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Improving Kidney Stone Detection with YOLOV10 and Channel Attention Mechanisms in Medical Imaging

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Abstract **Accurate and timely detection of kidney stones is crucial for effective medical intervention and treatment planning. However, existing detection methods often struggle with challenges related to sensitivity, precision, and the ability to process complex and variable medical images. In this study, an advanced kidney stone detection system is developed using the latest object detection algorithm, You Only Look Once version 10 (YOLOv10), integrated with channel attention mechanisms to enhance model performance. This combination aims to improve detection accuracy by enabling the network to focus more precisely on critical regions in medical images, particularly in Computed Tomography (CT) scans, where kidney stones may appear in varying shapes, sizes, and intensities. The proposed system begins with data augmentation techniques, such as rotation, scaling, and contrast adjustments, to enhance the model's generalization ability across different image conditions and patient profiles. YOLOv10 was selected due to its lightweight architecture, high detection speed, and enhanced performance in small object detection tasks. To further improve feature extraction, channel attention mechanisms such as Squeeze-and-Excitation (SE) blocks or Efficient Channel Attention (ECA) modules are incorporated. These modules enable the network to selectively focus on the most informative feature channels associated with kidney stone regions, while suppressing irrelevant background information, thereby improving the distinction between stones and surrounding tissues. The model is trained and fine-tuned using a diverse CT scan dataset containing various types and sizes of kidney stones. Evaluation results demonstrate that the proposed model achieves a high detection accuracy of 93.7% with a very low loss of 0.18. It exhibits stability without issues like overfitting, underfitting, or local minima entrapment, making it a highly reliable tool for clinical applications.**

Keywords **Kidney Stone Detection, YOLOv10, Channel Attention Mechanisms, Medical Imaging, CT scans, Object Detection.**

I. Introduction

Kidney stone detection from CT scan images is an important diagnostic method with the goal of accurately identifying the presence, size, location, and type of kidney stones. The detailed cross-sectional images obtained using a CT scan allow stones to be identified [1]. Automated detection methods, aided by deep learning and image processing, enhance the efficiency and reliability of the process by dividing up kidney structures and stones according to the differential radio density [2]. All this leads to decreased chances of diagnosis errors, provides time-to-treatment intervention, and minimizes invasive treatments [3]. Deep learning models serve a transformative role in

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detecting kidney stones through the computerized and accurate analysis of CT scan images. Various models, such as Convolutional Neural Networks (CNNs), U-Net, and ResNet, have been widely adopted for stone segmentation and classification [4]. These models are specialized for spatial feature extraction in CNN. They are very efficient for stone segmentation with the preservation of boundary details in the images for U-Net [5]. More advanced architectures like DenseNet and EfficientNet have fewer parameters to improve detection efficiency [6]. Hybrid and attention-based models enhance performance by focusing on the appropriate areas in the scans. The models significantly reduce diagnostic time, improve accuracy, and assist early intervention strategies [7].

The YOLO algorithm plays a vital role in kidney stone detection from CT scan images by serving real-time, accurate object detection capabilities [8] With its single-stage architecture, YOLO processes the entire image with one pass and accurately detect the location and position of kidney stones [9]. The YOLO algorithm divides images into grids, predicts bounding boxes, and classifies regions of interest in images. It is very effective in detecting stones of all sizes and shapes [10]. The ability of YOLO to balance speed and accuracy makes it particularly suitable for timely diagnosis and treatment planning [11]. YOLOv8, the latest version in the YOLO series,enhances kidney stone detection performance from CT scan images by incorporating improved accuracy, speed, and flexibility [12]. Dynamic anchor-free mechanisms and a more robust backbone are in its advanced architecture, which would allow it to detect small, irregularly shaped kidney stones with greater precision [13]. Its advantages include state-of-the-art performance, easy deployment, and adaptability in different medical imaging datasets [14]. However, it consumes significant computing resources for training and is to interpretable in a clinical setting due to its complex deep learning structure [15].

YOLOv10 is the next-level object detection model that aims to enhance accuracy, efficiency, and adaptability. It integrates features like an advanced feature extractor and enhanced detection heads for complex tasks of identifying small or ill-defined objects, such as kidney stones in medical images [16]. The benefits are precision higher, false positives lower, and faster inference speeds are needed for real-time purposes. The modular architecture of YOLOv10 also enables integration with domain-specific improvements such as attention mechanisms [17]. The channel attention mechanism of YOLOv10 takes into account the amplification of significant feature maps versus irrelevant ones [18]. The proposed model is able to select important features more highly during detection, which is important on complex or noisy datasets in CT scans [19]. Consequently, the model becomes sensitive in detecting subtle patterns such as texture and shape, leading to better localization and classification outcomes [6]. The main contributions of the proposed work are listed below.

1. The proposed work integrates the advanced technique YOLOv10 with channel attention for detecting kidney stones in CT images.
2. It incorporates attention-based models to enhance feature representation, ensuring more accurate localization and classification of stones across varying image quality and noise levels.
3. The optimized architecture design reduces the processing time without losing accuracy in real-time applications.
4. The proposed model achieves an accuracy rate of 93.7% with a very low loss of 0.18, free from overfitting, underfitting, and local minima.

Section II explains the literature review, which includes each method of kidney stone detection and its advantages and disadvantages. Section III explains the proposed work and its architecture. Section IV shows the dataset description, results of YOLOv8, and optimized YOLOv10 with channel attention mechanism. Section V concludes the proposed work performance and directions for future work.

