Performance Assessment of Deep Learning-Models for Kidney Tumor Segmentation using CT Images

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Abstract. As of Globocan-2020 statistics, more than 0.4 million new kidney cancer/tumor cases have been listed and 0.2 million deaths were aroused due to it across the world. Hence, Kidney tumor investigation and diagnosis is one of the prime cancer treatment processes in medical field. Manual identification of kidney tumor from clinical scan images such like CT and MRI may lead to affect the diagnosis process accuracy. Therefore, semi-automated and fully-automated methods have been developed tremendously since past decade by using image segmentation approaches, convolutional neural network (CNN) and deep learning models to locate the kidney cancer/tumor from medical images and these approaches helps the experts in clinical diagnosis process. Therefore, here a detailed comparative report in terms of dice similarity index score (DSC) has been presented on deep learning-based kidney cancer/tumor segmentation approaches made by various researchers.

Keywords: Clinical diagnosis · convolutional neural network (CNN) · deep learning · dice similarity coefficient (DSC) · fully-automated · image segmentation · kidney tumor · medical image · semi-automated

1 Introduction

The kidneys are essential parts of the human urinary system because they carry out a number of critical processes, such as eliminating waste from the blood, preserving the proper ratio of bodily fluids to electrolytes, controlling blood pressure, and contributing to hormone secretion [1]. The most varied types of cancer are found in developing nations, which makes sense given social and economic considerations. But lifestyle also plays a significant role in these figures [2]. Around 4,31,288 new occurrences and 1,80,000 new deaths have been listed across the world by kidney cancer in 2020. It places

P. Pareek et al. (Eds.): IC4S 2024, LNICST 597, pp. 124–134, 2025.
https://doi.org/10.1007/978-3-031-77075-3_11

in 16th and 18th positions among 36 various cancer incidences and deaths across 185 nations [3]. In Fig. 1, the pie chart depicted the number of new kidney cancer incidences and deaths listed in 2018 and 2020 across the globe as of International Agency for Research on Cancer (IARC) statistics [3, 4]. From these statistics, almost 7% and 2.44% of growth has been encountered in new cases and deaths from 2018 to 2020 and it shown as bar graph.

