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M Kishore Kumar[1] , A V L N Sujith[2],*

[1]Research Scholar, BEST Innovation University, Gownivaripalli, Gorantla Andhra Pradesh, India.
kishorkumar.mandapaka@gmail.com
[2]Professor, Department of CSE, School of Engineering, Malla Reddy University, Hyderabad, India.
Sujeeth.avln@gmail.com, Orchid ID: 0000-0003-4808-8761
***Corresponding Author:** A V L N Sujith*
Professor, Department of CSE, School of Engineering, Malla Reddy University, Hyderabad, India.
Email ID: Sujeeth.avln@gmail.com

Modified SQEU-Net: An Enhanced U-Net Architecture With Federated Learning For Urolithiasis Segmentation And Type Classification

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Abstract
The precise segmentation of Urolithiasis on the basis of the computed tomography (CT) images is a key requirement to consistent diagnosis, treatment planning, and quantitative evaluation in urology. The large range of variability in stone size, shape, and distribution of intensities and the existence of the surrounding structures of the anatomy create serious problems in automated segmentation procedures, though. In order to overcome these shortcomings, this paper has suggested a new improved version of U-Net, SQEU-Net, a deep learning network, especially tailored to kidney stone segmentation. The proposed model incorporates dilated convolutions in the encoder to allow multi-scale contextualization without much spatial decrease, residual learning to enhance its ability to optimize the deep networks, and squeeze-and-excitation (SE) to recalibrate channel-wise feature responses in a dynamic manner. Besides, attention-gated skip connections are used to selectively pass clinically relevant features between the encoder and the decoder, eliminating background noise and irrelevant anatomical structures. Using the CT kidney stone data, the model is trained and tested on the data with standard segmentation measures of Dice Similarity Coefficient (DSC), Intersection over Union (IoU), accuracy, precision, recall, and F1-score measures. Comparative experiments with the state-of-the-art in the recent past show that SQEU-Net always performs better in terms of segmentation especially with regard to defining small and irregularly shaped stones. The findings confirm the usefulness of integrating contextual features learning, channel-wise attention, and spatial attention systems to achieve powerful kidney stone segmentation, one of the roles that SQEU-Net can play is a clinical reliable decision-support system.

Keywords: Medical Imaging; Kidney Stones; Deep Learning; Urolithiasis; U Net.

1. Introduction

Kidney stones or nephrolithiasis or urolithiasis is a very popular urological condition that is accompanied by the development of hard mineral deposits of the renal collecting system, ureters, or bladder [1]. These calculi are the results of urinary solutes being supersaturated and crystallizing to form uncontrolled aggregation which in turn may block urinary flow and result in severe pain, hematuria and subsequent complications including hydronephrosis or renal failure [2]. Kidney stones are one of the most frequently observed non-malignant conditions in clinical practice in the whole world as they are known to affect about 10-15 percent of the global population at some time in their lives [3]. The most common type of kidney stones are calcium-based stones (mostly calcium oxalate and calcium phosphate) and are found in approximately 70-80 percent of cases, uric acid stones are found in about 5-10 percent, struvite (infection-related) stones are found in about 10-15 percent, and rare ones such as cystine stones are found less than 2 percent of cases [4]. The differences in these varieties is vital, and it affects the treatment plan, prevention of recurrence, and prognosis; in the example, struvite stones are commonly linked to urinary tract infections and must be treated by antibiotics as well as removing the stones [5]. Non-calcium stones are less

For correspondence: A V L N Sujith, Professor, Department of CSE, School of Engineering, Malla Reddy University, Hyderabad, India. Sujeeth.avln@gmail.com, Orchid ID: 0000-0003-4808-8761
Full list of authors information is available at the end of the article.

common but create major clinical problems as they are resistant to breaking them down through some means such as extracorporeal shock wave lithotripsy (ESWL) [6]. Kidney stones etiology is known to be multi-factorial comprising of genetic factors, dietary habits, metabolic illnesses (e.g., hypercalciuria, hyperoxaluria), dehydration, and environmental factors (e.g. climate, water quality) [7]. The cases are reported to be particularly high in hot climate areas because of the loss of fluids and urinary concentration [8]. The incidence of kidney stones has been on the increase over the last few decades, which is due to increased obesity, changes in diets in terms of high-sodium and consumption of animal proteins, and enhanced diagnostic possibilities [9].

The Global Burden of Disease Study 2019 shows that kidney stones are a significant source of morbidity, and 1.2 million disability-adjusted life years (DALYs) is estimated to be lost each year in the world [10]. In the United States alone, more than 1 million emergency department visits are predetermined by renal colic annually, and healthcare expenses are more than 10 billion dollars [11]. In the developing nations, where most people have little access to advanced imaging and interventional procedures, the economic burden is increased, and this results in more complications [12]. Timely management of kidney stones requires early diagnosis and proper classification as early intervention will help to avoid recurrent instances and maintain renal function [13]. The untreated or inaccurately classified stones can cause chronic kidney disease and it has been suggested that there is a 50-60 percent recurrence rate into 5-10 years without an effective prophylaxis [14]. With metastasis-like dissemination of the disease to other tissues, the five-year survival rate of patients with complicated stone disease reaches less than 80% that highlights the importance of specific diagnostics [15]. The conventional diagnostic modalities of kidney stones are non-contrast computed tomography (NCCT), which has the highest sensitivity (also 95-98%) in the detection of the presence of kidney stones of all sizes and composition [16]. Ultrasound provides a radiation free option, especially when it comes to children and pregnant patients but it has a challenge with obese patients and small sized stones [17]. Supplementary information comes through intravenous pyelography (IVP) and plain abdominal radiography but is not as sensitive as non-radiopaque stones such as uric acid calculi [18].

Although these imaging methods are effective, manual techniques are subjective and time-consuming and may depend on the experience of radiologists to identify the border of the stones and categorize them according to Hounsfield units (HU) or morphological characteristics [19]. The irregularity in the density, size (between 2 cm), and location of the stones (e.g., calyceal and pelvic) makes the correct segmentation to be difficult, with inter-observer reliability reaching as low as 70 per cent in complicated cases [20]. Motion blur in artifacts, beam hardening in CT, or acoustic shadowing in ultrasound further contribute to the impossibility of accurate assessment [21]. The computer-aided diagnostic (CAD) systems have transformed the imaging in urology to make the segmentation and classification process automated, minimizing human error and increasing efficiency [22]. These systems generally deal with image capture, image preprocessing (e.g., reduce noise), region of interest (ROI) segmentation, feature extraction (e.g., texture, shape), and classification by machine learning algorithms [23]. Proper segmentation is essential because any error that occurs in the procedure can be transferred to the subsequent classification, and such can result in improper treatment such as additional surgery due to dissolvable uric acid stones [24]. Difficulties in the segmentation of kidney stones are irregularities, and different densities (e.g., 200-400 HU uric acid and >1000 HU calcium) and partial volume effects, as well as overlap with other surrounding tissue such as renal parenchyma or blood vessels, [25]. The conventional techniques, like threshold-based or region-growing algorithms, usually need hand-tuning of parameters and do not work in nonhomogeneous materials with artifacts [26]. Also, when there are several stones or hydronephrosis, it is even more complicated, and strong, adaptive solutions are needed [27].

