Efficacy of Yolo Deep Learning Algorithm Kidney Tumor Cancer Detection

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Abstract:- Kidney Tumor cancer is difficult to detect and can be difficult for doctors to detect, the growth of abnormal in some may lead to cancer or may get worse in another way which can affect daily activity. the main objective of this research titled " kidney tumor cancer detection using Yolo deep learning algorithm "is to build a deep learning model that will facilitate the way used to detect the kidney tumor cancer which used to take long to get a patient's results and not much trusted which can lead to serious cancer. The usual method to detect kidney tumor cancer is to use Magnetic Resonance Imaging scan to get images and be handed over to doctors to study on them which used to take long time to study on it and some decide without having much experience, some decide based on their feelings or some may be stressed by the work they have done and they decide quick without being diligent on what they currently have. this developed deep learning based kidney tumor cancer detection and diagnosis system will automatically detect and classify important regions on an input biopsy image. this research will increase accuracy in results which come from radiologist analysis of MRI image and will also reduce time which used to take to get result not only that but also the chance of getting cancer from kidney tumor cancer will be reduced for that kidney tumor cancer surgery will be right way after passing MRI image into my kidney tumor cancer detection using Yolo deep learning algorithm to detect if it is kidney tumor cancer or not.many new treatments for kidney tumor cancer have been developed, some are currently being developed by scientists. this research will provide kidney tumor cancer detection, diagnosis, and treatment information that offers new hope to the lives of kidney cancer patients. In this research, it is aimed to detect kidney tumor cancer using Yolo deep learning algorithm.

I. INTRODUCTION

In medical terms, kidney tumor cancer is known as renal cell carcinoma. The term "kidney" is derived from the Latin word "kidney".Kidney tumor cancer can manifest itself in a variety of ways (ACS,2008).

While cancer is diagnosed in some patients after it has spread throughout the body, it can also cause symptoms in others. If the patient mentions metastatic spread, depending on the condition, surgical or systematic medical treatment may be required. If only surgery is desired, additional treatments to treat metastatic spread or to delay cancer progression may be recommended. kidney tumor cancer, like many other cancers, usually develops by chance. external factors, such as smoking and obesity, do, however, increase the risk of kidney cancer. It is important to know which factors increase the risk of kidney tumor cancer during patient treatment but seeking past behaviour does not benefit healing. the patient's smoking habit does not always indicate a high risk of cancer. a higher risk of developing kidney cancer may be linked to genetic factors. a genetic disorder known as von Hippel-Lindau (VHL), for example, may increase the risk of developing kidney cancer (ACS,2008).

II. METHODOLOGY

A. Data Presentation
Findings are presented by respecting objectives of the research study. This research presents both background information and deep learning are proficient in areas such as speech recognition, image recognition, data analysis.

B. Deep Learning Framework
A CT scan is used as an input in our framework. Using a shared 3D segmentation model, the framework first generates kidney and tumor masks for each phase. The framework then aligns the tumor regions across phases and generates a probability distribution over five renal tumor subtype classes using a classification model. The segmentation results show the kidney and tumor are represented by green and magenta, respectively where all tumors in the dataset have been surgically pathologically confirmed We chose 50 cases with at least three CT phases at random to test the model, and the remaining cases were used for training.

Table 1 Summarizes patient demographics, the distribution of kidney tumor subtypes, tumor size, and CT phases for training/testing.

	Total	Training set	Test set
Patients (*n*)	308	258	50
Age (years)			
−40	29	23	6
40–50	73	62	11
50–60	96	80	16
60–70	71	57	14
70–	39	36	3
Gender			
Female	167	140	27
Male	141	118	23
Subtype			
ccRCC	66	54	12
pRCC	69	58	11
chRCC	68	58	10
AML	60	51	9
Oncocytoma	45	37	8
Tumor size (cm)			
1–2	79	66	13
2–3	84	71	13
3–4	56	51	5
4–5	33	27	6
5–6	29	21	8
6–	27	22	5
CT phases			
Four phase	183	145	38
Three phase	66	54	12
Two phase[a]	46	46	–
Single phase[a]	13	13	–

[a]The single-phase and two-phase CT scans are used only for training our segmentation model.

