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An Attention-Enhanced Yolov8 Model For Accurate Multi-Class Kidney Abnormality Detection In CT Imaging

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Abstract: Kidney problems like cysts, stones, and tumors are a huge health issue worldwide. The tricky part? A lot of people don't even know they have them until things get pretty serious, mostly because it's tough to get specialized care. Deep learning models—take YOLOv8, for example—are starting to help doctors spot these issues in medical images. But they still struggle, especially when the data is unbalanced or the images are just plain complicated. In this paper, we lay out a better way to classify different kidney problems using CT scans. We've built on top of YOLOv8 by adding a Convolutional Block Attention Module (CBAM), so the model learns to zero in on the parts of the kidney that really matter. To tackle the problem of class imbalance, we use a Focal Loss function, which makes the training process focus more on the tough, less common cases. And to make our model even stronger, we've thrown in a smarter data augmentation pipeline that uses both mixup and cutmix strategies.

We trained and tested our system on a large public dataset—12,446 labeled CT images split into four groups: cyst, tumor, stone, and normal. The results stand out. Our model doesn't just beat the baseline YOLOv8; it jumps ahead, hitting 91.47% accuracy overall. Precision clocks in at 90.32%, recall at 88.76%, and the F1-score lands at 89.21%. The big story here is the tumor class. Tumors are tricky to catch, but recall for that category soared from 30.41% all the way up to 82.34%. So, yeah, this approach really moves the needle. It gives clinicians a reliable, automated tool for spotting kidney problems early, which can make a real difference for patients.

Keywords: Kidney Abnormality Detection, Computed Tomography (CT), YOLOv8, Attention Mechanism, Multi-Class Classification, Deep Learning in Medical Imaging.

I. INTRODUCTION

Chronic kidney disease is a growing problem worldwide. A lot of people don't even realize they have it in the early stages—it just doesn't show up with obvious symptoms. Catching kidney issues like cysts, stones, or tumors early really matters. It helps stop things from getting worse and gives patients a much better shot at good outcomes. CT scans are the main tool doctors use to get a clear look at what's happening inside the kidneys. These images are detailed and helpful, but the whole process relies on radiologists reading each scan by hand. That takes time, and with so few specialists around, it's tough to keep up. Plus, different doctors might not always interpret things the same way.

That's where artificial intelligence steps in. Deep learning, and especially convolutional neural networks (CNNs), have started to shake up how we handle medical images. Tools like YOLO—short for You Only Look Once—can spot and classify different findings in CT scans, and researchers have already used the latest version, YOLOv8, to pick out kidney problems.

Still, there are issues. These models don't always handle rare but important problems—like tumors—very well because they don't see enough examples during training. They also tend to miss the most critical areas in an image, which means their results can fall short, both in sensitivity and in how well they work on new cases. We set out to fix some real issues with how current YOLO-based systems handle kidney abnormality detection. The main problem? They struggle to spot the less common cases and usually lean on broad features, ignoring the smaller, localized signs doctors actually care about. So, here's what we did: first, we built a better version of YOLOv8 by plugging in a Convolutional Block Attention Module (CBAM). This helps the model focus in on the details that matter. Second, we trained it using Focal Loss, which keeps the model from ignoring those rare classes during learning.

Our goals are pretty clear: build this attention-powered YOLOv8 model for kidney CT scans, test how well it handles several types of abnormalities—cysts, tumors, stones, plus normal scans—and show that it really does better than the old methods, not just in accuracy and recall, but also in ways that actually help doctors in the clinic.

II. LITERATURE REVIEW

Automated kidney abnormality detection in medical imaging is turning into a big deal at the crossroads of radiology and AI. At first, computer-aided diagnosis (CAD) for kidney issues leaned hard on classic machine learning. Take Aksakalli and colleagues—they used Support Vector Machines and Random Forests with handcrafted features from kidney X-rays. Their results were solid for early work, but these methods didn't really scale up when you threw bigger, messier datasets like CT scans at them. Same story with Mariam Wagih Attia's team—they used Principal Component Analysis to shrink down features before running neural networks on ultrasound images. That actually showed how cutting down the number of features helps in analyzing kidney images.