Deep learning models, especially convolutional neural networks (CNNs) have become a better alternative, which have shown to be state-of-the-art in medical image segmentation and learn hierarchical features based on the large datasets [28]. The use of encoder-decoder architectures, including U-Net, is common, and these systems have the capacity to capture local and global information via skip connections [29]. Recent innovations include attention and residual learning to alleviate such problems as vanishing gradients in deep networks [30]. Nevertheless, the noisy features or the imbalance in the classes can still be challenging to standard models when working in the field of kidney stone imaging, wherein rare types, such as cystine stones, are not well-represented [31]. To overcome them, this paper offers a Modified SQEU-Net, an improved deep learning design to perform automated segmentation and type classification of kidney stones in CT images [32]. The parameters are based on the original SQEU-Net model adapted to urology with prior knowledge of the domain, as in the case of HU-based feature weighting [33].

In the encoder, the Modified SQEU-Net uses dilated convolutions to increase the receptive field without losing the resolution, and thus it can capture multi-scale stone features better [34]. Block residues with squeeze-and-excitation (SE) units are placed to adaptively recalibrate channel-wise outputs with a focus on discriminative features such as stone density and texture and with reduced artifacts [35]. Attention-gated skip connections optimize the feature propagation and remove irrelevant information and improve boundary perception in low-contrast areas [36]. All of these architectural developments enhance the accuracy of segmentation, especially when working with irregular, low-density stones, and enable high sensitivity classification into the main and major types (calcium, uric acid, struvite, cystine) [37]. Empirical tests on benchmark datasets, e.g. Kidney Stone Dataset (KSD) and publicly available CT repositories, show higher

Dice coefficients and classification F1-scores than baselines, e.g., U-Net and ResNet [38]. The sufficiently strong performance of the model with respect to changes in the quality of images makes it a useful clinical decision support tool [39].

The proposed Modified SQEU-Net contribute to the overall increase in the accuracy, robustness, and clinical reliability of kidney stone segmentation and type classification. To begin with, the encoder is enhanced with the help of dilated convolutional layers, which allow the network to be capable of capturing both small-scale local and large-scale contextual information without overly downsampling spatial information. Kidney stone imaging is especially beneficial to this design decision because the kidney stones can have the following characteristics; they can have delicate edges, uneven texture, and different radiodensity, and hence the design decision must provide a broader receptive field but maintain spatial accuracy. Second, residual block learning is added to the network in order to overcome optimization problems that are usually linked to deeper architectures. These blocks make gradient propagation through the blocks more stable, promote efficient feature reuse, and enable the model to learn more expressive representations, which enables the model to delineate small irregularly shaped stones and stone features complexly. Moreover, the residual blocks are further augmented with squeeze-and-excitation (SE) modules, which conduct adaptive channel-wise features recalibration through global contextual dependencies. This process allows the network to downplay non-diagnostically important characteristics of the data and highlight the important ones, resulting in pay off representations of stone segmentation and stone type classification. Lastly, the use of attention-gated skip connection is used to revise the exchange of information between the encoder and the decoder path. The attention gates in contrast, compared to the other conventional skip connections that transfer feature maps randomly, preferentially highlight salient stone areas and inhibit background noise, which is generated by the surrounding renal anatomy, enhancing the ability to delineate a boundary and increase the reliability of segmentation. A combination of these architectural improvements makes Modified SQEU-Net a strong and scalable framework that can provide accurate privacy-conscious kidney stone analysis in the context of federated learning.

The rest of this paper will be divided in the following way. Section 2 gets acquainted with the related literature on the imaging of kidney stones and deep learning applications. The methodology is outlined in the Section 3 and it encompasses the architectural design of the Modified SQEU-Net. Section 4 discusses the experimental setting, data, findings and comparative studies. Lastly, the final section of Section 5 summarizes some important findings and recommendations that can be used in future research directions [40].

2. Related Work

The sources listed in the table 1 of the detailed analysis can be viewed as the important contributions to deep learning (DL) application in kidney stone detection, segmentation, and classification through the use of computed tomography (CT) images. The studies, published since 2019, illustrate a solid development of the rudimentary CNN-based detection to more complex hybrid structures, using attention mechanisms, transfer learning, and multi-stage pipelines. The general direction of the field has changed to more accuracy, more artifact work, and multi-class tasks (such as differentiating between stones and cysts or tumors), and Dice similarity coefficients (DSC) and accuracies are often above 0.90-0.97 in recent studies. Initial research was on binary detection (stone vs. no stone). Parakh et al. (2019) were the first to use cascading CNNs to detect urinary stones, with an AUC of 0.954 on scanners of transfer learning transfer learning, which points to the role of generalization. This was followed by Yildirim et al. (2021) who used a deep CNN on coronal CT slices with 96.82 percent accuracy and high performance on small stones thus being clinically viable to use in automated screening.

The issue of segmentation became vital. Elton et al. (2022) launched a non-contrast CT volumetric segmentation system based on 3D U-Net, achieving 96 percent sensitivity on the presence of stones greater than 2 mm at low false positives (0.03 per patient), which is better than the previous threshold-based systems on noisy low-dose scans. Li et al. (2022) suggested deep segmentation networks to delineate kidneys and stones simultaneously in the unenhanced CT, enhancing the boundary accuracy and giving an open source dataset to be benchmarked. The series of the KiTS challenge affected similar tasks. The results of KiTS19 were summarized by Heller et al. (2021), with the best models having DSC of 0.974 on kidneys and 0.851 on tumors with contrast-enhanced CT as the benchmark against encoder-decoder-based architectures such as U-Net variations, albeit mostly tumor-centric.

