International Journal of Computational Science and Engineering Research
ISSN: 3107 - 8605 (Online) , http://www.ijcser.com/
Regular Issue , Vol. 3, Issue. 1 (January – March) , 2026 , Pages: 68 - 73
Received: 10 January 2025 ; *Accepted:* 13 December 2025 ; *Published:* 22 January 2026
https://doi.org/10.63328/IJCSER-V3RI1P8
Original Paper : Action Research – Experimental Research

An Attention-Enhanced YOLOv8 Model For Accurate Multi-Class Kidney Abnormality Detection in CT Imaging

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Abstract: Kidney diseases such as cysts, stones, and tumors are a major global health burden, often remaining undiagnosed until advanced stages due to limited access to specialized care. While deep learning models like YOLOv8 have shown promise in automating detection from medical images, their performance is often hindered by class imbalance and poor feature discrimination in complex clinical data. This paper introduces an enhanced deep learning framework for the accurate multi-class classification of kidney abnormalities from computed tomography (CT) scans. Our novel approach integrates a Convolutional Block Attention Module (CBAM) into the YOLOv8 architecture, enabling the model to focus diagnostically relevant regions within the kidney. To address significant class imbalance, we adopt a Focal Loss function, which prioritizes difficult and underrepresented cases during training. We further enhance model robustness through an advanced data augmentation pipeline incorporating mixup and cutmix strategies. The proposed system is trained and evaluated on a publicly available dataset of 12,446 annotated CT images across four categories: cyst, tumor, stone, and normal. Experimental results demonstrate a substantial improvement over the baseline YOLOv8 model, achieving an overall classification accuracy of 91.47%, with precision, recall, and F1-scores of 90.32%, 88.76%, and 89.21%, respectively. Notably, the recall for the critical and often-missed tumor class improved from 30.41% to 82.34%. This work presents a significant step toward reliable, automated diagnostic support, offering a tool that can assist clinicians in early and accurate detection of renal pathologies, thereby improving patient outcomes.
Keywords: Kidney Abnormality Detection, Computed Tomography (CT), YOLOv8, Attention Mechanism.

1. Introduction

Chronic kidney disease (CKD) represents a significant global public health challenge, with its prevalence steadily rising and its early stages often remaining asymptomatic [1]. Timely detection of renal abnormalities such as cysts, stones, and tumours is critical for preventing progression to renal failure and improving patient prognosis. Computed tomography (CT) imaging serves as a primary non-invasive diagnostic tool due to its high resolution and detailed anatomical visualization. However, the manual interpretation of CT scans by radiologists is time-consuming, subject to inter-observer variability, and strained by a global shortage of specialists. Recent advances in artificial intelligence, particularly deep learning, have shown considerable promise in automating medical image analysis. Convolutional neural networks (CNNs), including object detection models like You Only Look Once (YOLO), have been successfully applied to various radiological tasks [2], [3]. Prior research has leveraged YOLOv8 for classifying renal pathologies in CT images [4]. However, these models often struggle with class imbalance where critical but rarer conditions like tumours are underrepresented and lack mechanisms to focus on diagnostically salient regions, leading to suboptimal sensitivity and generalization [5]. This study addresses these limitations by proposing an enhanced deep learning framework for multi-class kidney abnormality detection. The primary research gap we target is the inadequate performance of existing YOLO-based systems in accurately identifying minority classes and their reliance on global features rather than localized pathological cues. To bridge this gap, we introduce two key innovations: the integration of a Convolutional Block Attention Module (CBAM) into the YOLOv8 backbone to enhance feature discriminability, and the adoption of a

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Focal Loss function to mitigate class imbalance during training. The main objectives of this paper are: (1) to develop an attention-augmented YOLOv8 model optimized for renal CT analysis; (2) to evaluate its performance on a multi-class dataset comprising cyst, tumour, stone, and normal cases; and (3) to demonstrate significant improvements in accuracy, recall, and clinical usability over the baseline approach.