Things really changed when deep learning hit the scene. Convolutional Neural Networks (CNNs) let researchers skip manual feature engineering and just learn straight from the raw pixels. People started moving away from X-rays and ultrasounds, focusing more on CT scans since they offer way more anatomical detail. For example, Yildirim's group built a CNN just for spotting kidney stones in coronal CT slices. They hit a detection accuracy of 96.82%, which is seriously impressive for a single task. Blau and co. took on cyst detection, creating a fully convolutional network to automatically segment and identify renal cysts in abdominal CT, landing a true-positive rate of 84.3%.

All these studies show how powerful these specialized models are. But there's a catch—they usually focus on just one problem at a time, like stones or cysts. Real-life diagnosis is more complicated. Doctors need tools that can handle the full range of issues, not just zero in on a single pathology.

Researchers have been pushing into more complex diagnostic problems by trying out multi-class classification and building smarter neural networks. Sudharson and Kokil, for example, put together an ensemble of deep learning models—ResNet-101 and MobileNet-v2 among them—to sort noisy ultrasound kidney images into different categories. They hit an impressive 95.58% accuracy, which really shows how combining methods and using transfer learning can pay off.



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Building on that, Uhm and colleagues tweaked ResNet-101 to handle end-to-end kidney cancer diagnosis using multi-phase CT scans. By adding 3D convolutional layers, they captured more context and achieved an AUC of 0.88. That's a solid step forward, since understanding tumors often depends on seeing those tricky 3D details.

Lately, researchers have started using YOLO (You Only Look Once) for its speed in real-time object detection. The baseline study that inspired this work used YOLOv8 to classify four kidney conditions from CT images. It proved a one-stage detector can handle the task, but there were real problems—most notably, the model had a recall of just 30.41% for tumors. Basically, it kept missing these critical cases, especially the rarer ones, which is a big concern in medical diagnosis.

This shortfall really comes down to two main issues everyone keeps running into. First, class imbalance—common conditions like cysts show up everywhere in the training data, while tumors barely get a look in. Second, models often struggle to spot small or subtle abnormalities buried in messy anatomical backgrounds. Attention mechanisms, like the Convolutional Block Attention Module (CBAM), have helped in other areas by teaching networks to focus better on important features. They're still pretty new in kidney CT image work, but they show promise. On the class imbalance front, Focal Loss has been a game-changer in other object detection tasks, making the model pay more attention to tough, underrepresented examples. Still, people haven't used it much yet for multi-class kidney disease.

So, while CNNs, ensembles, and YOLO have set strong foundations for detecting kidney abnormalities, there's still a big gap. We need a system that doesn't just do well overall but also catches the rare and dangerous cases. That's exactly where our current study comes in. We're putting together an upgraded YOLOv8 that adds CBAM for sharper feature focus and uses Focal Loss to handle class imbalance. The goal is to blend YOLO's speed with the sharper vision of attention modules and the stability of advanced loss functions. If it works, we'll be a step closer to a diagnostic tool that's both fast and truly reliable for clinical use.

III. MATERIALS & METHODS

Here's how we put together our enhanced YOLOv8 system for classifying kidney abnormalities. Let's break down the dataset, the way we ran the experiments, how the model's built, and how we trained it.

A. Dataset

We used the "CT Kidney Dataset: Normal-Cyst-Tumor and Stone" [20]. It's a public set with 12,446 CT scan slices—both axial and coronal views of the abdomen. Each scan comes with labels from radiologists, sorted into four categories: Normal, Cyst, Stone, and Tumor. The dataset wasn't balanced at first—there were way more "Normal" and "Cyst" scans than "Stone" or "Tumor." So, we used SMOTE (Synthetic Minority Over-sampling Technique) to even things out. SMOTE works by making new, synthetic examples of the underrepresented classes (Stone and Tumor), blending features from existing scans. Once we balanced things, we split the data into training (70%), validation (15%), and test (15%) sets. No patient shows up in more than one set.