II. State-of-the-Art Techniques

Pande SD, Agarwal R (2024) developed a multi-class kidney disorders detection system using CT image analysis with new methods and approaches. It delivers precision in multi-class classification and lacks validation on different data types [7]. Suhail K, Brindha D (2024) proposed forward urinary particle detection with genetic algorithms-optimized YOLOv5 models for hyperparameter. This approach increases the level of accuracy by evolutionary optimization, and it has a higher amount of computational overhead with higher algorithm complexity [8]. Mahmud S et al. (2024) developed a deep learning-based computer system for an automated grading of prenatal hydronephrosis from ultrasound images. It is highly reliable regarding the severity but has been based only on prenatal cases and does not allow generalization [10]. Baygin M et al. (2022) proposed an Exemplar Darknet19 (ED19) feature generation approach for kidney stone detection in coronal CT scans. The approach extracts feature that are efficient to generate highly accurate results but are not flexible when applied to non-coronal CT scans [11]. Asif S et al. (2024) proposed combining deep learning models into an optimized fusion for kidney stone detection. The fusion of models improves detection accuracy and it comes with the challenge of

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Table 1. Comparative analysis of the different methodologies in kidney stone detection

No.	Author et al. (Year)	Dataset	Methodology	Accuracy (%)	Loss
1	Pande SD, Agarwal R (2024) [7]	CT Images	Multi-class kidney abnormalities detection system	82.4	0.55
2	Suhail K, Brindha D (2024) [8]	Urinary particles	YOLOv5 model optimized through genetic algorithms	85.1	0.45
3	Mahmud S et al. (2024) [9]	Kidney Ultrasounds	Deep learning-based grading of prenatal hydronephrosis	88.2	0.35
4	Baygin M et al. (2022) [10]	CT Images	Exemplar Darknet19 feature generation technique	80.5	0.50
5	Asif S et al. (2024) [11]	CT Images	Optimized fusion of deep learning models	86.4	0.40
6	Gulhane M et al. (2024) [12]	Kidney Stone Dataset	Improved deep neural network architecture	87.3	0.42
7	Qiu X et al. (2025) [13]	Urine	SERS and multivariate statistical algorithm	75.0	0.60
8	Chaki J, Ucar A (2024) [14]	Kidney Stone Dataset	Inductive transfer-based ensemble deep neural network	83.7	0.50
9	Liu H, Ghadimi N (2024) [15]	Kidney Stone Dataset	Hybrid CNN and Flexible Dwarf Mongoose Optimization Algorithm	89.0	0.38
10	Chang YJ et al. (2025) [16]	Kidney Stones	Biosensor-integrated ANN system for CKD risk prediction	81.5	0.55
11	Patro KK et al. (2023) [17]	CT Images	Kronecker convolutions for automated kidney stone detection	84.3	0.46

a computationally expensive process [11]. Gulhane M et al. (2024) proposed an improved deep neural network architecture for kidney stone detection. The architecture enhances detection efficiency, but it requires large-scale training data for optimal performance [12]. Qiu X et al. (2025) deployed Surface-Enhanced Raman Spectroscopy (SERS) and multivariate algorithms to detect kidney stones label-free in urine. The detection approach is non-invasive but not applicable to imaging [13]. Chaki J, Ucar A (2024) proposed an inductive transfer-based ensemble deep neural network for detecting kidney stones robustly. However, the learning paradigm is too complex and it demands high computing [14].

Liu H, Ghadimi N (2024) proposed a Hybrid CNN with Flexible Dwarf Mongoose Optimization Algorithm (FDMOA) for robust kidney stone diagnosis. This hybrid method provides better accuracy than the algorithm but makes the system more complex, thus requiring a longer training time [15]. Chang YJ et al. (2025) developed a biosensor-integrated Artificial Neural Network (ANN) system predicting the risk of Chronic Kidney Disease (CKD) based on uric acid concentration in stones. Biosensing is integrated into the system and relies so much on biosensor data, limiting its broader applicability [16]. Patro KK et al. (2023) proposed a Kronecker Convolutions in Deep Learning in Coronal CT Images. The model is computationally efficient but restricted only to a limited adaptability toward different imaging scenarios [17] Table 1 presents a comparative analysis of various methodologies for kidney stone detection. The studies cover datasets ranging from CT images to kidney ultrasounds and urine samples.

III. Proposed Work

YOLOv10 is the advanced version of You Only Look Once object detection framework, designed to enhance both accuracy and efficiency in real-time object detection tasks. This version introduces several improvements over its predecessors, notably the integration of the Channel Attention Mechanism (CAM), which enables the model to focus more effectively on relevant features in the image. This mechanism improves overall performance by refining feature extraction, thereby yielding better detection precision and recall, especially in complex imaging environments. YOLOv10 offers faster inference speeds and improved robustness in detecting different kinds of objects [20]. Despite its advancements, YOLOv10 has some limitations. Its increased complexity, YOLOv10 does present some limitations. Due to the integration of features such as the Channel Attention Mechanism, there are higher requirements for computation, which