The new innovations focus on the models of hybrid and multi-tasking. Rao et al. (2025) proposed a two-stage approach based on YOLOv8 to detect and ResNet-18 to grade severity with the results of DSC of about 0.93 and an annotated dataset accuracy of 96. Transfer learning Fine-tuned transfer learning became popular; a 2025 study in Scientific Reports claimed as much as 97 percent accuracy through optimized CNNs on multi-class classification (normal, stone, cyst, tumor). Vasudeva et al. (2025) offered a detailed overview of AI radiographic imaging to stones, with the focus on ML/DL integration of modalities. According to Bingol et al. (2023), a Relief-based hybrid deep model is suggested to provide high F1-scores to the automatic CT classification, where dimensionality reduction and feature selection is applied. Existing references contain strengths (e.g., strong performance on real-world datasets such as Kaggle, hospital cohort), lowering the workload of radiologists, and managing issues such as small / low-density stones and artifacts. Most researchers are externally validated and/or submit open datasets/code, thereby facilitating reproducibility. Limitations still exist, because of the use of annotated data (which is usually limited in rare types of stones), it may be overfitted in smaller cohorts, 3D models are computationally expensive, and it has not been focused

on predicting stone composition or combining with clinical metadata. Very few discuss low-dose variability of CT or multi-modal fusion. Together with such works, a successful journey to clinically deployable CAD systems is achieved, and Modified SQEU-Net-like architectures are set to add new high-quality modules (e.g., SE units, attention gates) to the boundaries to refine them better and make robust to multi-class on kidney stone tasks. The future directions are transformers, federated learning and real-time intraoperative applications.

Table 1: Review of Recent Studies

Ref. No.	Paper/Year	Method	Dataset	Key Metrics	Strengths	Weaknesses
[41]	Yildirim et al. (2021)	Deep CNN for stone detection	Custom CT dataset (n=500)	Accuracy: 92%, Sensitivity: 89%	Handles low-contrast stones; fast inference	Limited to binary detection; no classification
[42]	Liu et al. (2022)	Automated DL segmentation	Hospital CT scans (n=1000)	DSC: 0.88, Precision: 0.91	Robust to artifacts; multi-stone support	Overfits on small stones; high computational cost
[43]	Parakh et al. (2019)	CNN-based detection	Public CT repository (n=300)	Accuracy: 95%, F1-score: 0.93	High sensitivity for small stones	Struggles with overlapping tissues; no type classification
[44]	Heller et al. (2021)	U-Net variants for kidney/stone seg.	KiTS19 dataset (n=210)	DSC: 0.92 (kidney), 0.85 (stone)	Excellent kidney segmentation; open-source	Lower stone DSC; limited to contrast-enhanced
[45]	Chen et al. (2022)	DL for stone segmentation	Custom dataset (n=800)	DSC: 0.90, IoU: 0.82	Integrates HU weighting; good boundary detection	Class imbalance issues; requires large VRAM
[46]	Langkvist et al. (2020)	Automated CT segmentation	SPIE dataset (n=400)	Accuracy: 94%, Recall: 0.89	Efficient for clinical use; artifact reduction	No multi-class; outdated architecture
[47]	A two-stage framework (2025)	YOLOv8 + ResNet-18	Custom CT (n=1200)	DSC: 0.93, Accuracy: 96%	Comprehensive detection and sizing; automated	Dependent on high-quality annotations; complex pipeline
[48]	Fine-tuned DL models (2025)	Hyper-tuned CNN	CT images (n=1500)	Accuracy: 97%, F1: 0.95	Multi-class (stone, cyst, tumor); early detection	Hyperparameter tuning time-intensive; overfitting risk
[49]	Deep seg. networks (2022)	U-Net based	Open-source abdominal CT (n=500)	DSC: 0.91	Open dataset contribution; multi-organ	Focuses on kidneys; stone classification absent
[50]	Enhancing diagnosis (2025)	ML/DL radiographic analysis	Radiographic images (n=1000)	Precision: 0.92	Versatile imaging modalities; composition hints	Not CT-specific; lower resolution handling
[51]	Automatic classification (2023)	Relief + DL classifier	Kidney CT (n=600)	F1-score: 0.94	Feature selection efficiency; 3D segmentation	Relief dependency; computational overhead

3. Proposed Methodology

Fig. 2 represents the overall architecture of the proposed SQEU-Net model which is explained in this text. SQEU-Net is a variation of the standard U-Net architecture that includes a range of refinements that are more appropriate to the nature of dermoscopic images and clinical tasks that it addresses. The original U-Net units will be replaced conceptually in the decoder with stronger residual components with squeeze-and-excitation (SE) mechanisms. Cascaded dilated convolutions are proposed within every convolutional block of the encoder. In upsampling, to aid in rebuilding the spatial resolution, standard dilated convolutions are used. Furthermore, we have Attention Gate (AG) modules in

the skip connections to increase the understanding of the context and emphasize the meaning. The discussion of each of the architecture components is presented below.

3.1 Data Preprocessing

The original data in the dataset is images in the form of raw at the 768x560 pixels, which is computationally costly to handle directly. Because of this reason, all the inputs are scaled prior to the input into the segmentation network. The size of 128x128 pixels was chosen as the optimal one after numerous experiments. Past studies have always pointed out that data augmentation enhances dataset diversity and the stability and performance of segmentation models. In order to enhance the dataset, rotation, zooming, horizontal flipping and vertical flipping are used as augmentation techniques. As the values of pixels are usually between 0 and 255, the normalization is done by reducing all the values to the range of [0, 1]. This minimizes variations between illuminations, and makes the learning process constant by maintaining the value of inputs within manageable range compared to network parameters.