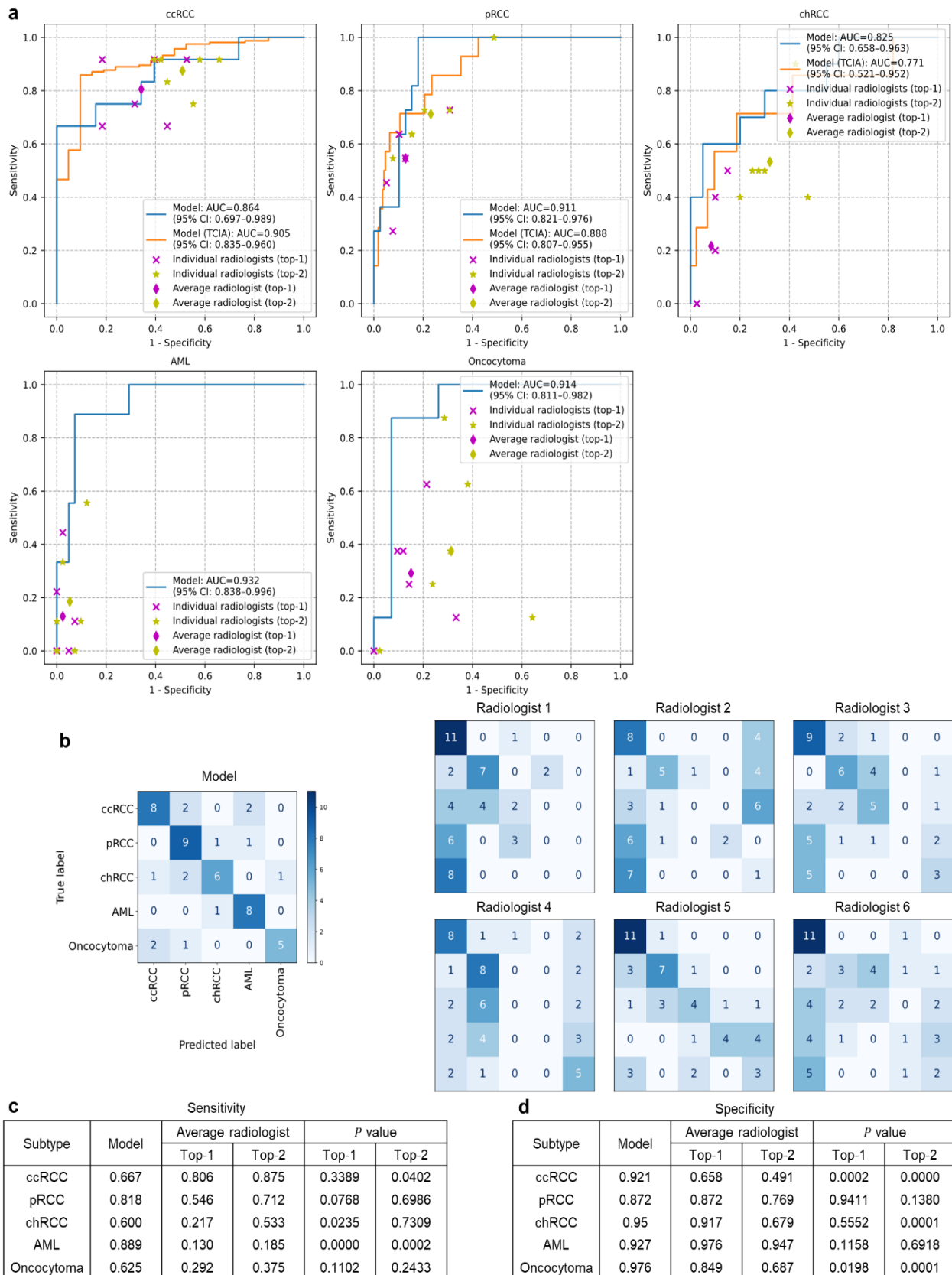Table 1: Patient demographics, subtypes and tumor size distribution for training/test dataset

Fig. 1: Predicted label, Model, Sensitivity, specificity

Sensitivity

Subtype	Model	Average radiologist		P value	
		Top-1	Top-2	Top-1	Top-2
ccRCC	0.667	0.806	0.875	0.3389	0.0402
pRCC	0.818	0.546	0.712	0.0768	0.6986
chRCC	0.600	0.217	0.533	0.0235	0.7309
AML	0.889	0.130	0.185	0.0000	0.0002
Oncocytoma	0.625	0.292	0.375	0.1102	0.2433

Specificity

Subtype	Model	Average radiologist		P value	
		Top-1	Top-2	Top-1	Top-2
ccRCC	0.921	0.658	0.491	0.0002	0.0000
pRCC	0.872	0.872	0.769	0.9411	0.1380
chRCC	0.95	0.917	0.679	0.5552	0.0001
AML	0.927	0.976	0.947	0.1158	0.6918
Oncocytoma	0.976	0.849	0.687	0.0198	0.0001

C. Dataset Description
- CT scans from 300 patients
- Only 210 CT scans have segmentation labels for kidney and kidney tumors

- Bounding box coordinates: Calculated from boundary of the segmentation maks of the kidneys
- Coordinates used as the ground truth of training
- The bounding box for each slice can be found by treating each slice of the volume individually.

