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KIDNEY TUMOR SEGMENTATION USING DEEP LEARNING

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Abstract:
Kidney tumor (KT) is one of the diseases that have affected our society and is the seventh most common tumor in both men and women worldwide. The early detection of KT has significant benefits in reducing death rates, producing preventive measures that reduce effects, and overcoming the tumor. Compared to the tedious and time-consuming traditional diagnosis, automatic detection algorithms of deep learning (DL) can save diagnosis time, improve test accuracy, reduce costs, and reduce the radiologist's workload. In this paper, we present detection models for diagnosing the presence of KTs in computed tomography (CT) scans. Toward detecting and classifying KT, we proposed 2D-CNN models; three models are concerning KT detection such as a 2D convolutional neural network with six layers (CNN-6), a ResNet50 with 50 layers, and a VGG16 with 16 layers. The last model is for KT classification as a 2D convolutional neural network with four layers (CNN-4

Introduction

The kidneys in the human body cleanse waste products and pollutants from the blood. The abnormal growth of cells causes tumors (cancers), affects people differently, and causes different symptoms.
Therefore, Early detection of kidney tumors (KT) is crucial for reducing disease progression and preserving life, as about one-third of KT cases are discovered after the disease has spread. Most kidney tumors are asymptomatic and are often detected incidentally during treatment for other conditions, appearing as masses, kidney cysts, or causing abdominal pain, which may not be linked to the kidneys. Subtle symptoms such as low hemoglobin, weakness, vomiting, stomach pain, blood in the urine, and high blood sugar are common, with anemia occurring in approximately 30% of KT patients. A case of KT is shown in Figure 1, highlighting a 4 cm renal mass in the left kidney, with a 3D volume rendering of the kidneys (kidney in pink and renal cancer in blue). Given the threat to life, accurate diagnosis through effective procedures is essential for timely intervention and treatment.

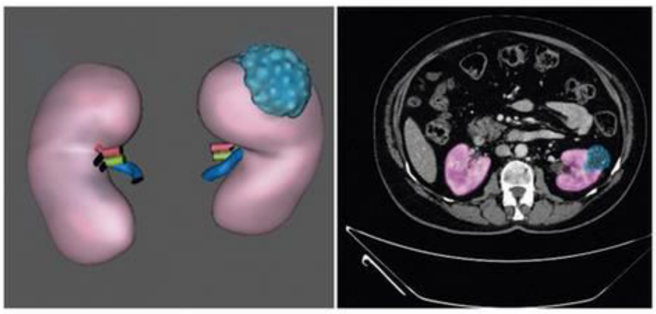

Figure 1: Sample renal CT taken from the dataset.

Deep learning (DL) is one of the most powerful machine learning technologies that can automatically learn multiple features and patterns without human intervention. DL enabled the building of predictive models for the early diagnosis of tumor disease, and scientists used proven pattern analysis methods. DL algorithms outperformed traditional machine learning due to their highly accurate results. Also, it often matches or surpasses human performance. That is why they are recommended as the best method for dealing with images. It has gained attention in image processing, especially in the medical field, because radiology is primarily concerned with extracting useful information from images.

Object detection is the method of identifying the class instance to which the object belongs. There are several types of detection, such as single-class object detection and multiclass object detection. Object detection has been applied in a wide field of medical images because of its precise effect on discovering diseases of all kinds. The convolutional neural network (CNN) is widely used to extract image characteristics and detect different objects. It is a neural network that operates on the principle of weight sharing. The convolution is an integral part of a function that explains how one function interferes with another. The size and the number of images, the number of working layers, and the form of activation functions used in CNNs vary. Variables of CNNs are selected experimentally and on a trial-and-error basis. Besides, every CNN consists of several layers, the most important of which are the convolutional and subsampling (pooling) layers. Figure 2 shows an illustration of CNN architecture.

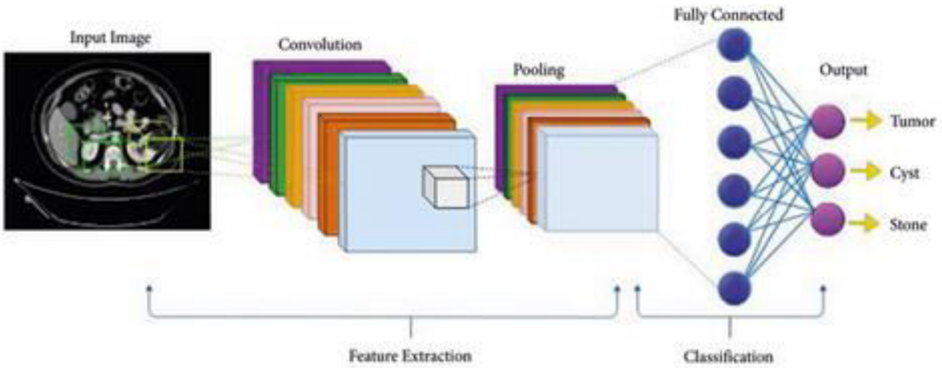

Figure 2:Architecture of a traditional CNN.