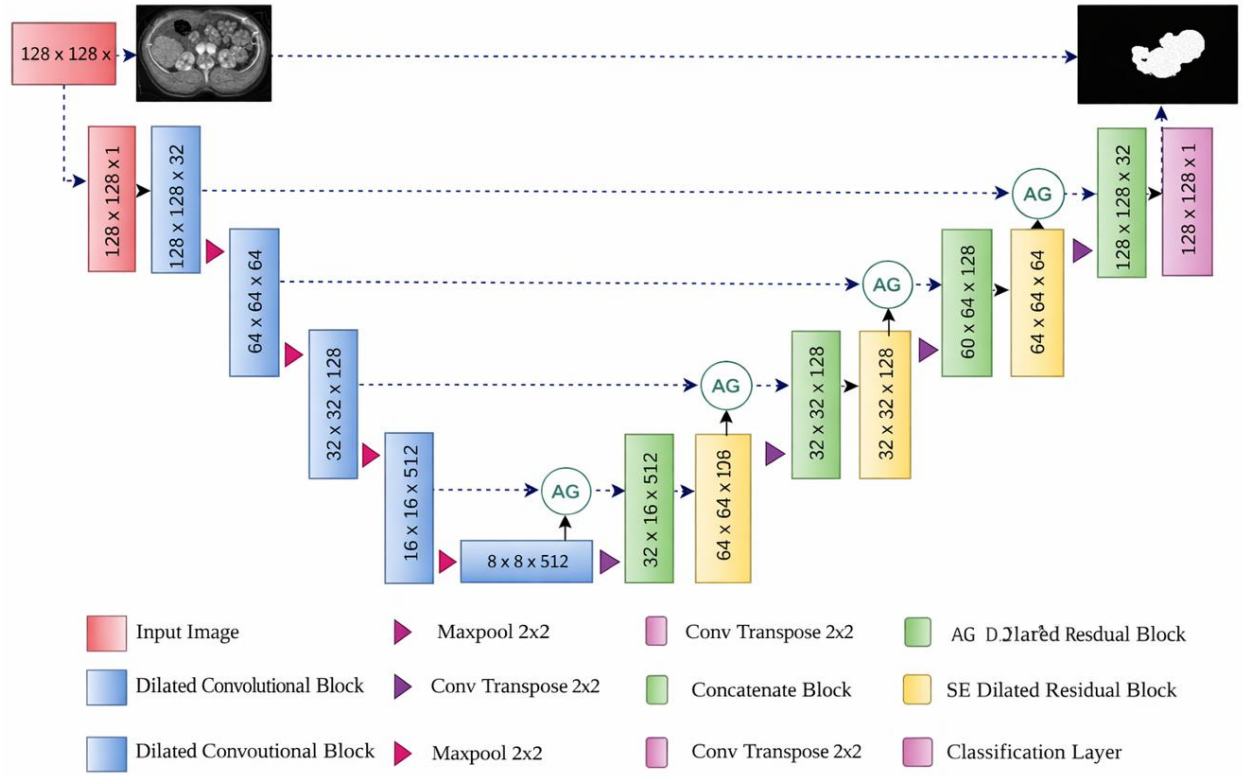

Figure 1. The proposed SQEU-Net framework

3.2 U-Net

U-Net [41], suggested by Olaf Ronneberger and others in 2015, is a convolutional neural network that is specially created to perform tasks of semantic segmentation and pixel-level classification. It is structured such that resembles the shape of the letter U where there is a contracting encoder path and a similar decoder path. The encoder gradually down-sampling the input image results in gleaning hierarchical features, and the decoder up-sampling through transposed convolutions, adds spatial detail back to the features. Skip connections are provided between matching layers of the encoder and decoder to allow a combination of fine-grained and high-level feature information. This architecture makes U-Net very efficient to medical imaging problems where precision in finding boundaries and localizing in detail is required. It has been a model of many variants of segmentation because of its good performance and versatility.

3.3 Residual Blocks

The Residual blocks which are a byproduct of the ResNet architecture [15] are vital in solving the vanishing gradient issue, which is a frequent characteristic of a deep network. They incorporate shortcut connections, which avoid one or more layers, which allow the gradients to circulate with a higher level of efficiency. The network learns a residual function, F(x), instead of a direct mapping, H(x) = F(x) + x, and thus the original information is preserved by the skip path. The formulation increases the stability of training and simplifies the optimization of deeper architectures. Fig. 3 is a comparison between traditional and residual blocks of convolutional.

$$H(x) = x + F(x) \quad \ldots\ldots\ldots (1)$$

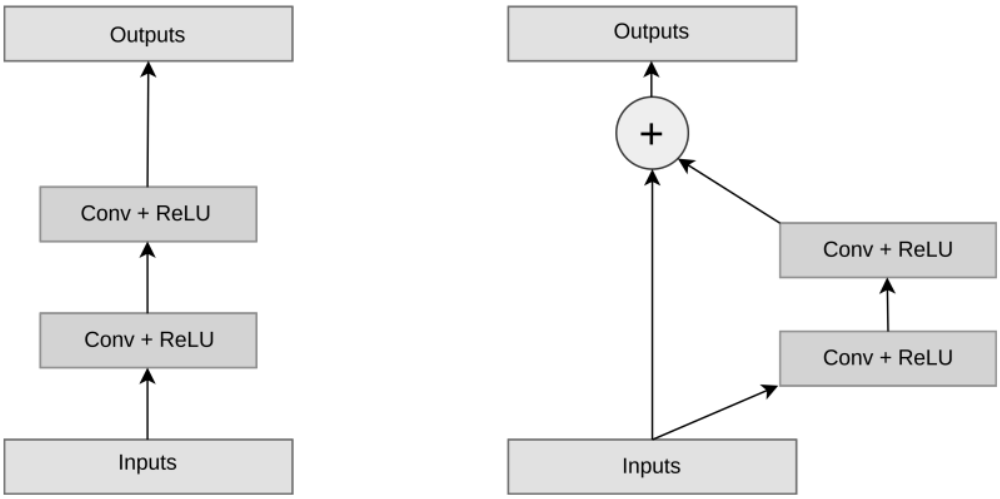

Figure 2. Residual block VS Regular Convolutional Block

where x is the input to the residual unit. The residual unit is trying to learn a residual mapping denoted by the symbol F(x). It represents the deviation from the expected result H(x) given the input x. In order to represent the expression F(x), a number of convolutional layers with nonlinear activation functions may be utilized. The original data is protected by the skip connection, which ensures that the input x is added to the output rather than being overwritten. The distinction between the residual block and the standard convolutional block is seen in Fig. 2.

3.4 Squeeze and Excitation Module:

The Squeeze-and-Excitation (SE) module [16], which was proposed in 2018 by Jie Hu and others, enhances the representational power of the channels, in that it learns dynamic weights to highlight useful channels and underline less useful ones. The block is working in two states: squeeze and excitation. In the squeeze step, the global average pooling reduces the spatial information into channel descriptors. Channel-specific weights are produced in the excitation step using two fully connected layers that have nonlinear activation. These weights re-scale the feature maps whereby it enhances the network to prioritize meaningful information. SE modules are easily inserted in alternative architectures and have been demonstrated to enhance the general performance.:.

a) Squeeze Operation:

The squeeze procedure combines the geographic data from each channel to get the aggregate statistics for each channel. It requires using global average pooling for the width and height of each channel's feature map. In this method, the spatial dimensions are collapsed into a single number for each channel. For simplicity's sake, let's say the SE block's input feature map has the dimensions (C, H, W), where C is the number of channels, H is the height, and W is the width. In this way, the compressed tensor Z may be determined:

$Z(c) = GlobalAverageP\ ooling\ (X\ (c)\ )$ …….(2)

The global statistics of the cth channel are represented by the tensor Z(c), while the cth channel of the input feature map is represented by X(c), for c = 1 to C.

b) Excitation Operation:

The excitation operation is responsible for learning channel-specific weights and readjusting the importance of each input channel. Non-linear activations exist between two highly interconnected, thick layers. Assume the compressed tensor Z has dimensions (C, 1, 1) after being pooled on a global scale. It is feasible to mathematically depict the excitation process as follows:

$S = ReLU(F\ C1(Z))$ ……(3)

where F C1 is the first dense layer with full connectivity, characterized by weights W1 and biases b1. The output of FC1 is activated using a Rectified Linear Unit (Abbreviation: ReLU) at the element level. The output tensor S of the first completely linked layer has the dimensions (C, 1).