D. Data imports

```
importsplitfolders
splitfolders.          ratio("../input/          -kidney-dataset-normal          /C-KIDNEY-DATASET-/          -KIDNEY-DATASET-
output="dataset",seed=1337,ratio=(.8,.1,.1),group_prefix=None)
channels=3
batch_size=25
test_batch_size=32
test_steps=1
train_path='./dataset/train'
test_path='./dataset/test'
val_path='./dataset/val'
print('test batch size: ',test_batch_size,' test steps: ',test_steps)
defscalar(img):
returnimg# EfficientNet expects pixelsin range 0 to 255 so no scaling is required
trgen=ImageDataGenerator(preprocessing_function=scalar,horizontal_flip=True)
tvgen=ImageDataGenerator(preprocessing_function=scalar)
train_generator=trgen.flow_from_directory(directory=train_path,target_size=(224,224),class_mode='categorical',
color_mode='rgb',shuffle=True,batch_size=batch_size)
test_generator=tvgen.flow_from_directory(directory=test_path,target_size=(224,224),class_mode='categorical',
color_mode='rgb',shuffle=False,batch_size=test_batch_size)

valid_generator=tvgen.flow_from_directory(directory=val_path,target_size=(22
4,224),class_mode='categorical',
color_mode='rgb',shuffle=True,batch_size=batch_size)
classes=list(train_generator.class_indices.keys())
class_count=len(classes)
train_steps=int(np.ceil(len(train_generator.labels)/batch_size))
```

test batch size: 32   test steps: 1
Found 9955 images belonging to 4 classes.
Found 1249 images belonging to 4 classes.
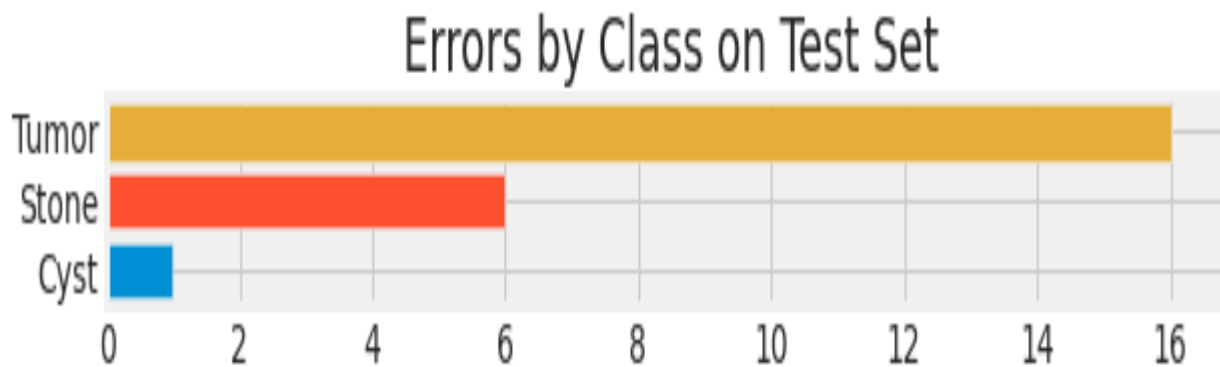Found 1242 images belonging to 4 classes.