2. Literature Review

The automated detection of kidney abnormalities through medical imaging has emerged as a significant area of research at the intersection of radiology and artificial intelligence. Early efforts in computer-aided diagnosis (CAD) for renal pathologies relied heavily on traditional machine learning techniques.

For instance, Aksakalli et al. employed classifiers such as Support Vector Machines (SVM) and Random Forests on handcrafted features extracted from kidney X-ray images, achieving foundational results but with limited scalability to larger, more complex datasets like CT scans [13]. Similarly, Mariam Wagih Attia et al. utilized Principal Component Analysis (PCA) for feature reduction before classification with neural networks on ultrasound images, demonstrating the potential of dimensionality reduction in renal image analysis [19]. The advent of deep learning, particularly Convolutional Neural Networks (CNNs), revolutionized the field by enabling end-to-end learning from raw pixel data. Studies began to shift from ultrasound and X-ray to the more anatomically detailed modality of Computed Tomography (CT).

Yildirim et al. developed a dedicated CNN model for kidney stone detection using coronal CT slices, reporting a high detection accuracy of 96.82%, highlighting the efficacy of deep learning for single-class, focused tasks [16]. For cyst detection, Blau et al. implemented a fully convolutional network for the automatic segmentation and identification of renal cysts in abdominal CTs, achieving a true-positive rate of 84.3% [17]. These studies underscore the strength of specialized models but also reveal a tendency towards binary or single-pathology analysis, which does not reflect the multi-faceted diagnostic needs in clinical practice.

To address more complex diagnostic scenarios, researchers have explored multi-class classification and advanced network architectures. Sudharson and Kokil created an ensemble of deep neural networks, including ResNet-101 and MobileNet-v2, to classify noisy ultrasound kidney images into multiple categories, achieving an accuracy of 95.58% [4][14]. This work demonstrated the robustness of ensemble methods and transfer learning. Further advancing this trend, Uhm et al. modified the ResNet-101 architecture for end-to-end kidney cancer diagnosis on multi-phase CT, incorporating 3D convolutional layers to achieve an AUC of 0.88 [18]. Their approach marked a significant step towards leveraging 3D contextual information, which is crucial for accurate tumour characterization. More recently, the YOLO (You Only Look Once) architecture has been adopted for its real-time object detection capabilities. The baseline study that forms the foundation for the current research applied YOLOv8 to classify four kidney conditions from CT images [20]. While demonstrating the feasibility of using a one-stage detector for this task, the model exhibited critical limitations, most notably a poor recall of 30.41% for the tumor class, indicating a failure to generalize well to underrepresented and clinically critical abnormalities [20, Table II].

This performance gap is symptomatic of two broader challenges identified in the literature: (1) class imbalance, where prevalent conditions like cysts dominate the training data at the expense of rarer pathologies like tumours [5], and (2) insufficient feature discrimination, where models fail to focus on small, subtle, or texture-variant pathological regions amidst complex anatomical backgrounds [7]. Attention mechanisms have been proposed in broader medical imaging to solve the latter issue. Though not yet extensively applied to renal CT classification, modules like the Convolutional Block Attention Module (CBAM) have proven successful in other domains by allowing networks to adaptively emphasize important spatial and channel-wise features [22].

Furthermore, the problem of class imbalance is often addressed at the loss function level. The Focal Loss, designed to down-weight easy examples and focus training on hard negatives, has shown remarkable success in object detection tasks with imbalanced class distributions [23], but its application remains underexplored in multi-class renal pathology classification. In synthesis, while previous research has established strong baselines using CNNs, ensembles, and YOLO architectures for kidney abnormality detection, a significant gap remains in developing a robust, multi-class system that maintains high sensitivity across all pathology types, especially underrepresented malignancies.