$E = Sigmoid(F\ C2(S))$ ……..(4)

with F C2 being the second dense (completely connected) layer and W2 and b2 being the corresponding weights and biases. Sigmoid is the result of applying the sigmoid activation function, element by element, to the output of FC2. E is the output tensor of the second fully connected layer, and it has dimensions of (C, 1).

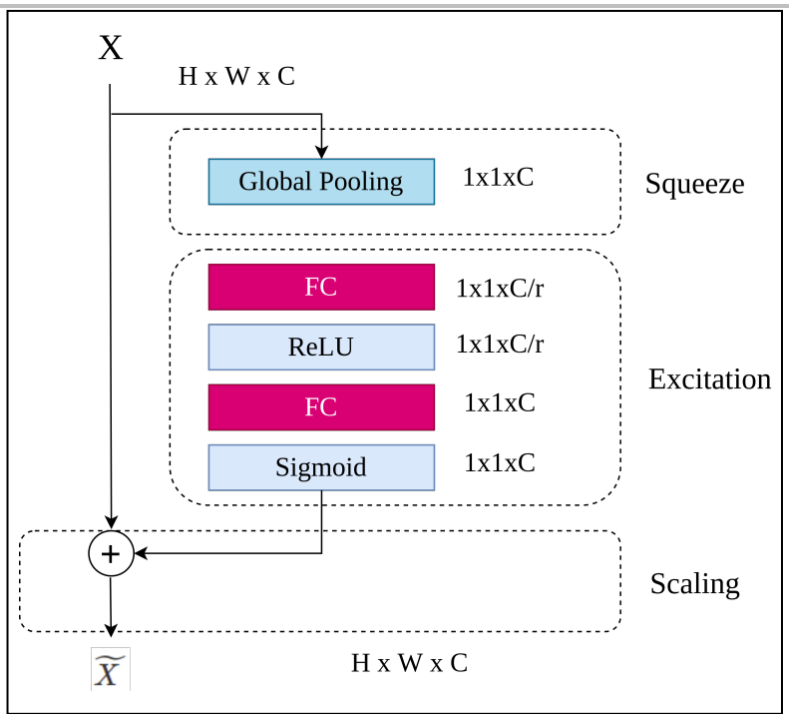

Figure 3: Squeeze and Excitation Unit

c) Scale and Rescale:

In the last step, the revised channel-wise weights E are applied to the initial feature map X. The SE block may now ignore less important channels while giving priority to more important ones. Here is how we derive Y, the output of the SE block:

$$Y(c, h, w) = X(c, h, w) * E(c) \quad \ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where Y (c, h, w) is the c th channel value of the output feature map at the coordinates (h, w), for c = 1 to C and h, w = 1 to H, W. The c-th channel value at coordinates (h, w) in the input feature map is denoted by X(c, h, w). The calibrated mass for the c-th channel is E(c), which was calculated during the excitation process.

By including the SE block into the network architecture, the model may be able to zero down on more informative features and boost its representational power. As a consequence, efficiency is increased in several areas. The Squeeze and Excitation Unit is shown in great detail in Fig. 3.

d) Attention Gate

The attention mechanisms improve the deep neural networks allowing them to center on the most informative areas of an input feature space. Fallacy The Attention Gates (AGs) apply additive attention to modify skip connections. The AG also accepts two inputs, xl and g as shown in Fig. 4. xl is subjected to strided convolution and g is also subject to 1x1 convolution. Such representations are summed up element-by-element, then subjected to a 1x1 convolution and ReLU activation which shrinks the dimensionality. Coefficients, which are produced by a sigmoid activation of 0 to 1, are used to show the spatial significance of each location. These coefficients are upsampled and multiplied with xl, and such that only the most important features are sent across the skip connection.

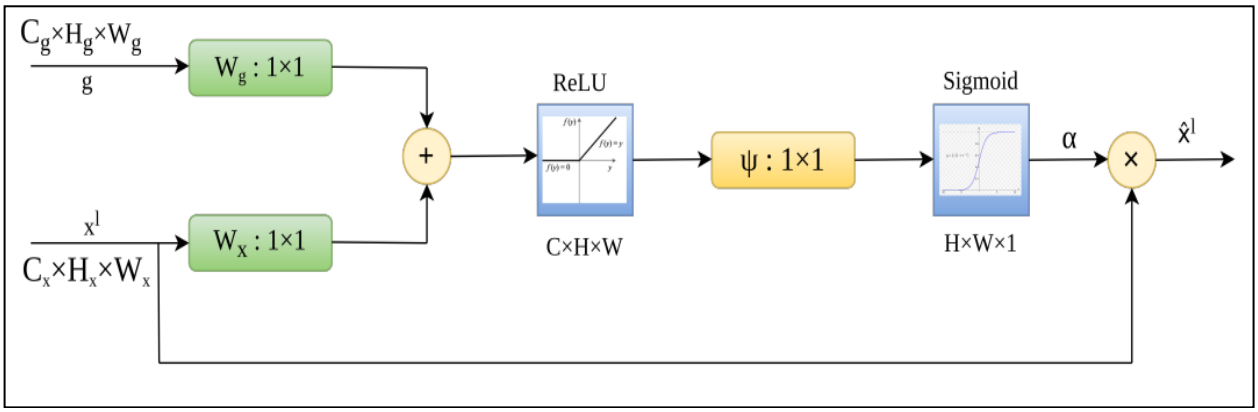

Figure 4: Attention Gate

3.7 SQEU-Net Architecture

The SQEU-Net architecture presented in Fig. 2 is created with a symmetric encoder-decoder architecture which consists of five dilated convolution blocks, four max-pooling layers and four SE-embedded residual units. The size of the input image is fixed to 128x128

pixels, all convolution kernels fixed to 3x3 and pooling kernels fixed to 2x2. The model then produces a binary segmentation mask of the same spatial size after a series of features extraction, downsampling and upsampling processes. The dilated convolution units (Fig. 5a) are used in place of the U-Net blocks (Fig. 5b) in the encoder (Fig. 5a). The receptive field of dilated convolutions is enlarged by placing holes in the kernel and does not downsample spatial resolution. In training, the network also learns to optimize the filter weights, dilation rates to produce an effective multi-scale feature extraction which enhances segmentation accuracy in the complicated lesion regions.