Literature survey:

Globocan estimates of incidence and mortality worldwide for 36 cancers in 185 countries.

This article provides an update on the global cancer burden using the GLOBOCAN 2020 estimates of cancer incidence and mortality produced by the International Agency for Research on Cancer. Worldwide, an estimated 19.3 million new cancer cases (18.1 million excluding nonmelanoma skin cancer) and almost 10.0 million cancer deaths (9.9 million excluding nonmelanoma skin cancer) occurred in 2020. Female breast cancer has surpassed lung cancer as the most commonly diagnosed cancer, with an estimated 2.3 million new cases (11.7%), followed by lung (11.4%), colorectal (10.0 %), prostate (7.3%), and stomach (5.6%) cancers. Lung cancer remained the leading cause of cancer death, with an estimated 1.8 million deaths (18%), followed by colorectal (9.4%), liver (8.3%), stomach (7.7%), and female breast (6.9%)

cancers. Overall incidence was from 2-fold to 3-fold higher in transitioned versus transitioning countries for both sexes, whereas mortality varied <2-fold for men and little for women.

Kidney tumor cases with clinical context, ct semantic segmentations, and surgical outcomes

The morphometry of a kidney tumor revealed by contrast-enhanced Computed Tomography (CT) imaging is an important factor in clinical decision making surrounding the lesion's diagnosis and treatment. Quantitative study of the relationship between kidney tumor morphology and clinical outcomes is difficult due to data scarcity and the laborious nature of manually quantifying imaging predictors. Automatic semantic segmentation of kidneys and kidney tumors is a promising tool towards automatically quantifying a wide array of morphometric features, but no sizeable annotated dataset is currently available to train models for this task.

U-net: Convolutional networks for biomedical image segmentation.

There is large consent that successful training of deep networks requires many thousand annotated training samples. The architecture consists of a contracting path to capture context and a symmetric expanding path that enables precise localization. We show that such a network can be trained end-to-end from very few images and outperforms the prior best method (a sliding-window convolutional network) on the ISBI challenge for segmentation of neuronal structures in electron microscopic stacks. Using the same network trained on transmitted light microscopy images (phase contrast and DIC) we won the ISBI cell tracking challenge 2015 in these categories by a large margin. Moreover, the network is fast. Segmentation of a 512x512 image takes less than a second on a recent GPU.

User guided 3D active segmentation of anatomical structure: Significantly improved efficiency and reliability.

Active contour segmentation and its robust implementation using level set methods are well-established theoretical approaches that have been studied thoroughly in the image analysis literature. Despite the existence of these powerful segmentation methods, the needs of clinical research continue to be fulfilled, to a large extent, using slice-by-slice manual tracing. To bridge the gap between methodological advances and clinical routine, we developed an open source application called ITK-SNAP, which is intended to make level set segmentation easily accessible to a wide range of users, including those with little or no mathematical expertise.

Methodology:

This section describes our proposed methodology for KT detection and classification using CT scans. It includes a detailed explanation of our preprocessing steps and the used data augmentation techniques and an illustration of the architecture of the four models we built for KT diagnosis. We examine the patient’s situation and define tumor presence to reduce the harmful effects of the injury and reduce the number of deaths and define the tumor type. Therefore, we have collected the new dataset from (KAUH) that contains images and metadata. We have also used the OpenRefine tool and tableau for preprocessing step to have a cleaned dataset. Furthermore, we used a DICOM converter to change the image format, and we have chosen 70 images of the kidneys from different dimensions for each patient. Figure 3 shows the workflow of the proposed framework.