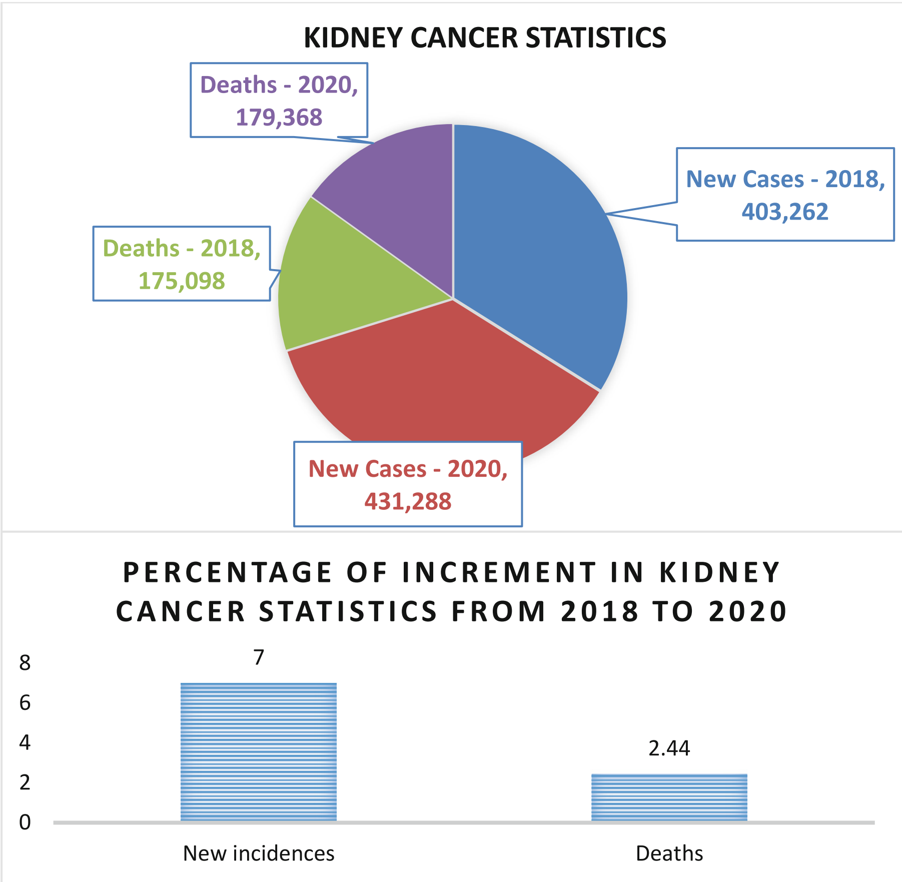

Fig. 1. Statistics of Kidney Cancer in 2018 and 2020.

The majority of kidney cancer diagnoses occurred in adults between the ages of 60 and 70, and the data also show an increase in the number of kidney tumors that do not cause any symptoms [5]. It was estimated that one in every 1000 live births carries the risk of autosomal dominant polycystic kidney disease (ADPKD) [6].

Malignant and benign are the most common varieties of kidney tumors. Most benign tumors are not harmful, but as they grow, some may produce symptoms like hematuria or pain in the muscles [7, 8]. Malignant tumors are regarded as dangerous and majority of these are carcinomas of the renal cells (RCC) [9]. The high-spatial-resolution images produced by computed tomography (CT) have sufficient anatomical detail. It is therefore crucial for the diagnosis of renal cancer. Segmentation of kidney tumor in CT imaging can help the clinical experts to plan surgical procedures and compute total kidney capacity [10, 11].

Hypertension, obesity, and smoking are a few of the factors that determine kidney cancer risk [12]. While removing a kidney or tumor was once an effective treatment option, preventive care is becoming more and more important because of today's advanced imaging techniques [13]. Although promising research focusing on preventing needless surgeries is also garnering attention, oncological treatments are still being given due consideration [14]. Surgical removal of localized RCC is considered curative, hence most localized kidney tumors are removed, despite the fact that a large fraction is later discovered to be benign [15, 16].

Most renal imaging studies focus on kidney segmentation rather than kidney tumors assessment since manual segmentation makes tracking the progression of kidney tumors challenging. This approach is not either time-consuming, but it may also lead to calculation errors and bias in 2D-tumor monitoring. It might be classifying cystic tissues [17]. It should be noted that certain kidney tumors may look different on CT scans [18]. From a decade ago, most of the kidney segmentation established works have been idiom of image segmentation based on thresholding, region growing, clustering, edge-detecting, or deformable model mechanisms [19, 20]. In these, predominantly setting of the threshold value was used mostly to segment images into black-and-white and these are not that must robust and accurate to diagnose clinically. Hence, from last decade huge number of automated approaches [21–23] have been experimented by researchers for cancer diagnosis, tumor segmentation and classification. They have been implemented by processing open-source image database of various diseases through existing CNN models and classifiers [24–27]. Still a lot of scope has to do investigations on implementation of deep-learning models in the field medical image processing to assist the specialists clinically for various cancer/tumor diagnosis process specifically brain tumor, lung cancer and kidney tumor identification and segmentation.