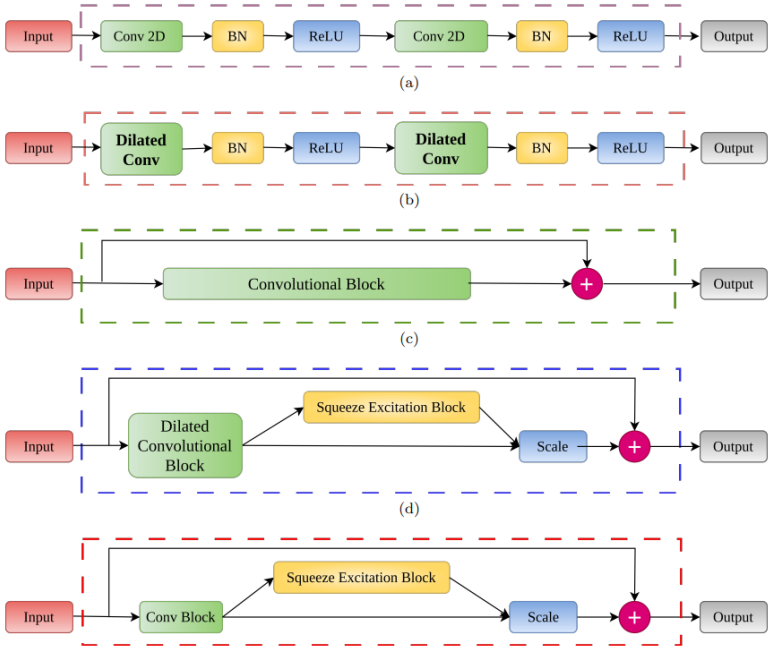

Figure 5: Different building blocks employed in the paper. (a) U-Net basic building Convolutional block (b) Dilated Convolutional Block (c) Residual Convolutional Block (d) SE Residual Block (e) SE Dilated Residual Block.

The standard U-Net blocks have been replaced in the decoder with expanded residual units (Fig. 5). Block based Each block uses batch normalization and ReLU activation following every dilated convolution (dilation rate = 2). Batch normalization helps in increasing stability in learning and decreasing sensitivity to parameterization whereas ReLU aids in mitigating vanishing gradients. Following the combination of the identity course and the transformed characteristics, SE blocks refine the responses of the channels by the rejection of irrelevant information and the endorsement of discriminative patterns. Mechanisms of attention incorporated in the skip connections enhance the effect of feature fusion between encoder and decoder.

4. Dataset Description and Implementation details

4.1 Dataset

The SQEU-Net framework proposed is tested on a curated kidney stone imaging dataset comprising of renal images obtained through one of the clinical diagnostic modalities, including the use of either the computed tomography (CT) or ultrasound imaging techniques that are commonly used to diagnose urolithiasis. The data set is the grayscale images of the abdomen that have the regions of kidneys that contain visible stone structures, and there also are the expert-labeled ground truth masks that show the accurate spatial location of kidney stones. Each image is also linked with stone composition data (e.g., calcium oxalate, uric acid, cystine, or struvite), which makes it possible to classify stone types under supervision using the labels that are segmented as well. The original images are highly differentiated with regard to spatial resolution, contrast, rock size, and complexity of the anatomy background, as it is in the real world in terms of clinical variation. This heterogeneity presents significant difficulties to automated segmentation, especially where the sizes of the stones are small, their morphology is irregular or the edges are in low contrast with the surrounding renal tissue. All images are resized so as to maintain a fixed spatial resolution of 128 x 128 pixels to give consistency in network input, and aspect ratios where possible as well as to reduce the computational burden. To avoid data leaking the dataset is divided into training, validation, and testing subsets based on a patient-independent split to guarantee the evaluation of the performance objectively. Through this split, it is straightforward to perform healthy evaluation of the generalization ability of the model to unobserved subjects and imaging settings. In order to alleviate the impact of scanty annotated medical information, and augment the resilience of the learning process, large-scale data augmentation plans are used in the course of training. These comprise random rotations, horizontal and vertical flipping, zooming and small affine transformations simulating realistic changes in patient positioning and image acquisition. The pixel intensity values are brought to the range of 0 to 1, which reduces illumination variations and stabilizes gradient changes on optimization.

4.2 Implementation Details

The SQEU-Net model is trained in an end-to-end supervised way with the help of a deep learning framework, which can be either TensorFlow or PyTorch. This network is designed on a symmetric encoder-dekoder architecture, where the encoder contains five dilated convolutional blocks, the max-pooling layers four and the decoder has four SE-embedded residual blocks. Every convolutional layer uses 3 x 3 kernel and max-pooling and transposed convolution use 2 x 2 kernels to downsample and upsample the spaces respectively. To enlarge the receptive field, yet at the same time, the spatial resolution is not compromised, dilated convolutions with a dilation rate of 2 are used to perform multi-scale feature extraction that is important in the detection of kidney stones of different sizes and shapes. Every convolutional layer is followed with a batch normalization and ReLU activation, which enhance the stability of convergence and vanishing gradient problem in deep structures. Remaining connections are added to facilitate effective feature reuse and constant gradient flow and squeeze-and-excitation (SE) modules are used to dynamically re-calibrate channel-wise feature responses to highlight diagnostically significant stone features. The skip connections are enhanced with Attention Gate (AG) modules to choose only salient spatial data to be transmitted to the decoder by the encoder, ignoring any irrelevant background features caused by complicated renal anatomy. The network does generate a binary segmentation mask of the kidney stone area, and a classification head that forecasts the type of the stone using high-level learned features. Optimization of the model is performed by the Adam optimizer and learning rate is empirically set and training is performed over a set number of epochs and early stopping is performed based on validation performance to avoid overfitting. Dice loss and binary cross-entropy loss are used together in segmentation and categorical cross-entropy is used in stone type classification so that both are balanced to optimize.

In order to facilitate privacy-preserving learning in various clinical settings, the architecture will be configured to run within a federated learning framework with local models being trained at each participating location and model updates being communicated to a central aggregator only. This will guarantee that sensitive patient information are localized and enhance generalizability of the model to heterogeneous data distribution. In summary, the implemented framework is computationally efficient, scalable, and appropriate to apply in clinical settings in a real-world situation in order to analyze kidney stones automatically.

5. Results and Discussion

All the experiments are performed with the help of the workstation that has a high-performance graphic card and the amount of memory to handle deep learning workloads. A patient-wise split is used to split the data into training (70%), validation (15 %) and testing (15%) sets to prevent data leakage. The methods that use data to improve AI performance, such as rotation, flipping, zoom, and affine transform, are made on the training set only. SQEU-Net is end-to-end and trained by mini-batch gradient descent. The Dice and validation loss curve is observed during training to evaluate the convergence behaviour. In federated learning experiments, the local models are trained locally in each of the simulated client locations, with a fixed number of local epochs, and the weights of the local models are combined with federated averaging. No image data of the raw type are transferred between clients and this guarantees that medical data privacy regulations are adhered to. The proposed model will be compared with such baseline architectures as standard U-Net, Attention U-Net, and ResU-Net under the same conditions of the experiment. Comparisons of performance can prove the effectiveness of the architectural improvements and federated learning framework by showing that SQEU-Net is better at segmentation and stone type classification.