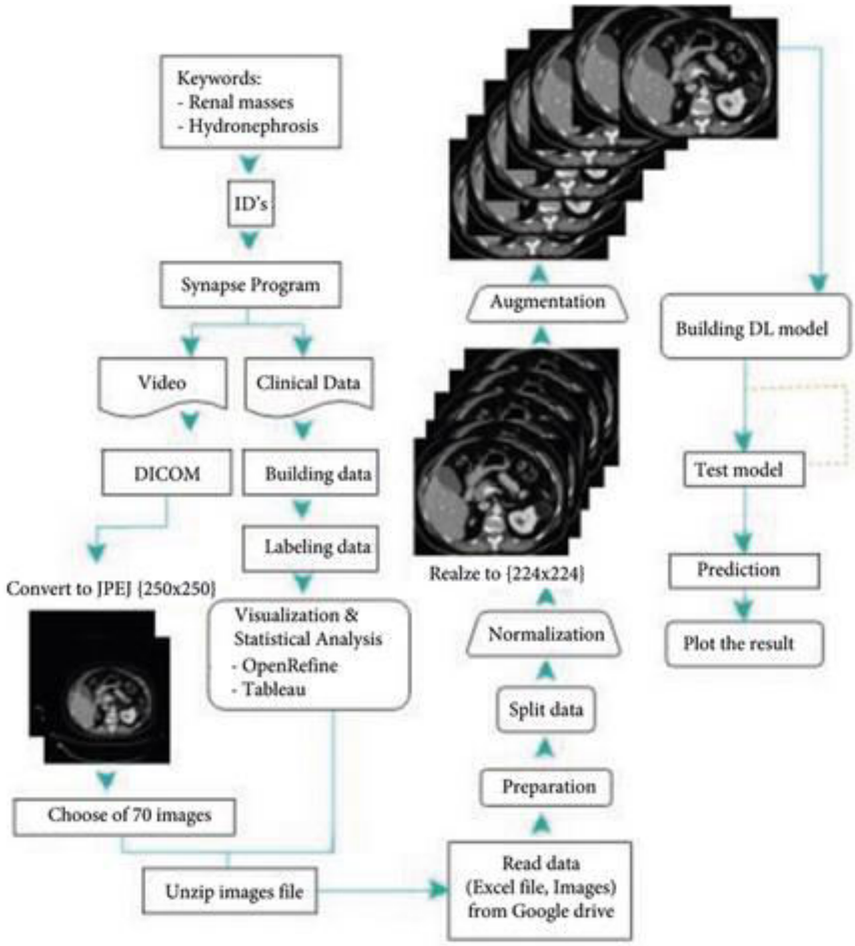

Figure 3:Methodology diagram.

We built prediction networks, three models to make multidiagnosis for the classification of different 4 labels revolving around two phases. In the first phase, we classify the case as normal case or tumor case, while in the second phase, we classify the tumor detected as benign tumor or malignant tumor where artificial neural network modeling is used where neurons correspond to receptive fields similar to neurons in the visual cortex of a human brain. These networks are very effective for tasks of detection, categorization of objects, image classification, and segmentation. The goal of CNNs is to learn higher-order characteristics using the convolution operation. Since convolutional neural networks learn input-output relationships (where the input is an image), the output is a feature map (image class label).

In this study, we examine the patient's situation and define tumor presence to reduce the harmful effects of the injury and reduce the number of deaths. Therefore, we have collected a new dataset from (KAUH) that contains images and metadata. We have also used the OpenRefine tool and tableau to make some preprocesses steps to have a cleaned dataset. Furthermore, we used a DICOM converter to change the image form, and we have chosen 70 images of the kidneys from different dimensions for each patient. Then, we started by implementing a convolutional neural network for binary classification with the labels (Normal/Tumor).

Artificial neural network modeling is very effective for detecting tasks, categorization of objects, image classification, and segmentation. The goal of CNNs is to learn higher-order characteristics using the convolution operation. Since CNN's learns input-output relationships (where the input is an image), in convolution, each output pixel is a linear combination of the input pixels [40].

We aim to implement a binary classification solution for the detection of kidney tumors. The use of CNN in such a case helps to identify the feature map for each image engaged in the tanning process for the adopted CNN model. Hence, the use of the pooling layer helps to determine the size of the feature segment that we are looking for to extract a featured image, which will be the primary feed data into the fully connected neural network in the CNN model. As represented in Figure 4, we have two classes to be trained on it.

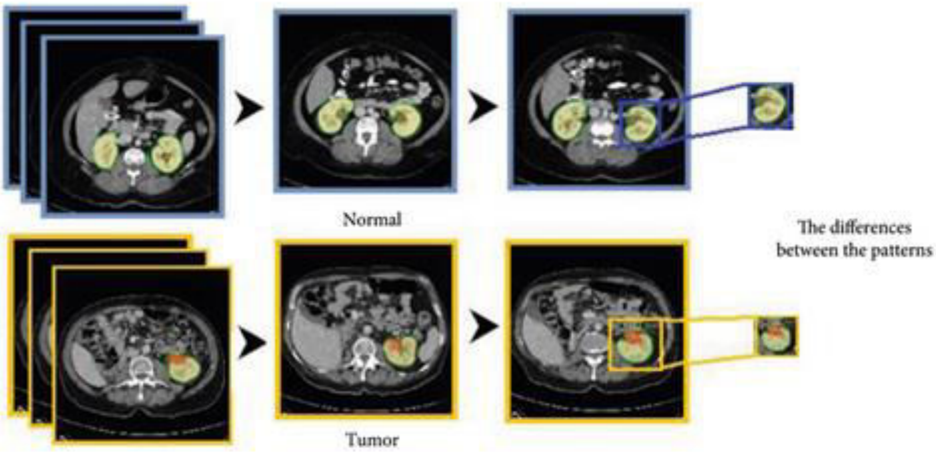

Figure 4:Detection labels.