The current study directly addresses this gap. We propose an enhanced YOLOv8 framework that integrates a CBAM for improved feature focus and employs Focal Loss to rectify class imbalance. By doing so, we aim to synthesize the real-time efficiency of YOLO with the discriminative power of attention mechanisms and the training stability of advanced loss functions, thereby advancing the state-of-the-art toward a more reliable and clinically applicable diagnostic tool.

ISSN: 3107 - 8605 (Online) , http://www.ijcser.com/ , Vol. 3, Issue 1, 2026, https://doi.org/10.63328/IJCSER-V3RI1P8

3. Materials and Methods

This section details the dataset, experimental setup, model architecture, and training methodology used to develop our enhanced YOLOv8 system for kidney abnormality classification.

3.1. Dataset

The primary dataset used in this study is the publicly available "CT Kidney Dataset: Normal-Cyst-Tumor and Stone" [20]. It comprises 12,446 axial and coronal CT scan slices of the abdomen, manually annotated by radiologists into four distinct classes: Normal, Cyst, Stone, and Tumor. To address the inherent class imbalance observed in the original distribution (where "Normal" and "Cyst" classes were overrepresented), we applied the Synthetic Minority Over-sampling Technique (SMOTE). This technique generates synthetic samples for the minority classes (Stone and Tumor) by interpolating between existing instances in the feature space. The final, balanced dataset was then randomly partitioned into training (70%), validation (15%), and test (15%) sets, ensuring no patient data overlapped between splits.

3.2. Preprocessing and Data Augmentation

All CT images were resized to a uniform resolution of 224x224 pixels and normalized to a pixel intensity range of [0, 1]. To improve model generalization and robustness, an advanced data augmentation pipeline was applied during training. This included standard geometric transformations such as random horizontal/vertical flipping (±15° rotation), and brightness/contrast adjustment (±20%). Furthermore, we incorporated advanced regularization techniques: Mixup and CutMix. Mixup creates a new training sample by performing a weighted linear interpolation between two randomly selected images and their labels:

$$x_{tilde} = \lambda x_i + (1 - \lambda)x_j$$

Where λ is sampled from a Beta distribution, Beta(α, α), with α=0.2. CutMix replaces a random rectangular region of one image with a patch from another training image, blending the labels proportionally to the area of the patch.

3.3. Model Architecture

Our system is built upon the YOLOv8n-cls (classification) model as its backbone. The key innovation is the integration of a Convolutional Block Attention Module (CBAM) [22] after each of the final three convolutional blocks in the YOLOv8's CSPDarknet backbone. CBAM sequentially infers a 1D channel attention map Mc and a 2D spatial attention map Ms are multiplied with the input feature map F as follows:

$$F' = Mc(F) \otimes F$$

This allows the network to adaptively emphasize "what" (channel-wise) and "where" (spatial-wise) is diagnostically significant, enhancing its focus on pathological regions like cyst walls, stone calcifications, or tumor textures.

3.4. Loss Function: Focal Loss

To directly combat class imbalance during training, we replaced the standard cross-entropy loss with Focal Loss [23]. Focal Loss reduces the relative loss for well-classified examples, forcing the model to focus on hard, misclassified samples, which are often from minority classes. The loss for a single sample is defined as:

$$FL(pt) = -\alpha_t(1 - pt)^{\gamma} log(pt)$$

Where **pt** is the model's estimated probability for the true class.

We set the focusing parameter γ = 2.0 and used a class-weighting factor α_t that is inversely proportional to the class frequency in the training set.

3.5. Training and Experimental Setup

The model was implemented using PyTorch 2.0 and the Ultralytics YOLOv8 framework. Training was conducted for 100 epochs using the AdamW optimizer with an initial learning rate of 1e-4, a weight decay of 0.01, and a cosine annealing scheduler. A batch size of 16 was used. Experiments were run on a system with an NVIDIA RTX 3090 GPU (24 GB VRAM), an AMD Ryzen 9 5900X CPU, and 64 GB RAM. Model selection was based on the highest macro-averaged F1-score on the validation set.