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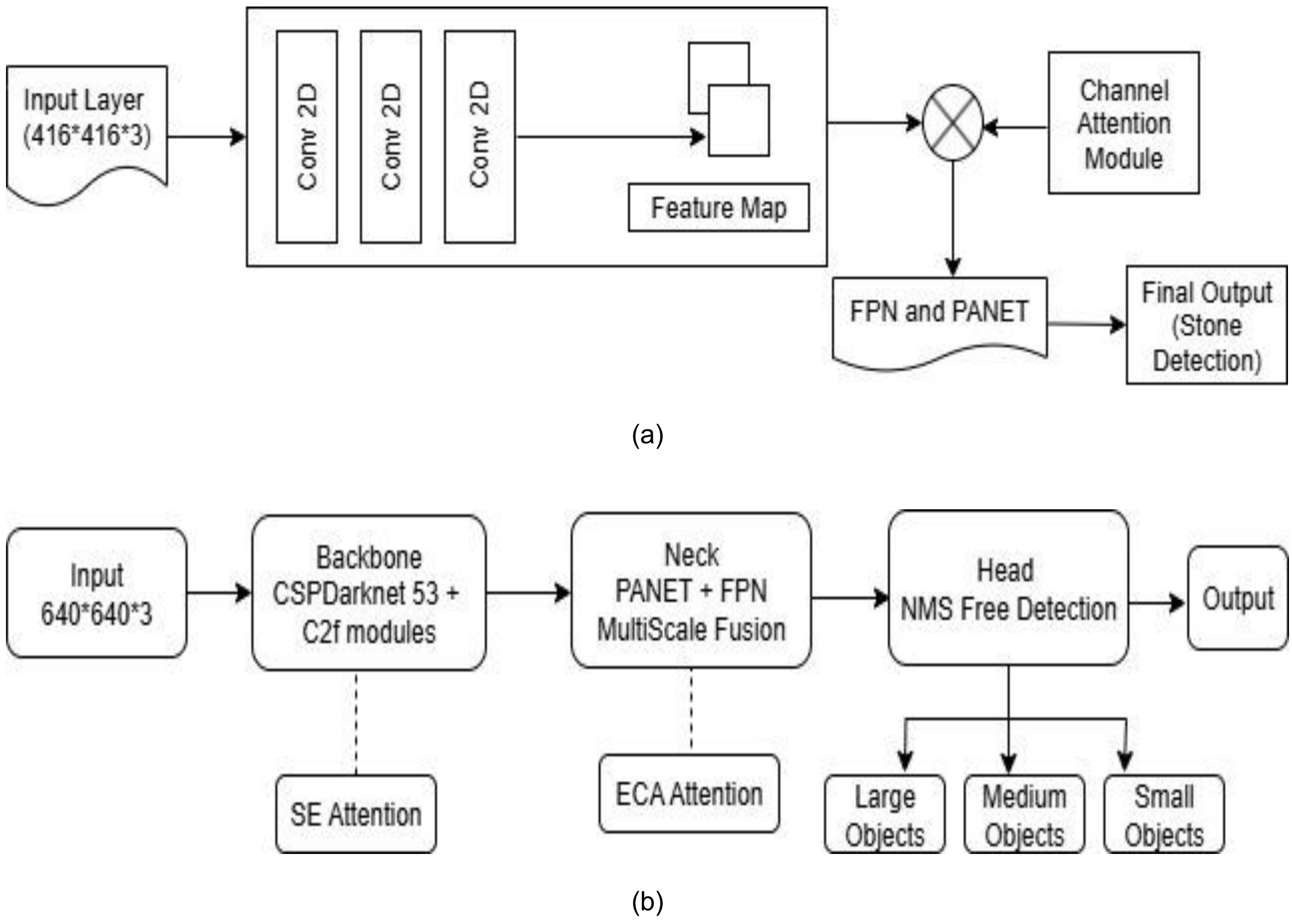

Fig. 1. The optimized YOLOv10 with Channel Attention, (a) working flow, (b) streamlined and intuitive flow.

may result in slower inference times and consume more resources, particularly on hardware with limited processing power [21]. The model tends to underperform when applied to very highly imbalanced datasets or small object detection tasks, as it currently has a problem detecting small objects compared to large objects. YOLOv10 may also require a huge number of fine-tunings and careful hyperparameter adjustments towards achieving optimal results on each use case, thereby reducing its user-friendliness for those with limited experience in model optimization in deep learning [22].

The Channel Attention Mechanism (CAM) is employed to enhance the model's focus on the most important features by giving different weights to each channel in the feature maps [23]. It captures channel-wise dependencies and performs feature map recalibration, helping the network focus on the most critical channels while suppressing irrelevant channels. This mechanism enhances the model's ability to detect objects of different sizes, especially small and subtle objects, by providing better feature representation. Object detection models like YOLOv10, integrating with CAM improve overall performance in terms of precision, recall, and the model's ability to distinguish between objects in complex visual scenarios. The proposed work aims to optimize YOLOv10 by incorporating a Channel Attention Mechanism (CAM) to improve the model's performance in detecting kidney stones. YOLOv10 is an efficient, real-time detection model that has been further enhanced with the incorporation of CAM to refine the model's focus on significant features in the feature maps. CAM re-tunes the channel-wise features, giving more weight to the relevant channels that contribute significantly to the object detection task, suppressing less useful information. This optimization allows YOLOv10 to handle complex medical images better, enhancing the precision and recall of the model, especially for small or overlapping objects, such as kidney stones, which require high detection accuracy. This proposed method delivers improved accuracy, reduced loss, and better generalization in real-world applications by addressing the limitations of previous