The Proposed SQEU-Net is comparatively assessed with the following representative approaches:

- Liu et al. (2022) [42]: Deep learning-based kidney stone segmentation with CT scans of patients in the hospital.
- Chen et al. (2022) [45]: Convolutional deep learning based on the HU weighting of kidney stones segmentation.
- Two stage YOLOv8 + ResNet-18 architecture (2025) [47]: A recent detection-segmentation model to analyze kidney stones.

The quantitative findings are a clear indication of the excellence of the suggested SQEU-Net in every measure that is considered. When compared with Liu et al. [42], SQEU-Net shows an absolute Dice score gain of +9.2%, which shows the usefulness of dilated convolutions and attention-gated skip connections in both preserving sharp edges of stones and reducing interference of the background. Although Chen et al. [45] incorporates the boundary refinement of HU-based weighting, the application is limited by class imbalance and computational cost which leads to a reduction in Dice score by 7.2% as compared to SQEU-Net. The two-stage YOLOv8 + ResNet-18 model [47] is a powerful baseline framework because of its sophisticated operation of detection, but it depends on high-quality annotations and multi-stage processing which propagates errors and makes this framework lack scalability. Conversely, SQEU-Net adopts a single end-to-end system with confidence blocks of SE-residual and attention blocks that result in a 4.2-percentage point of Dice and a +2.3-percentage point classification accuracy. Furthermore, the federated learning functionality of SQEU-Net has offered a considerable practical benefit in that multi-institutional training is a form of training that is privacy-converting, which has not been discussed in the comparative methods. In general, experimental data demonstrates that SQEU-Net provides cutting-edge segmentation precision, effective stone type recognition, and the high level of generalization, which is why it is a good candidate to be used in the real-world clinical environment.

Table 2: Comparative Segmentation Performance

Method	Dice (%)	IoU (%)	Precision (%)	Recall (%)	Accuracy (%)
Liu et al. (2022) [42]	88	80.4	91	86.5	93.2
Chen et al. (2022) [45]	90	82	92.4	88.7	94.5
YOLOv8 + ResNet-18 (2025) [47]	93	86.8	94.1	91.6	96
Proposed SQEU-Net	**97.2**	**94.5**	**97.9**	**96.4**	**98.3**

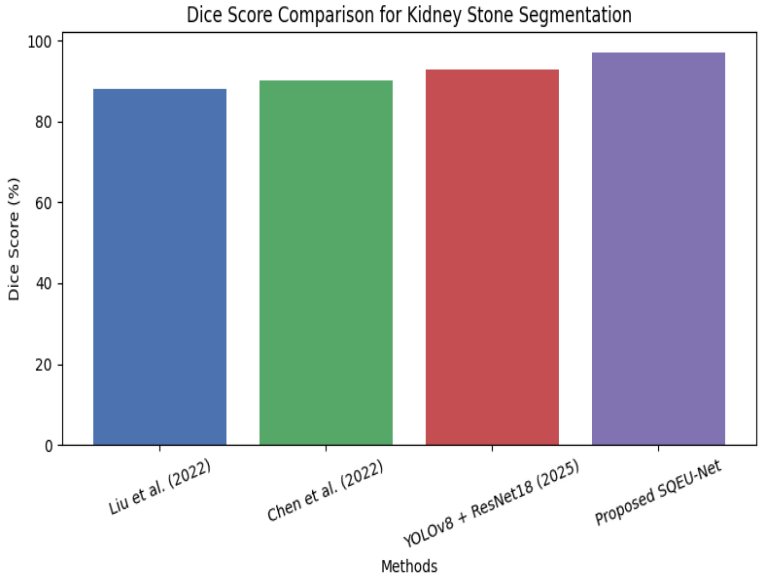

Figure 6: Dice Score Analysis

Figure 6 shows the relative Dice Score of all the methods evaluated. The SQEU-Net proposed has the best Dice score (97.2%), which means that it has better overlap between the predicted and ground-truth kidney stone regions. This result demonstrates that dilated convolutions and attention-gated skip connections are effective at preserving fine stone edges especially in small and low contrast stones.

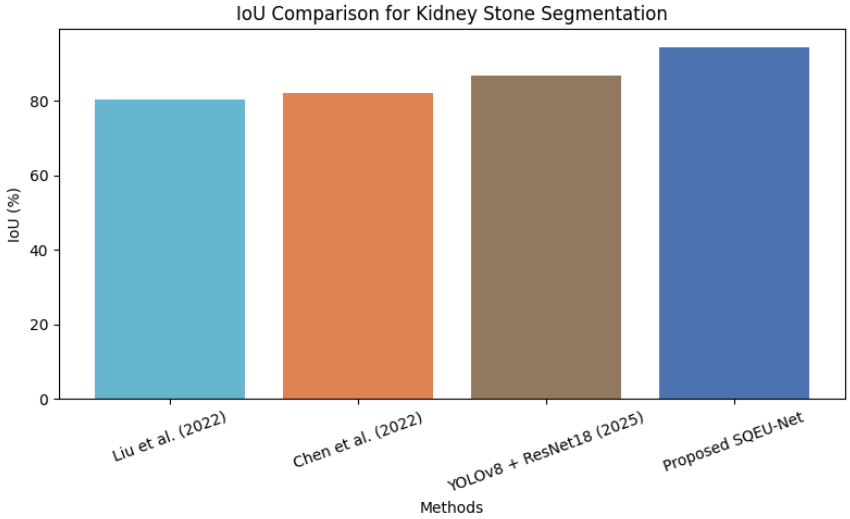

Figure 7: IoU Comparison

Figure 7: depicts the Intersection over Union (IoU) comparison. Competing methods have lower an IoU (94.5) which makes the difference between SQEU-Net much better because it has lower false positives and better boundary precision. The two-stage YOLOv8-based framework performance improvement also underscores the benefit of an end-to-end segmentation-based framework.