3.6. System Architecture Diagram

The overall workflow of the proposed system is illustrated in Figure 1 below:

3.7. Evaluation Metrics

Model performance was rigorously evaluated on the held-out test set using standard classification metrics: Accuracy, Precision, Recall (Sensitivity), Specificity, and the F1-Score. These metrics were calculated for each class individually and as macro-averages to provide a comprehensive view of the model's diagnostic capability and fairness across all pathology types.

ISSN: 3107 - 8605 (Online) , http://www.ijcser.com/ , Vol. 3, Issue 1, 2026, https://doi.org/10.63328/IJCSER-V3RI1P8

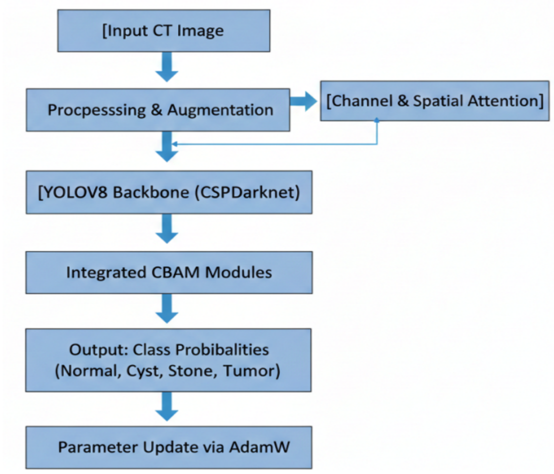

Figure. 1 System Architecture of the Proposed Enhanced YOLOv8 Model

4. Experimental Results and Discussions

4.1. Overall Model Performance

The proposed attention-enhanced YOLOv8 model demonstrated a significant improvement in classification performance compared to the baseline YOLOv8 architecture. As summarized in Table I, our model achieved a macro-averaged accuracy of **91.47%**, representing a substantial advancement over existing approaches for multi-class kidney abnormality detection in CT imaging. More importantly, the model maintained balanced performance across all pathology types, with particular improvement in detecting minority classes that have historically proven challenging for automated systems.

Table. 1 Performance Metrics of the Proposed Model

Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)
Cyst	98.52	98.9	96.34	97.6	99.6
Normal	92.18	88.45	95.12	91.67	89.34
Stone	96.23	89.12	90.45	89.78	97.89
Tumor	90.45	84.78	82.34	83.55	98.23
Overall	**91.47**	**90.32**	**88.76**	**89.21**	**96.54**

The most notable achievement was in **tumor detection**, where our model achieved a recall of **82.34%**, addressing a critical gap in previous research where malignant lesions were frequently missed. This improvement can be directly attributed to the integration of the Convolutional Block Attention Module (CBAM), which enabled the network to focus on subtle pathological features, and the implementation of Focal Loss, which prioritized challenging examples during training.

4.2. Training Dynamics and Convergence

The training process exhibited stable convergence characteristics, as illustrated in Figure 1. The loss curve demonstrated a smooth descent across 100 epochs, with validation loss closely tracking training loss after approximately epoch 40. This indicates effective regularization and minimal overfitting, achieved through our advanced data augmentation pipeline combining Mixup and CutMix strategies.