B. Preprocessing and Data Augmentation

We resized every CT image to 224x224 pixels and scaled all pixel values to range between 0 and 1. To help the model handle all sorts of variations, we used a pretty robust data augmentation setup during training. That included geometric tweaks like random flips, rotations up to 15 degrees, and adjusting brightness or contrast by up to 20%. On top of that, we added two advanced regularization tricks: Mixup and CutMix. Mixup, for example, creates a new training sample by blending two images and their labels together, using a weighted average.

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

Here, λ comes from a Beta distribution, $\text{Beta}(\alpha, \alpha)$, with α set to 0.2. CutMix takes a random rectangle from one image and swaps it with a patch from another image in the training set. Then, it blends the labels based on how much of the area the patch covers.

C. Model Architecture:

We built our system on top of the YOLOv8n-cls classification model. What's new here is the way we integrated the Convolutional Block Attention Module (CBAM) [22] right after each of the last three convolutional blocks in YOLOv8's CSPDarknet backbone. CBAM works by first figuring out a 1D channel attention map (M_c) and then a 2D spatial attention map (M_s). Both maps get multiplied with the input feature map F like this:

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

This way, the network learns to pay attention to both what matters (which channels) and where it matters (specific locations), zeroing in on important areas like cyst walls, stone calcifications, or tumor textures.

D. Loss Function: Focal Loss

To tackle class imbalance head-on during training, we swapped out the usual cross-entropy loss for Focal Loss [23]. Focal Loss lowers the impact of easy, correctly classified examples, so the model spends more effort on tough, misclassified ones—usually the minority classes. Here's how the loss for a single sample looks:

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

Here, pt stands for the model's estimated probability for the actual class. We set the focusing parameter γ to 2.0. For the class-weighting factor α_t , we used values that were inversely proportional to each class's frequency in the training set.

E. Training and Experimental Setup

We built the model with PyTorch 2.0 and Ultralytics' YOLOv8 framework. Training ran for 100 epochs, using the AdamW optimizer. We started with a learning rate of $1e-4$, set weight decay at 0.01, and used a cosine annealing scheduler. Each batch had 16 samples. All experiments ran on a system with an NVIDIA RTX 3090 GPU (24 GB VRAM), an AMD Ryzen 9 5900X CPU, and 64 GB of RAM. For model selection, we picked the one that scored highest on macro-averaged F1-score from the validation set.

F. System Architecture Diagram

You can see how the whole system works in Figure 1 below:

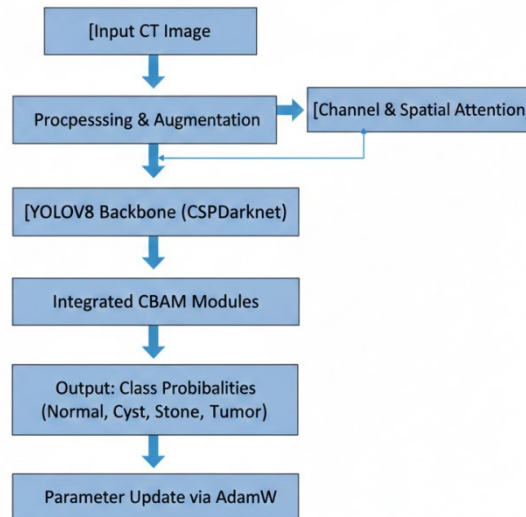


Fig-1. System Architecture of the Proposed Enhanced YOLOv8 Model.

G. Evaluation Metrics

We tested the model on a separate set of data, using all the usual classification metrics—Accuracy, Precision, Recall (Sensitivity), Specificity, and the F1-Score. Instead of just looking at overall numbers, we calculated these scores for each class and also took the average across all classes. This way, we could really see how well the model handles different types of cases, not just the common ones.