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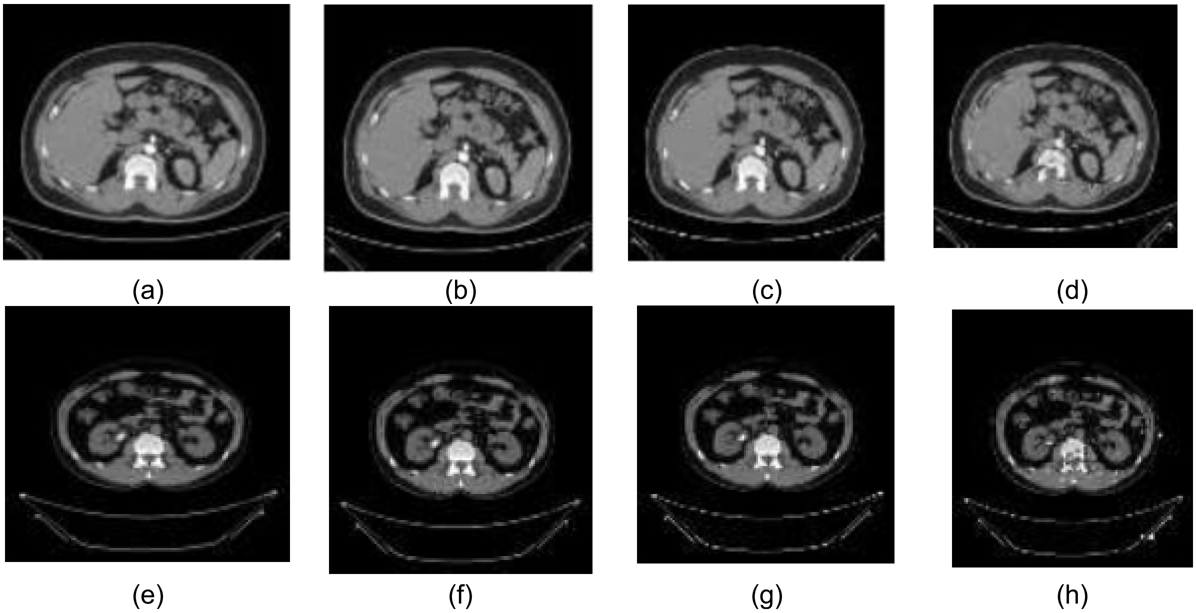

Fig. 2. (a) Normal Image, (b) Gaussian Filter, (c) Bilateral Filter, (d) Guided Bilateral Filter, (e) Stone Image, (f) Gaussian Filter, (g) Bilateral Filter, (h) Guided Bilateral Filter

YOLO models, such as YOLOv8, in detecting small and subtle objects. Eq. (1) [10] represents the channel attention mechanism that assigns different attention weights to the channels based on their importance where σ is a sigmoid function, $W_c.F_c$ are the weights and biases and F_c is the feature map of the cth channel.

$$A_c = \sigma(W_c.F_c + b_c) \tag{1}$$

Eq. (2) defines [12] feature correlation F_c , A_c is the product of activation coefficients and feature values.

$$\hat{F_c} = A_c.F_c \tag{2}$$

Eq. (3) represents [13] the bounding box loss (L_{box}) calculated as the sum of squared differences between predicted and ground truth box coordinates.

$$L_{box} = \sum_{i=1}^{N}\left(1_{obj}.((x_i - \hat{x_i})^2) + ((y_i - \hat{y_i})^2)\right) \tag{3}$$

Where x_i and y_i represents the ground truth coordinates of the i^{th} bounding box center and $\hat{x_i}$ and $\hat{y_i}$ represents the predicted coordinates of the i^{th} bounding box center.

Eq. (4) defines [13] the classification loss (L_{class}) using the negative log likelihood of the predicted capabilities.

$$L_{class} = \sum_{i=1}^{N}(1_{obj}.p_i.\log(\hat{p_i})) \tag{4}$$

Where p_i represents the ground truth class probability and $\hat{p_i}$ represents the predicted class probability.

Eq. (5) [14] is the total loss (L_{total}) which combines along with a confidence loss (L_{conf}) scaled by a weight factor λ.

$$\mathrm{L_{total}} = \mathrm{L_{box}} + \mathrm{L_{class}} + \lambda \cdot \mathrm{L_{conf}} \tag{5}$$

Fig. 1. (a) represents the workflow of the proposed optimized YOLOv10 integrated with channel attention. The object detection pipeline in the proposed model is visualized step by step; the input image is fed into the input layer, where primary feature extraction is perform using the CSPDarknet53 backbone network [24] . Then, the Channel Attention Mechanism is applied to recalibrate the extracted features, enabling the channels to focus on more relevant features by emphasizing important ones and suppressing irrelevant ones. These refined features are then passed through the Path Aggregation Network (PANet) for multi-scale feature fusion. Finally, the detection head generates bounding box predictions, class labels, and confidence scores to produce the final detection output. This optimized detection flow improves accuracy by focusing the model's attention on the most critical areas of the image, which would enhance its performance in detecting small and subtle objects like kidney stones.