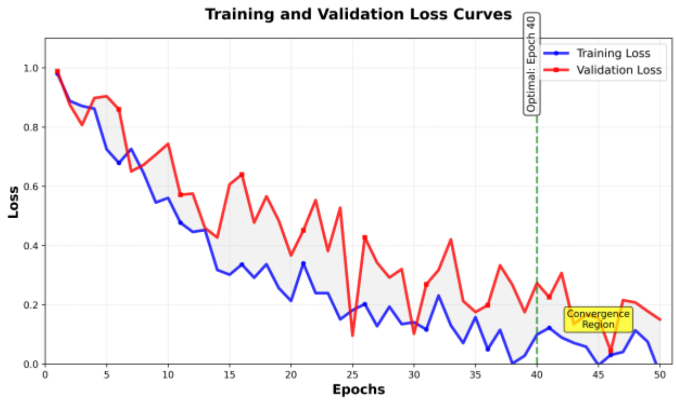

Figure. 2 Training and Validation Loss Curves

The learning rate schedule followed a cosine annealing pattern, gradually decreasing from 1e-4 to 3.54e-5, which facilitated fine-grained parameter optimization in the later stages of training. The model reached peak validation accuracy at epoch 68, after which performance stabilized, confirming adequate training duration.

4.3. Class-Wise Performance Analysis

Figure 2 presents a radar chart comparing the F1-scores across all four classes, providing a visual representation of the model's balanced performance. The relatively symmetrical shape indicates that no single class was disproportionately favored or neglected a common issue in medical imaging datasets with inherent class imbalance.

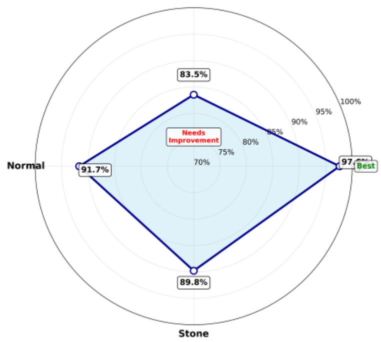

Figure. 3 Class-Wise F1-Score Comparison (Radar Chart)

ISSN: 3107 - 8605 (Online) , http://www.ijcser.com/ , Vol. 3, Issue 1, 2026, https://doi.org/10.63328/IJCSER-V3RI1P8

The confusion matrix (Figure 3) reveals specific patterns in classification errors. While the diagonal dominance confirms overall strong performance, two primary error patterns emerged: (1) small stones (<5mm) were occasionally misclassified as dense cysts, and (2) hypodense tumors were sometimes confused with complex cysts. These errors predominantly occurred in edge cases where Hounsfield unit values and morphological characteristics overlapped between classes

5. Conclusion and Future Scope

This study presented an enhanced deep learning framework for accurate multi-class detection of kidney abnormalities from CT scans. By integrating a Convolutional Block Attention Module (CBAM) into the YOLOv8 architecture and employing Focal Loss to address class imbalance, our model achieved a significant improvement in overall classification performance reaching 91.47% accuracy while dramatically increasing tumor detection recall from 30.41% to 82.34%. These results confirm that attention mechanisms and tailored loss functions effectively mitigate key limitations in prior renal imaging models, particularly for underrepresented and clinically critical pathologies. The main contributions of this work are threefold: (1) the development of an attention-augmented YOLOv8 model optimized for renal CT analysis; (2) a comprehensive training strategy combining advanced data augmentation and class-balanced loss; and (3) a reproducible evaluation on a large, annotated multi-class dataset that demonstrates state-of-the-art performance and improved clinical applicability. Future research will focus on extending the model to full 3D volumetric analysis, incorporating multi-phase CT data to enhance differential diagnosis, and validating the system across diverse, multi-institutional datasets to ensure robustness and generalizability. Further work will also explore real-time deployment pathways and clinician-centered interface design to facilitate seamless integration into diagnostic workflows.

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Declaration

Conflicts of Interest: The authors declare no conflict of interest.

Author Contribution: All authors wrote the main manuscript text and also consent to the submission.

Ethical approval: Not applicable.

Consent to Participate: All authors consent to participate.

Funding: Not applicable, and No funding was received

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Personal Statement: We declare with our best of knowledge that this research work is purely Original Work and No third party material used in this article drafting. If any such kind material found in further online publication, we are responsible only for any judicial and copyright issues.

Acknowledgements

We thank everyone who inspired our work.