2 Related Work

A deep CNN framework [28] that can autonomously segregate kidney and liver cancers from CT images has been developed. A completely automated technique for CT kidney segmentation with tumors has described in [29]. A 3D U-Net based multi-scale superintended framework to segment tumor from kidney CT images has been built by the authors of [30]. A novel U-Net framework [31] called Crossbar-Net to segment kidney tumor in CT images has been developed. An automated kidney and renal mass segmentation approach has developed by authors of [32] in the Corticomedullary phase (CMP) of CT-Urography (CTU) based on the 3D U-Net. An advanced hybrid V-Net model introduced in [33], that incorporates the best features of existing V-Net models. Encoder and decoder stages of the model's more successful system have improvements not seen in earlier iterations and it might be a reliable approach for soft tissue organs segmentation. A unique renal tumor segmentation model employing a deep learning framework introduced in [34], known as the Hyper vision Net model. This architecture introduces supervision layers in the decoder section, and it refines even minor regions in the output. Multi-branch feature sharing generative adversarial network MB-FSGAN has been developed to segment and quantifying the renal tumors concurrently using CT scan images [35]. Another automated cascaded system to segment kidney and renal tumor using CT images has been showcased in [36]. It includes two volumetric fully convolutional networks. The first one is responsible to coarsely segment the kidney using a low-resolution input and estimate its location and second is used more precisely to separate the kidney and tumor from the cropped patch that covers the entire kidney. A tri-stage self-guided framework [37] to segment renal tumor in 3D CT images has been implemented. A kidney and renal tumor syntactic segmentation framework [38] of end-to-end boundary aware fully Convolutional Neural Networks (CNNs) from arterial phase abdominal 3D CT images has been demonstrated. A kidney and renal tumor segmentation approach [39] has been created, it was a variant of U-Net designed by collaboration of residual and attention model. It extracts more obvious syntactic features, segments smaller items, and effectively avoids gradient loss by deepening network layers. Meanwhile, combining image and semantic information can increase segmentation accuracy and object edge smoothness. A knowledge-driven augmentation strategy [40] has been suggested to deal the problem of insufficient labeled images in CT renal tumor segmentation. A multi-way framework [41] has been demonstrated. In this firstly multiple scale supervision in the decoder pathway may help the network anticipate accurate outcomes from the deep layers. Second, to offset the harmful impacts of kidney and tumor sample imbalance, exponential logarithmic loss was employed. Third, a connected-component-based post-processing method was created to eliminate the plainly erroneous voxels. A framework [42] by combining advanced features of SE-Net, ResNeXT and U-Net models has been developed to segment renal tumor from 2D scan images. A novel cascaded model [43] such as atrous dual attention U-Net had implemented to segment the renal tumor. Firstly, Network architecture concatenates features to preserve volumetric information and increase resolution with segmentation accuracy by combining features from 3D liver segmentation with 2D tumor segmentation. Secondly, integrated dual attention gate, which chooses discriminative features to focus on to find tumor segmentation in various organs. Finally, the suggested method uses an atrous encoder, which recovers more contextual data from computed tomography than a standard encoder. A deep learning model [44] has been developed based on FR2PAttU-Net model for kidney tumor segmentation., it was designed to enhance kidney tumor segmentation, particularly in cases where the tumors are poorly defined. A unique approach has developed by authors of [45] to detect stones in kidney and segmenting them was created by utilizing an ANN and the multi-kernel k-means clustering algorithm. Following the extraction of GLCM features from the image, a pre-processing step is conducted using the median filter. The normal and abnormal classes are classified using a neural network classifier, and the abnormal images are sent to the segmentation step, where the stone and tumor parts are segmented individually using many methods. Kernel K-means clustering technique. All these existing models' methodologies and limitations are summarized in Table 1.

Table 1. Summary of Deep learning models of Kidney cancer/tumor segmentation.

Author Name & Reference	Technique	Limitations
Efremova et al. [28]	deep CNN	Huge training time is used to train the data
da Cruz et al. [29]	CNN, U-Net	High false positives results are produced in kidney segmentation
Zhao et al. [30]	MSS U-Net	Couldn't use for other datasets
Qian et al. [31]	Crossbar-Net	The Crossbar-Net model didn't find symmetric information from horizontal and vertical axes
Lin et al. [32]	3D U-Net	Less performance in segmentation
Türk et al. [33]	Hybrid V-Net	More training time is requiring to train data
Sabarinathan et al. [34]	Hyper vision Net	Takes more time in segmentation process
Ruan et al. [35]	MB-FSGAN	More time is needed to train data and computationally very high
Zhang et al. [36]	CNN	Require large amount of training data and computational power to train data
Hou et al. [37]	Dilated convolution block	Higher processing expense when compared to standard convolutions using the same filter size and stride
Myronenko et al. [38]	CNN	Require large amount of training data and computational power to train data
Guo et al. [39]	Residual and attention U-Net model	Less efficient feature extraction layer
Qin et al. [40]	DRL	Generated data contains low diversity
Wenshuai et al. [41]	Multi scale supervised 3D U-Net	More time required and also need more GPU memory
Xie et al. [42]	SE-ResNeXT U-Net	More complex model
Liu et al. [43]	Cascaded Atrous Dual-Attention UNet	Cascaded Atrous model require more parameter and memory to implement