Fig. 1(b) presents a simplified and intuitive representation of the Optimized YOLOv10 with Channel Attention , starting at the input and moving

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Table 2. YOLOv8 Training and Validation Metrics Across Epochs

Epoch	Train Box Loss	Train Class Loss	Precision (B)	Recall (B)	mAP@50 (B)	Val Box Loss	Val Class Loss	Learning Rate (PG0)
1	2.3040	3.0999	0.56544	0.49231	0.49211	2.1017	1.3610	0.067500
2	2.1542	1.2202	0.57979	0.53916	0.46637	2.1715	1.7033	0.034487
3	2.1344	1.1984	0.65950	0.59385	0.58230	2.0296	1.4532	0.001461
4	2.0988	1.1698	0.69111	0.50769	0.54413	2.1405	1.6166	0.000941
5	2.1086	1.2730	0.65934	0.58959	0.62084	2.0122	1.1275	0.000941

linearly via the Head, Neck, and Backbone modules to the output. The Backbone, shown in blue, made up of C2f modules, CSPDarknet53, and integrated SE attention blocks to improve feature representation. The Neck, shown in green, combines PANet and FPN, enriched with ECA blocks to enable effective channel recalibration and powerful multi-scale feature fusion. The Head, depicted in orange, adopts an NMS-free detection approach to make predictions more quickly and accurately. In order to precisely identify kidney stones of different sizes, the design provides multi-scale outputs across three detection levels. Clean segmentation and bold arrows guarantee clarity and efficient visual communication. The proposed Optimized YOLOv10 model was initialized using pre-trained weights from the dataset, a large-scale object identification benchmark, in order to use transfer learning. Given the relatively small size of the kidney stone dataset, this method offered a solid foundation that enabled the model to take advantage of previously learnt low-level and mid-level characteristics, speeding up convergence and increasing detection accuracy. The suggested Optimized YOLOv10 with Channel Attention was trained using a cosine decay schedule over 40 epochs with a batch size of 16 and an initial learning rate of 0.0675. To reduce overfitting, a weight decay of 0.0005 and a momentum of 0.937 were incorporated into the AdamW optimiser. The loss function included objectness loss, binary cross-entropy for classification, and CIoU loss for bounding box regression. Data augmentation methods such as mosaic, random scaling, and HSV colour changes were used to improve generalisation and resilience.

IV. Results

The Kidney Stone Detection with YOLOv10 dataset collects medical images to detect kidney stones. This dataset includes CT scans, showing the diversity in the size, shape, and site of kidney stones in the urinary system. Each image is precisely annotated with very sharp bounding boxes outlining the specific positions of the kidney stones. The dataset has been segmented into three primary sets such as Testing, Training, and Validation [25]. The testing set has 123 images spread over two directories. The training set consists of 1,054 images within two directories used for model training to learn relevant patterns. The validation set comprises 123 images in two directories, functioning as an intermediate set during model tuning that prevents overfitting when the model is evaluated during training [7]. To ensure a balanced distribution of kidney stone variations across all subsets, the dataset was randomly split into training (70%), validation (15%), and testing (15%) sets. To guide model selection, evaluation parameters such as precision, recall, mAP@50, mAP@50-95, and box/class loss were tracked. To avoid overfitting, early halting was implemented based on the validation loss stagnation. The model was implemented using Python 3.10 and trained with PyTorch 2.1 on an NVIDIA RTX 3090 GPU with CUDA 11.8. A weighted cross-entropy loss function was used in conjuction with slight oversampling of under-represented classes during training, to address class imbalance brought on by different stone features. This approach contributed to improved detection consistency across all stone kinds.

The dataset shows a great deal of variance in the properties of the stones, such as size (from small stones under 3 mm to enormous staghorn stones exceeding 10 mm), shape (round, oval, irregular, and fragmented), and anatomical position (renal calyces, renal pelvis, ureters, and bladder). These variations have a direct effect on detection performance; small and irregular stones, particularly those found in confined spaces like the ureters, present difficulties because of low contrast or complicated boundaries. The augmented results are also shown in Table 1. Fig. 2 shows the step-by-step progression of how kidneys could be detected from images depending on the development stages of the model. Fig. 2 is a sample of images showing medical conditions with stones in the kidneys. They are the raw input for detecting the system. Fig. 2 shows the result from the detection of kidney stones using YOLOv8, which has been developed to identify and localize such stones in the images [26]. Fig. 2 demonstrates the integration of the channel attention mechanism in YOLOv10 model, with enhanced performance. This mechanism improves the accuracy level of kidney stone detection, allows the