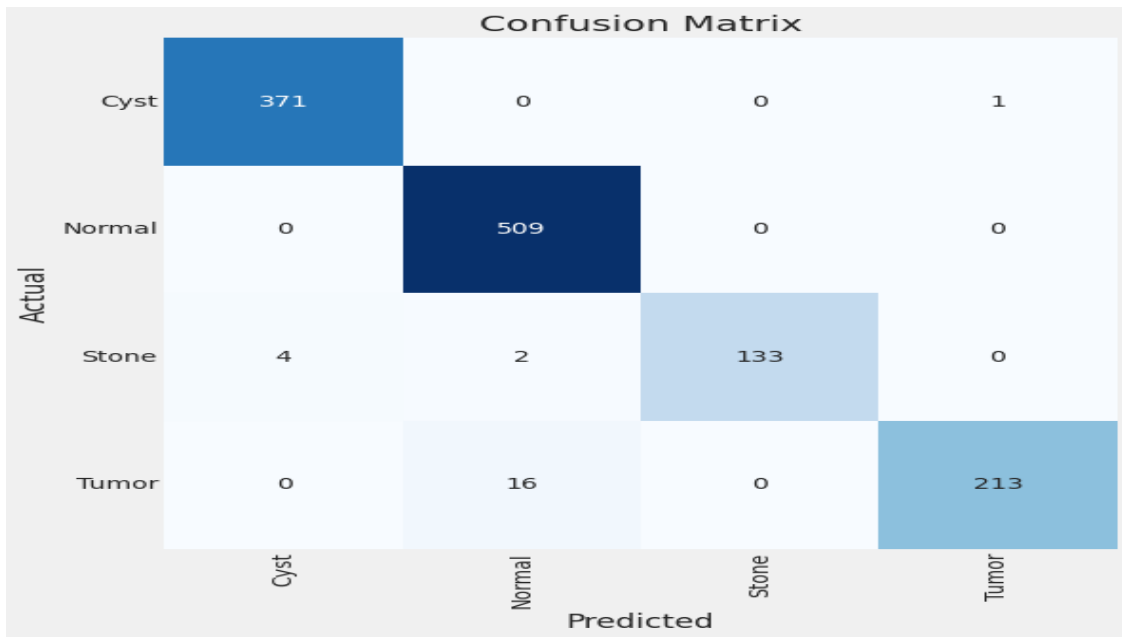
Fig. 2: Errors by Class on Test Set
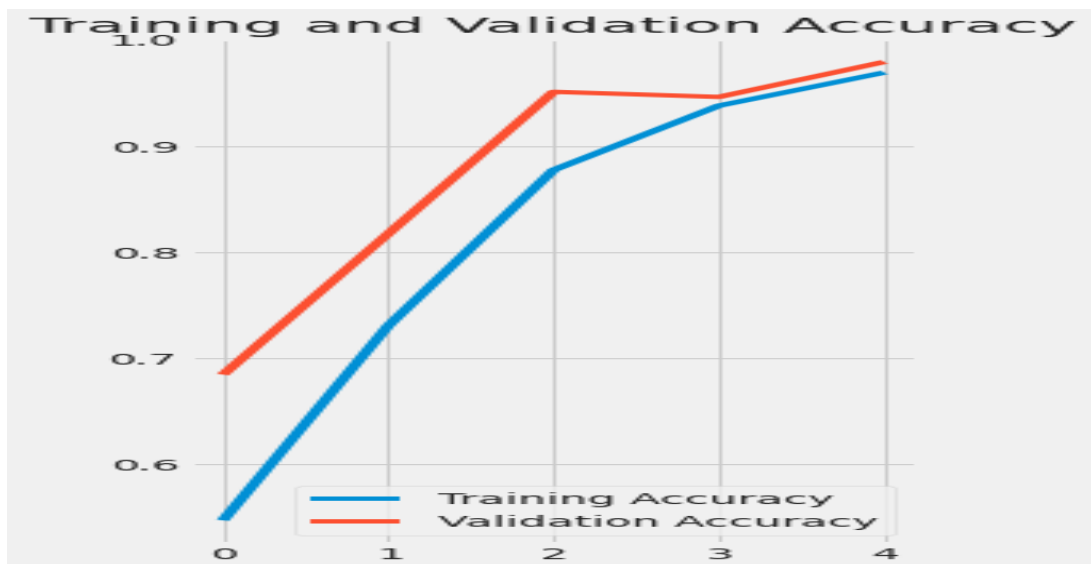
Fig. 3: Confusion Matrix

Fig. 4: Training and Validation Accuracy

Fig. 5: Training and Validation Loss

III. RESULTS

A. Pre-processing

To produce accurate results in object detection with a high mean Average Precision (mAP), it causes multiple iterations in the same image, slowing the algorithm's detection speed and preventing real-time detection. Detecting possible object regions: they operate in two stages. In the first step, we select interesting regions from the image. The regions are then classified using convolutional neural networks. Because we must run prediction for each selected region, this solution may be extremely slow. Region-based convolutional neural network (RCNN), Fast-RCNN, and Faster-RCNN are the most well-known examples of this type of algorithm. Classifying the image in those regions into object classes and Algorithms based on regression: instead of picking out interesting areas of an image, we predict classes and bounding boxes for the entire image in a single run of the algorithm. We use YOLO (You only look once) algorithm, which is commonly used for real-time object detection. task is to predict an object's class and the bounding box that specifies the object's location. Each boundary box has five elements (x, y, w, h) as well as a box confidence score. The confidence score reflects the likelihood that the box contains an object (objectness) as well as the accuracy of the boundary box. The image width and height are used to normalize the bounding box width and height. The offsets x and y are to the corresponding cell. As a result, x, y, w, and h, all have values between 0 and 1. There are 20 conditional class probabilities in each cell.the conditional class probability is the likelihood that the detected object belongs to a particular class (one probability per category for each cell). As a result, YOLO's prediction has the form (S, S, B5 + C) = (7, 7, 25 + 20) = (7, 7, 30).