(*continued*)

Table 1. (*continued*)

Author Name & Reference	Technique	Limitations
Sun et al. [44]	FR2PAttU-Net	Process limited data
Nithya et al. [45]	Artificial neural network, multi-kernel k-means clustering algorithm	Overfitting issue may occur during classification

3 Performance Measures

Dice Coefficient Score (DSC) [28–45] expressed as Eq. (1) is a one of the most suitable and popular metrics that has been evaluate the similarity between predicted segmented portion with ground truth segmented label. It has been used to validate the network models designed for tumor segmentation from medical images.

$$Dice\ Coefficient(DSC) = \frac{2 * |U \cap V|}{|U| + |V|} \tag{1}$$

$\mathrm{U:}$ Set of predicted segmented portion pixels, $\mathrm{V:}$ Ground truth labeled pixels

Accuracy, Sensitivity and Specificity [29, 45], are the three more metrics to validate the network performance by measuring the Real Positive ($\mathrm{R_p}$), Real Negative ($\mathrm{R_n}$), Fake Positive ($\mathrm{F_p}$) and Fake Negative ($\mathrm{F_n}$) cancerous tissue cases identified by the network from overall examined test input cases. Finally, these metrics are expressed as Eq. (2) to Eq. (4).

$$\text{Accuracy (A)} = \frac{\text{faultless detections count}}{\text{All examined samples}} = \frac{\mathrm{R_p} + \mathrm{R_n}}{\mathrm{R_p} + \mathrm{R_n} + \mathrm{F_p} + \mathrm{F_n}} \tag{2}$$

$$\text{Sensitivity (Sen)} = \frac{\text{Real positive detections}}{\text{Number of all positive assessments}} = \frac{\mathrm{R_p}}{\mathrm{R_p} + \mathrm{F_n}} \tag{3}$$

$$\text{Specificity(Spec)} = \frac{\text{Real negative detections}}{\text{Number of all negative assessments}} = \frac{\mathrm{R_n}}{\mathrm{R_n} + \mathrm{F_p}} \tag{4}$$

4 Datasets and Evolution of Kidney Tumor Segmentation Methods

Datasets that are mentioned along with reference number in Table 2 have been used to validate the deep-learning frameworks discussed in related work section.

The Kidney Tumor Segmentation Challenge 2019 dataset (KiTS 2019) has been widely used to validate most of the networks that were designed for kidney cancer/tumor segmentation. It consists multiscale CT scans, segmentation masks and clinical outcomes

Table 2. Datasets used in related works discussed in Sect. 2.

Reference(s)	Dataset
[28–30, 32–34] [37, 39] and [41–44]	KiTS 2019
[31]	Real CT Kidney Tumor
[35]	Kidney Tumor in CT images
[36] [38]	MICCAI 2019 KiTS
[40]	Kidney Tumor Dataset
[45]	Kidney Image Dataset

of three hundred clinical patients who encountered the treatment at the University of Minnesota Medical Center from 2010 to 2018. Out of these, 210 (70%) randomly selected patients' information as the training set for the 2019 MICCAI KiTS Kidney Tumor Segmentation Challenge and released publicly [8]. Along with these, Real CT Kidney Tumor, Kidney Tumor in CT images, MICCAI 2019 KiTS, Kidney Tumor and Kidney Image Datasets has been to evaluate the performance of the various CNN and deep learning networks used to segment the kidney tumor.