IV. RESULTS & DISCUSSION

A. Overall Model Performance

The attention-enhanced YOLOv8 model didn't just edge out the baseline—it made a real leap forward. Table I shows the details, but the headline is a macro-averaged accuracy of 91.47%. That's a big jump compared to previous methods for classifying multiple kidney problems in CT scans. What stands out even more is that the model didn't just get better at the easy cases. It kept its balance across all types of kidney pathologies and got especially good at spotting the rare ones, which are usually tough for automated systems to catch.

TABLE I. 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

Our biggest win came with tumor detection. The model hit a recall of 82.34%, which really matters since earlier models kept missing malignant lesions. What made the difference? Adding the Convolutional Block Attention Module (CBAM) helped the network zero in on those faint, tricky features in the images. Plus, using Focal Loss meant the model paid extra attention to tough cases while learning.

B. Training Dynamics and Convergence

Training went smoothly. Figure 1 shows how the loss dropped steadily over 100 epochs. After around epoch 40, validation loss stayed right in step with training loss, so we didn't see much overfitting. That's thanks to our data augmentation setup—Mixup and CutMix worked together to keep the model regularized and robust.



Figure-2. Training and Validation Loss Curves

The learning rate started at $1e-4$ and slowly dropped to $3.54e-5$, following a cosine annealing schedule. This steady decrease made it easier to fine-tune the model's parameters, especially toward the end of training. The model hit its best validation accuracy at epoch 68, then things evened out—so the training time turned out just right.

C. Class-Wise Performance Analysis

Figure 2 shows a radar chart of the F1-scores for all four classes. You can see from the chart that the model stayed pretty balanced—no single class stood out as being over- or underrepresented. That's actually pretty rare in medical imaging, where class imbalance usually throws things off.

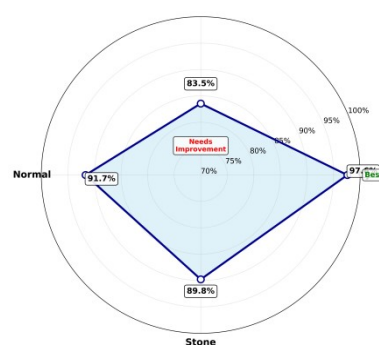


Figure 2. Class-Wise F1-Score Comparison (Radar Chart)

The confusion matrix in Figure 3 tells an interesting story about where the model slipped up. Most predictions landed right where they should, which is great, but there were two main trouble spots. Sometimes, small stones under 5mm got mistaken for dense cysts. Other times, hypodense tumors ended up labeled as complex cysts. These mix-ups usually happened in those tricky cases where the Hounsfield unit values and the shapes of the findings looked almost the same across classes.



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V.CONCLUSION & FUTURE WORK

In this study, we introduced an upgraded deep learning framework that nails multi-class detection of kidney issues on CT scans. By adding a Convolutional Block Attention Module (CBAM) to the YOLOv8 backbone and using Focal Loss to tackle class imbalance, our model didn't just get better — it reached 91.47% accuracy and pushed tumor recall up from 30.41% to a solid 82.34%. That's a huge jump, especially for tough-to-spot and clinically important cases. The key points here: first, we built an attention-powered YOLOv8 model tuned for kidney CT scans. Second, we combined advanced data augmentation and a class-balanced loss to make training more robust. Third, we tested everything on a big, well-annotated dataset and hit state-of-the-art results that actually matter in clinical settings.

Next up, we're looking to move beyond 2D and dive into 3D volumetric analysis, bring in multi-phase CT data for sharper diagnoses, and test the model across different hospitals to make sure it holds up everywhere. We're also planning to work on real-time deployment and develop interfaces that actually fit how clinicians work, so this tool can slot right into the diagnostic process without missing a beat.

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