The study aims to implement a binary classification solution for the detection and classification of kidney tumors. Artificial neural network modeling effectively detects tasks and categorizes objects, image classification, and segmentation. The use of CNN in such a case helps to identify the feature map for each image engaged in the tanning process for the adopted CNN model. As represented in Figures 4 and 5, two categories are used to be trained for each phase. In the first phase, we classify the case as; Normal case, or Tumor case, while in the second phase, we classify the detected tumor as Benign tumor or Malignant tumor.

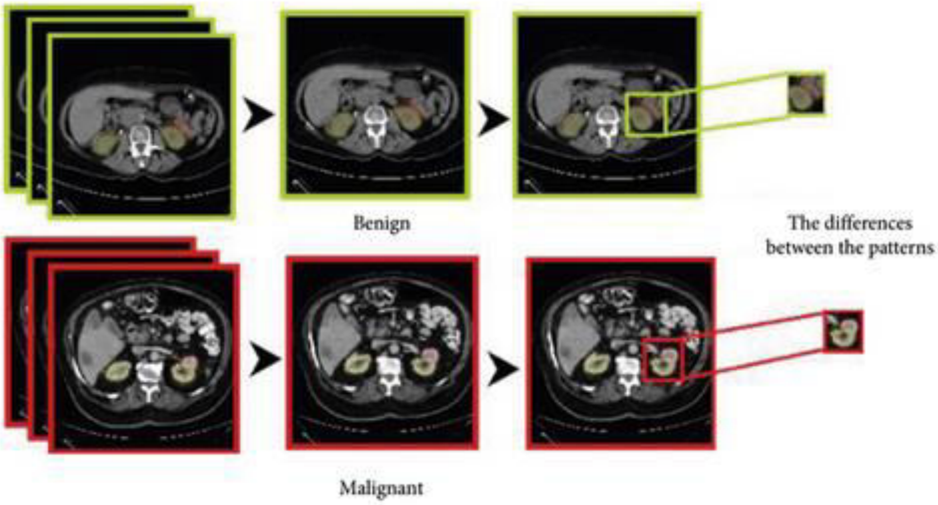

Figure 5:Classification labels.

The attribute of our interest in the first phase is the "situation," which is shown in Table 4. It comprises different values that are merged to balance the number of labels in the first case of detection of the tumor. We have merged the situation for the normal cae "healthy" and normal case with the cyst, as "Normal" of the tumor (Normal = 0) label and the situation of tumors as "tumor" (Tumor = 1) label. Finally, the attribute comprised new binary labels (0 and 1). Table 1 shows the new labels.

Table 1. Situation attribute labels merged description.

Label	Description
0	Normal
1	Tumor

The attribute of our interest in the second phase is the "tumor type," we present the benign tumor as (benign = 0) label and the malignant of tumors as (malignant = 1) label. Finally, the attribute became composed of new binary labels (0 and 1). Table 2 shows the new labels.

Table 2. Tumor type labels merged description.

Label	Description
0	Benign
1	Malignant

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5)Discussion and Conclusion

This study uses four methods—VGG16, ResNet50, and two modified 2D-CNN models—to analyze kidney tumor conditions and classify tumor types from renal CT scans. The results showed the effectiveness of our proposed 2D-CNN models, with detection accuracies of 60%, 96%, and 97% for VGG16, ResNet50, and 2D-CNN, respectively, and 92% accuracy for the classification model. Collecting patient data, labeling, and converting image formats is time-consuming, requiring collaboration with radiologists to ensure data validation. Previous studies often used a single image per patient, limiting diagnostic accuracy. Our dataset is comprehensive, with 70 images per patient covering kidney-related issues, including tumors and stones. Key contributions include creating a new dataset from a Jordanian hospital, analyzing kidney tumor cases, and enhancing tumor detection and classification accuracy. These results improve diagnosis, reduce workloads for doctors and radiologists, provide a tool for automatic assessment, and help predict kidney tumor presence while minimizing misdiagnosis risk.

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