Table 3 shows performance evolution metrics such as Dice Similarity Score (DSC), Accuracy, Sensitivity and Specificity of deep learning-models discussed in related work for kidney tumor segmentation and they were used KiTS 2019 dataset.

Table 3. Performance measures comparison of various Kidney Tumor Segmentation Models on KiTS 2019 Dataset.

Reference	Methodology	Dice Score (%)	Accuracy(%) Sensitivity(%) Specificity(%)
[28]	Deep CNN	Kidney: 96.38 Tumor: 67.38	—
[29]	CNN, U-Net	Tumor: 96.33	99.92, 97.42, 99.94
[30]	MSS U-Net	Kidney: 96.90 Tumor: 80.05	—
[32]	3D U-Net	Kidney: 97.3 Tumor: 84.4	—

(*continued*)

Table 3. (*continued*)

Reference	Methodology	Dice Score (%)	Accuracy(%) Sensitivity(%) Specificity(%)
[33]	Hybrid V-Net	Kidney: 97.7 Tumor: 86.5	—
[34]	Hyper Vision Net	Kidney: 96.63 Tumor: 95.52	—
[37]	Dilated Convolution Block	Kidney: 96.74 Tumor: 84.54	—
[39]	RAU-Net Model	Kidney: 96 Tumor: 77	—
[41]	Multiscale Supervised U-Net 3D	Kidney: 96.9 Tumor: 80.5	—
[42]	SE-ResNeXT U-Net	Kidney: 96.77 Tumor: 74.32	—
[43]	Cascaded Atrous Dual Attention U-Net	Kidney: 95.4 Tumor: 90.83	—
[44]	FR2PAttU-Net	Kidney: 94.8 Tumor: 91.1	—

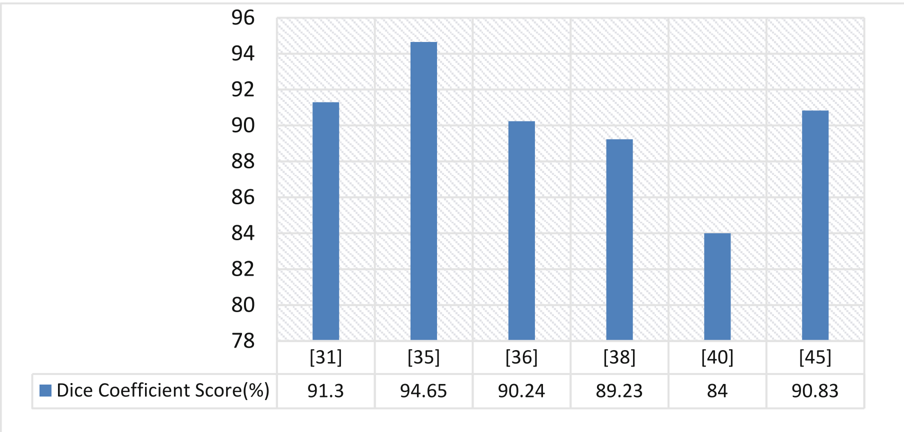

Fig. 2. Dice coefficient similarity index comparison of Kidney tumor segmentation models used other than KiTS 2019 dataset.

Bar graph shown in Fig. 2 is a DSC comparison of kidney tumor segmentation methods [31, 35, 36, 38, 40] and [45] discussed in related work section have been verified on various datasets mentioned earlier in Table 2.

5 Conclusion

Open access of various illness/diseases image datasets has enabled the deep learning based automatic disease segmentation and classification systems since past fifteen years. This study evolves the segmentation exactness of various kidney tumor segmentation frameworks that were used CT scan datasets of KiTS 2019 and other than KiTS 2019. Hence, this assessment has been analyzed the performance of renal tumor segmentation in-terms of dice similarity coefficient scores (DSC's) of kidney and tumor. It is clear from validation metrics of the various deep learning models discussed in this assessment process were segment the kidney and tumor from CT scan images satisfactorily. Hence, Deep learning models' implementations are encouraged now-a-days to help the medical experts in diagnosis process of various diseases like kidney tumor, brain tumor and lung cancer.

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