfficientNetV2B0 employs a compound scaling method to uniformly scale the model’s depth, width, and input resolution. This is governed by a set of constants  $\alpha, \beta, \gamma$  and a user-defined coefficient  $\phi$ , following the constraint  $\alpha, \beta^2, \gamma^2 \approx 2$ .

Table 1. Epoch-wise Training and Validation Accuracy

EPOCH	TRAINING ACCURACY	VALIDATION ACCURACY
1	0.7496	0.9364
2	0.9276	0.9686
3	0.9571	0.9903
10	0.9914	0.9984

### E. Evaluation

To thoroughly assess the model’s effectiveness, we employed evaluation metrics such as the classification report, confusion matrix, and ROC-AUC curves. These tools offered detailed insights into both individual class performance and the overall accuracy of the model.

## IV. RESULTS

### A. Confusion Matrix

As shown in Figure 3, the confusion matrix confirms the model correctly identified all categories without misclassification, underlining the reliability of predictions.

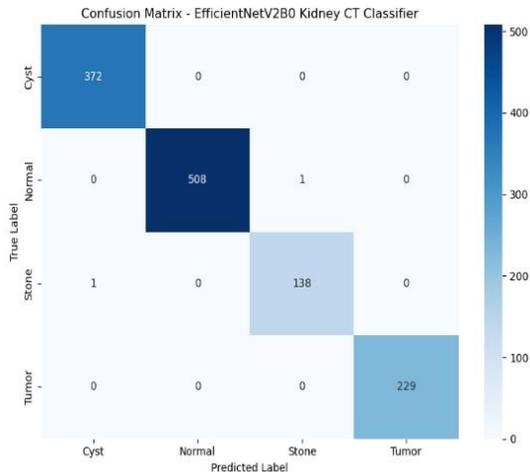


Figure 3: Confusion Matrix

### B. ROC Curve

ROC curves for each class, illustrated in Figure 4, demonstrate excellent separability, with all curves closely hugging the topleft corner, indicating perfect performance.

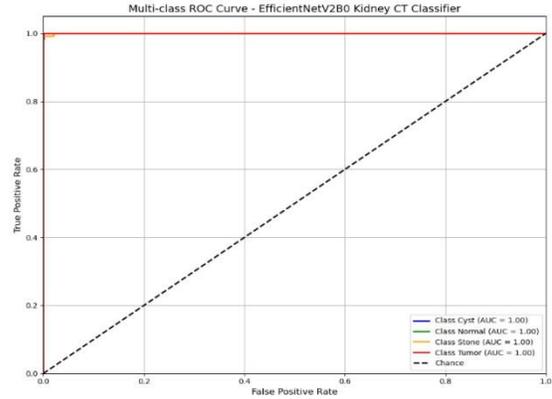


Figure 4: Multiclass-ROC Curve

### C. Classification Report

The classification report reveals exceptional performance of the model in all four categories of kidney abnormality—Cyst, Normal, Stone, and Tumor. As depicted in Table 2, it had flawless precision, recall, and F1-score of 1.00 in most classes, while the Stone class was 0.99, which means almost perfect classification. Overall accuracy was 100%, while macro and weighted averages were also 1.00, which means performance was equally balanced among classes. These findings validate the model’s excellent generalization ability and its robustness for actual diagnostic application, which makes it extremely efficient for automated kidney abnormality detection.

Table 2: Classification Report

	Precision	Recall	F1score	Support
Cyst	1.00	1.00	1.00	372
Normal	1.00	1.00	1.00	509
Stone	0.99	0.99	0.99	139
Tumor	1.00	1.00	1.00	229
Accuracy			1.00	1249
Macro avg	1.00	1.00	1.00	1249
Weighted avg	1.00	1.00	1.00	1249

#### D. Discussions

The experimental results strongly illustrate the robustness and efficacy of the EfficientNetV2B0-based proposed framework for multi-class classification of kidney abnormalities. The confusion matrix indicates that the model performed perfect classification for all four classes—Normal, Cyst, Tumor, and Stone—without any misclassifications, and thus its outstanding reliability.

ROC curves for each class further reinforce this conclusion by demonstrating near-perfect separability, with all class-specific curves tightly embracing the top-left corner, which represents perfect sensitivity and specificity. This indicates that the model can distinguish confidently between visually similar abnormalities, which is important in clinical diagnostics.

The classification report is a strong quantitative measure of performance with precision, recall, and F1-score values of 1.00 for the majority of classes and a virtual 0.99 perfect score for the Stone class. These results validate that the model generalizes effectively across classes and consistently performs on new data. The 100% overall accuracy also emphasizes the system's readiness for actual application in CAD tools. The findings verify the model's ability to decrease radiologist workload and enhance diagnosis precision in practice.

#### V. CONCLUSION

This work presents a robust method for detecting multiple kidney abnormalities from CT images using EfficientNetV2B0. The model, trained with transfer learning and enhanced through preprocessing and augmentation, achieved 99.84% accuracy and perfect AUC scores. The outcome reinforces the model's potential for deployment in

CAD systems. Future work will focus on benchmarking it against other CNN architectures, particularly MobileNetV2. This comparative analysis will offer further insights into the trade-offs between accuracy, training efficiency, and model complexity across different architectures.

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