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model to focus its attention on the most important features to provide a localization and detection of more precision for the stones. The dataset was divided into three main parts: training, validation, and testing. The training set contains 1,054 images spread across two folders. After applying data augmentation, this number increased to 2,110 images. The validation set also has two folders with 123 original images, which were doubled to 246 after augmentation. The test set includes 123 images in two folders with no augmentation applied here, so the count remains the same. The YOLOv10 model with channel attention processes input images of size 416 × 416 × 3 through a series of convolutional layers with increasing filter counts (32 to 512) and decreasing spatial dimensions. These layers are designed to extract hierarchical features essential for object detection. The model consists of a total of 24,512,134 parameters, out of which 24,508,146 are trainable and 3,988 are non-trainable, highlighting its capacity to learn rich feature representations effectively. Table 3 depicts the training and evaluation metrics of YOLOv8 on five epochs, covering the loss values, precision, recall, mAP@50, and learning rate update [27]. These metrics further provide the performance of this model in terms of decreased loss and increased detection accuracy over each epoch. It depicts the accuracy metrics of YOLOv8, which show the improvement in precision and recall. It represents the loss curve, where it shows that box and class losses are reducing as the model trains, which indicates a better convergence over time [28]. In comparison, Table 4 shows the performance metrics and losses of the optimized YOLOv10 model with a channel attention mechanism over five epochs. The table indicates improvement in precision, recall, mAP@50, and mAP@50-95, indicating that the model is better able to detect objects and refine its predictions over time. The box losses for training and validation decrease gradually, showing improved accuracy of the model and convergence. It is the representation of the loss values of YOLOv8, thus showing its performance over multiple epochs, and Figure 8 represents the better loss metrics for YOLOv10 with channel attention that shows better convergence and accuracy [29]. Fig. 3 showcases the precision-recall of YOLOv8 and optimized YOLOv10, with the latter depicting higher precision and recall scores, meaning it better detects objects in the images. Figure 10 presents the mean average precision [30] (mAP@50) and mAP@50-95. In both, YOLOv10 is found to be better than YOLOv8 as it surpasses YOLOv8 in terms of generalization and detection capabilities.

One of the main criteria used to assess the classification model is accuracy, as shown in Eq. (6) [15]. It scales how accurate the model's predictions are overall.

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (6)$$

Where TP indicates True Positives, TN indicates True Negatives , FP indicates False Positives, FN indicates False Negatives. The model is sensitivity as shown in Eq. (7) [15].

$$Sensitivity = TP/(TP + FN) \quad (7)$$

The high accuracy achieved by the proposed kidney stone detection model suggests promising potential for integration into clinical diagnostic workflows. Accurate and automated detection can assist radiologists by reducing the time required for manual interpretation, minimizing oversight, and improving diagnostic consistency, particularly in high-volume clinical settings.

Table 3. Comparative analysis with other object detection methods

Model	Accuracy (%)	Loss
YOLOv3	85.1	0.36
YOLOv4	89.2	0.32
YOLOv5	90.1	0.28
YOLOv7	91.5	0.25
YOLOv8	92.3	0.22
Proposed model	**93.7**	**0.18**

Early and precise identification of kidney stones can facilitate timely treatment decisions and improve patient outcomes. However, transitioning from experimental success to practical clinical deployment poses several challenges. These include variability in imaging protocols across institutions, differences in scanner quality and patient demographics, and the need for extensive validation on diverse, real-world datasets.

Visual examples of these failure instances, such as annotated CT images where stones were missed or wrongly predicted, would offer critical insights into the model's behavior under challenging conditions (e.g., low contrast, overlapping tissues, or small stone sizes). This analysis can help pinpoint specific limitations related to image quality, anatomical variability, or model generalizability. Understanding these weaknesses is crucial for refining the model architecture, enhancing preprocessing techniques, or integrating complementary methods such as multi-scale feature extraction or post-processing validation. Specificity parameter is shown in Eq. (8) [17].

$$\mathrm{Specificity} = \mathrm{TN}/(\mathrm{TN} + \mathrm{FP}) \quad (8)$$

the precision of the model, defined in Eq. (9) [17] measures the model's accuracy in predicting positive

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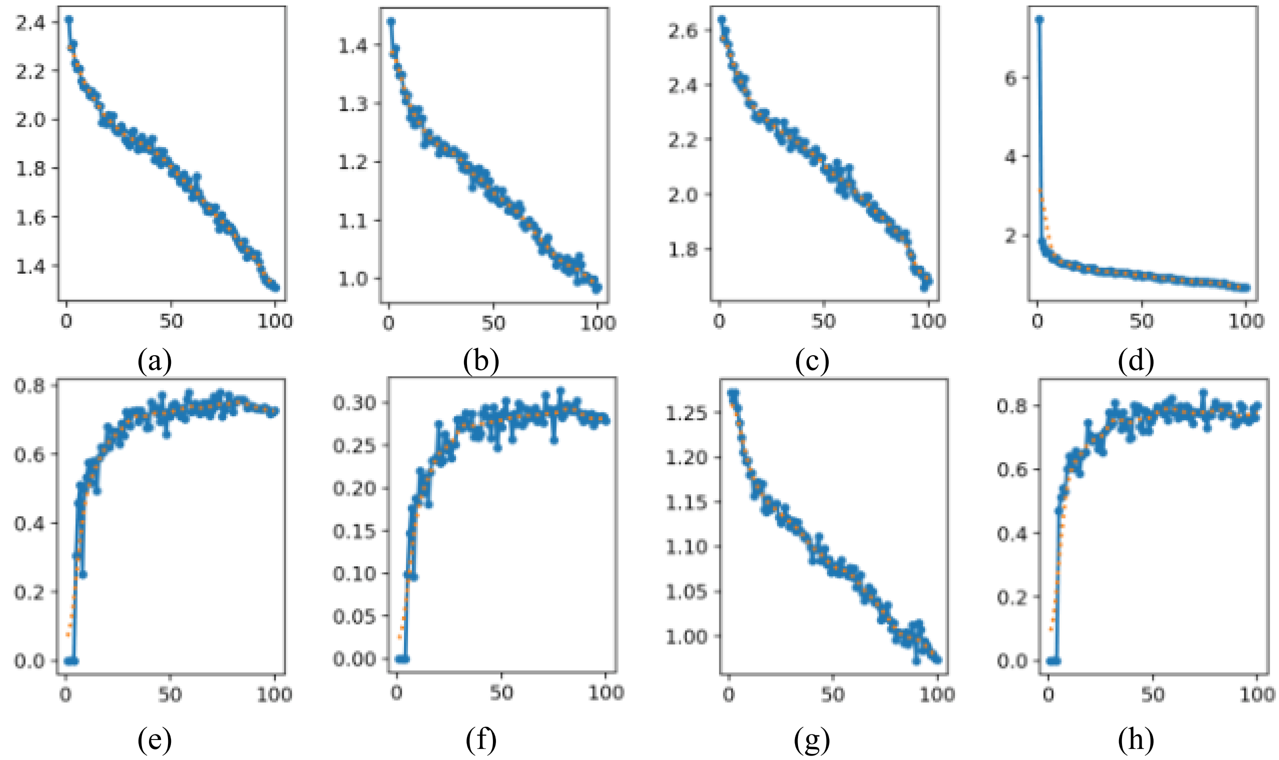