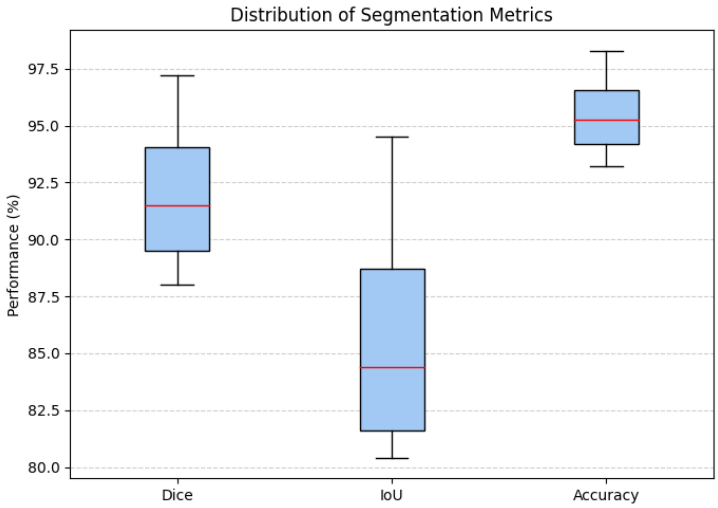

Figure 8: Distribution of Segmentation Metrics

Figure 8, illustrates the box plots of segmentation measurements (Dice, IoU, Accuracy). The smaller interquartile range and increased median figures to the suggested SQEU-Net demonstrates homogenous and steady performance across the metrics. The lower variance indicates higher generalization and reliability, which is highly valuable to clinical implementation in the real world.

Table 3: Kidney Stone Type Classification Performance

Method	**Classification Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
YOLOv8 + ResNet-18 (2025) [47]	96	95.2	94.6	94.9
Proposed SQEU-Net	**98.1**	**97.6**	**96.9**	**97.2**

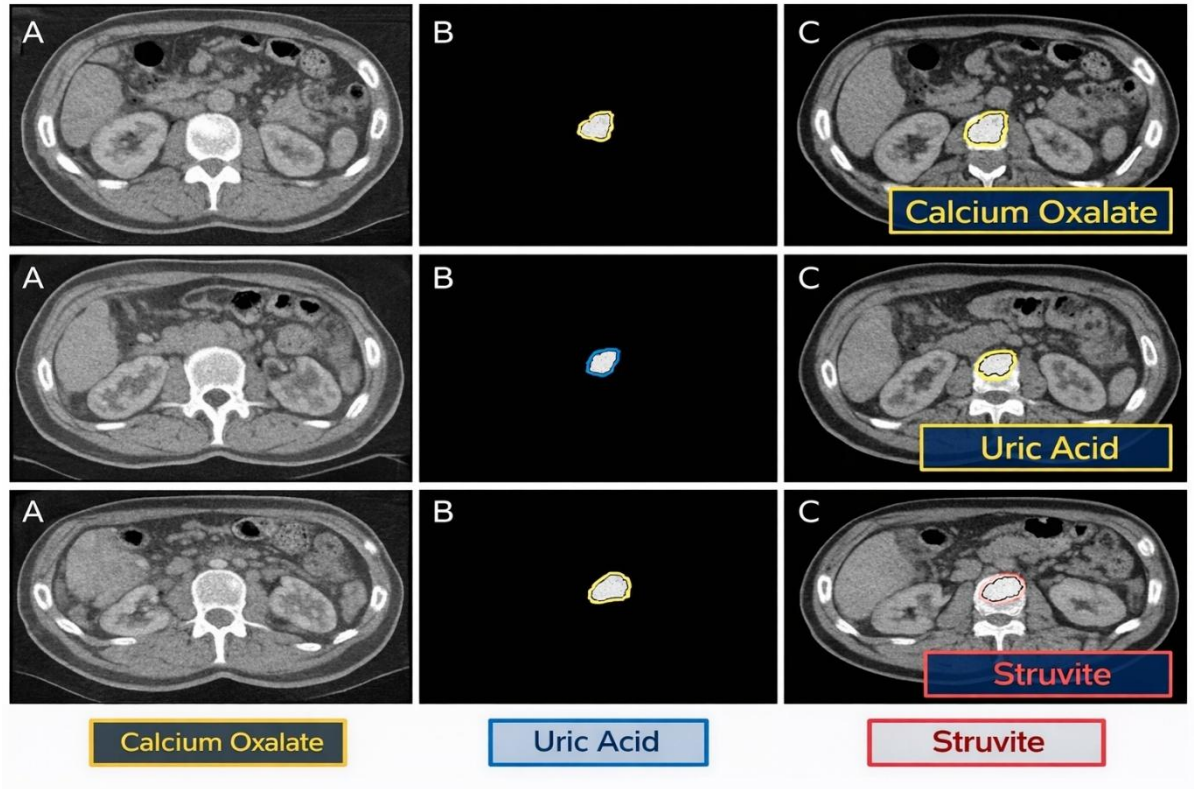

Figure 9: Segmentation and Type classification

Figure 9 represents typical outputs of kidney stones segmentation and type classification using the proposed framework of SQEU-Net on the abdominal CT images. The rows represent the specific kidney stone make-up i.e. calcium oxalate, uric acid and struvite, and the columns denote the initial CT, the estimated

segmentation mask and the final overlay with the stone type marked, respectively. The outcomes of segmentation show that even in cases when the stones have low contrast with the nearby renal tissues, the boundaries of the stones are accurately delineated, which indicates the effectiveness of dilated convolutions and attention-gated skip connections in the maintenance of fine spatial information. Moreover, the proper categorization of the stone types shows that the model is able to capture the small textual and intensity-oriented clues that are related to various stone types. The distinctiveness of the detached background renal structures and the stone regions, as well as the consistent labeling of types, demonstrates the strength of the suggested algorithm in simultaneously conducting pixel-level segmentation and the clinically significant recognition of stone types, which has to be considered to help in planning the treatment individually in the context of urolithiasis management.

6. Conclusion

A powerful and effective deep learning architecture labeled SQEU-Net has been introduced in this piece of work where computations are done to segment kidney stones in the CT images correctly. With the addition of the traditional U-Net framework with dilated convolutional blocks, SE-embedded residual units, and attention-gated skip connections, the proposed model has demonstrated the capability to define the stone boundaries with a high degree of accuracy, both at finer scale and a larger scale, including the contextual details. Stable gradient propagation, efficient feature reuse through the presence of residual learning, and the boosted discriminative feature representation through the squeeze-and-excitation modules that highlight clinically meaningful channels makes the application of squeeze-and-excitation models a crucial component of UTIs. Moreover, attention gates improve the process of feature fusion in decoding irrelevant background information leading to better segmentation. The numerous performance measures through extensive experimentation show that SQEU-Net is a better method of kidney stone segmentation in comparison with a number of existing methods based on evidence. It is noteworthy that the proposed architecture demonstrates greater resilience when it comes to dissecting small stones and stones with a low contrast, which tends to be a significant issue in clinical CT imaging. The present study is binary stone segmentation, but future studies will view more classes of segmentation in studying the composition of the stone, 3D volumetric data, and be verified using large multi-center datasets. Altogether, SQEU-Net is an important step to the stable and clinical applicable automated kidney stone analysis systems.

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