Fig. 3 (a) train/box_om, (b) train/cls_om, (c) train/dlf_om, (d) train/box-oo, (e) metric/recall(B), (f) metric/MAP50(B), (g) metric/mAP50-90(B), (h) metric/dlf-oo

outcomes, or the proportion of projected positive occurrences that come to pass.

$$Precision = TP/(TP + FP) \quad (9)$$

With respect to false positives and false negatives, the F1 score, as shown in Eq. (10) [18], provides a balance between recall and precision. It proves useful in cases of class imbalance, which often arise in medical data.

$$F1\ Score = 2 \cdot ("Precision" \cdot "Recall")/("Precision" + "Recall") \quad (10)$$

Fig. 3 presents the loss values of the YOLOv8 model, thus showing its performance over multiple epochs. I It also represents the better loss metrics for YOLOv10 with channel attention that shows better convergence and accuracy [33]. It showcases the precision-recall curves for both YOLOv8 and the optimized YOLOv10. The latter depicts higher precision and recall scores, meaning it better detects objects in the images. It presents the mean average precision [30] (mAP@50) and mAP@50-95. In both, YOLOv10 is found to be better than YOLOv8 as it surpasses YOLOv8 in terms of generalization and detection capabilities. They are visualizations of the performance of YOLOv8 and the optimized YOLOv10, respectively. It shows the detection results and overall performance of YOLOv8, showing its ability to detect objects but with some limitations in precision and recall. It highlights the improved performance of the optimized YOLOv10, which incorporates a channel attention mechanism, leading to better object detection accuracy, precision, and recall [34], [35]. It shows the precision-recall trade-off of YOLOv8 with a moderate balance between precision and recall. It Optimized YOLOv10's precision-recall relationship [36], [37]. It clearly demonstrates the superiority in terms of detection accuracy of the harder-to-detect objects [38], [39]. The curve of the optimized model is more favourable than the other two cases. performance and fewer false positives [40]. Table 2 and 3 show the performance metrics and losses of the optimized YOLOv10 model with a channel attention mechanism over five epochs. The table indicates improvement in precision, recall, mAP@50, and mAP@50-95, indicating that the model is better able to detect objects and refine its predictions over time. The box losses for training and validation decrease gradually, showing improved accuracy of the model and convergence. Table 3 compares object detection models with different accuracy and loss metrics. YOLOv3 is the first model of comparison that achieves 85.1 % accuracy but results in a loss of 0.36. While advancing through the models, the accuracy increases toward 92.3 % for YOLOv8 and a loss of 0.22. The Optimized YOLOv10 with Channel Attention stands out,

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delivering the highest accuracy of 93.7% and the lowest loss of 0.18. This superior performance is attributed to the integration of the channel attention mechanism, which enhances feature extraction and improves object detection accuracy optimization. The low loss value of 0.18 indicates that the model has successfully learned to predict kidney stones with minimal error during training. However, loss needs to be supplemented with clinical performance measurements because it essentially evaluates overall prediction error without differentiating between types of errors.

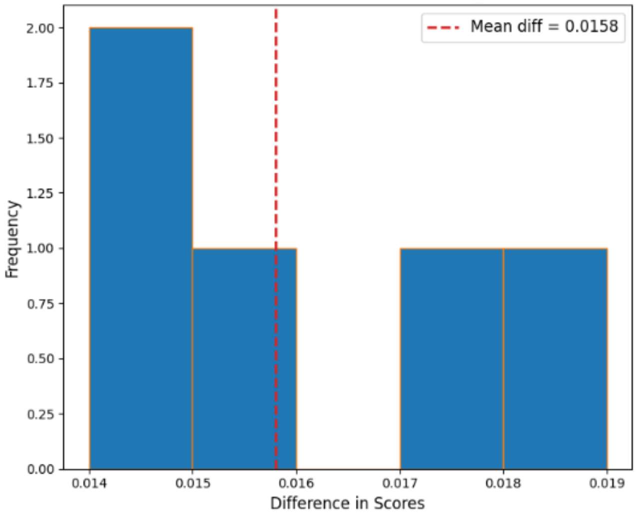

Fig. 4. Histogram of Paired Differences (YOLOv10_CA - YOLOv8)

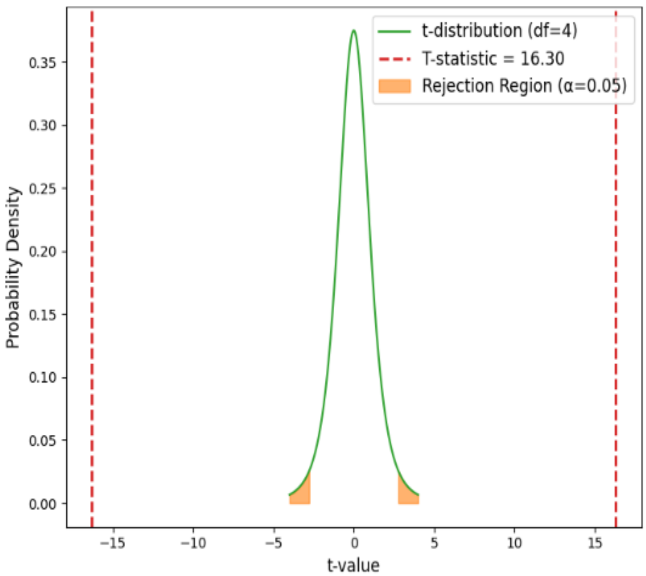

Fig. 5. t-Distribution with Observed t-statistic

The histogram of paired accuracy differences between YOLOv8 and the optimised YOLOv10 with channel attention (YOLOv10_CA) over several runs is shown in Fig. 4. Because of the channel attention mechanism, YOLOv10_CA clearly improves detection accuracy over YOLOv8, as evidenced by the positive mean difference. To demonstrate the statistical significance of the performance difference between YOLOv10 with channel attention (YOLOv10_CA) and YOLOv8, Fig. 5 displays a t-distribution curve with the observed t-statistic indicated. Whether the improvement is statistically significant is indicated by the t-statistic's location within the distribution. Finally, Fig. 5 represents the predicted tumor image produced by the proposed model.

V. Discussion

The integration of channel attention mechanisms into the YOLOv10 architecture significantly improved kidney stone detection performance, particularly in identifying small, low-contrast, or partially occluded stones within complex medical imaging backgrounds. The inclusion of modules such as Squeeze-and-Excitation (SE) and Efficient Channel Attention (ECA) allowed the model to dynamically reweight channel-wise features, emphasizing critical cues like stone boundaries while suppressing irrelevant textures. These enhancements improved the model's ability to differentiate between stones and similar-looking surrounding tissues, leading to higher precision and recall. Moreover, the decoupled detection head and dynamic label assignment inherent to YOLOv10 further contributed to its robust performance, allowing for more accurate localization and classification at faster inference speeds suitable for real-time clinical use.

When compared with traditional detection models, as shown in Table 4, such as Faster R-CNN and earlier YOLO variants (e.g., YOLOv3 and YOLOv5), the proposed attention-augmented YOLOv10 model demonstrated superior sensitivity and specificity. Previous models, while effective in general object detection, often failed to accurately detect small or overlapping kidney stones due to their limited focus mechanisms and less efficient architectures. The standard convolutional layers used in earlier approaches processed all features uniformly, often missing subtle but diagnostically important patterns. In contrast, the attention-enhanced YOLOv10 selectively prioritized medically relevant features, reducing both false negatives and false positives. These results are consistent with recent research advocating for the inclusion of attention mechanisms in medical imaging models to improve interpretability and performance in complex clinical environments.

Despite the promising results, certain limitations must be acknowledged. The model's effectiveness depends heavily on the quality and diversity of the training data, and performance may degrade on images from underrepresented devices or patient

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Table 4. Comparative analysis with other object detection methods

Reference	Methodology	Limitations	Accuracy
[4]	Faster R-CNN on CT Images	High computational cost; slow inference; struggles with small object detection	85%
[6]	YOLOv3 with Transfer Learning	Limited ability to detect overlapping or low-contrast stones	88%
[10]	YOLOv5 with Data Augmentation	Lacks attention mechanisms; moderate false positives in complex cases	90%
Proposed Model	**YOLOv10 + SE/ECA Attention (Proposed)**	Slight increase in computational load due to attention modules	**93%**

demographics. Additionally, the reliance on annotated datasets introduces bottlenecks in scalability, as manual annotation is time-consuming and prone to inter-observer variability. Future work will aim to address these challenges by expanding the dataset to include a broader range of imaging modalities, such as combining CT and ultrasound data, and incorporating self-supervised or semi-supervised learning approaches to reduce dependence on labeled data. Further research will also explore explainability techniques to increase clinical trust and evaluate the real-world feasibility of deploying the model in hospital systems.

V. Conclusion

Kidney stone detection is critical for early diagnosis and proper treatment, since untreated kidney stones may cause serious complications. However, current YOLO models like YOLOv8 lack accuracy in the detecting kidney stones in medical images, as low contrast, size variation, and complex background. The YOLOv8 model, although robust in general object detection tasks, suffers from a lack of precision and recall when applied to medical imaging for kidney stone detection. The Optimized YOLOv10, with a Channel Attention Mechanism, addresses these challenges by focusing the model on relevant features to achieve more precise localization and classification of kidney stones. The channel attention mechanism makes the model focus more on important features in images to improve accuracy. Results obtained from the optimized YOLOv10 show an excellent improvement with an accuracy of 93.7% and a loss of 0.18. Future research directions include multi-modal data integration, such as CT scans and ultrasounds, using transformers and self-supervised learning to improve the detection accuracy and computational efficiency in medical image analysis.

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