YOLO deep learning algorithm used to build a CNN network to predict a (7, 7, 30) tensor. It uses a CNN network to reduce the spatial dimension to 7×7 with 1024 output channels at each location. YOLO algorithm performs a linear regression using two fully connected layers to make 7×7×2 boundary box predictions (the middle picture below). To make a final prediction, we keep those with high box confidence scores (greater than 0.25) as our final detections.

A-B: Normal kidneys with different CT scan mean intensities. C-D: Cystic kidneys. E: Failed detection of hypertrophied kidney. F: Tumoral kidney.
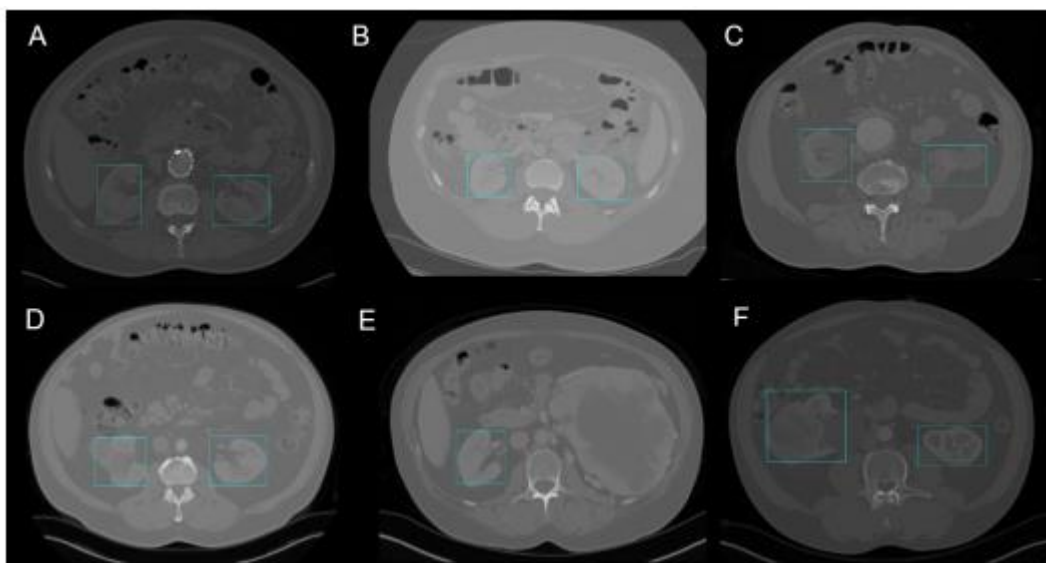

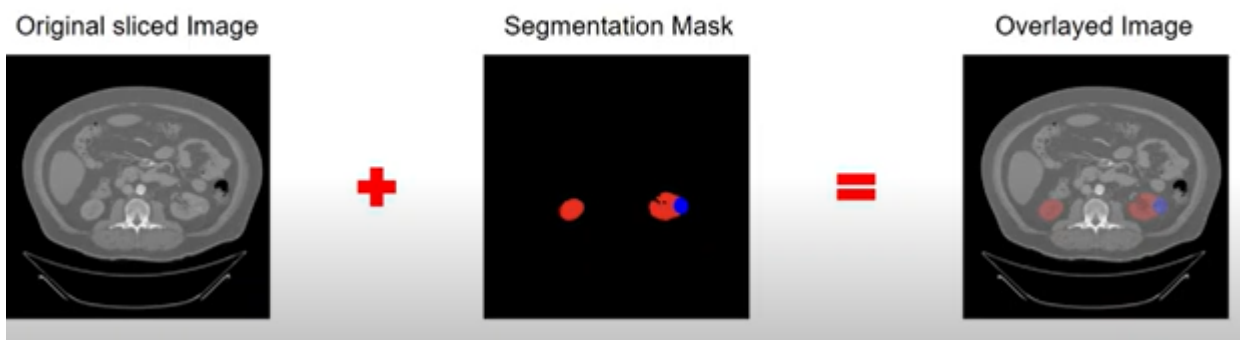Fig. 6: kidney detection by YOLO

B. Data Visualization
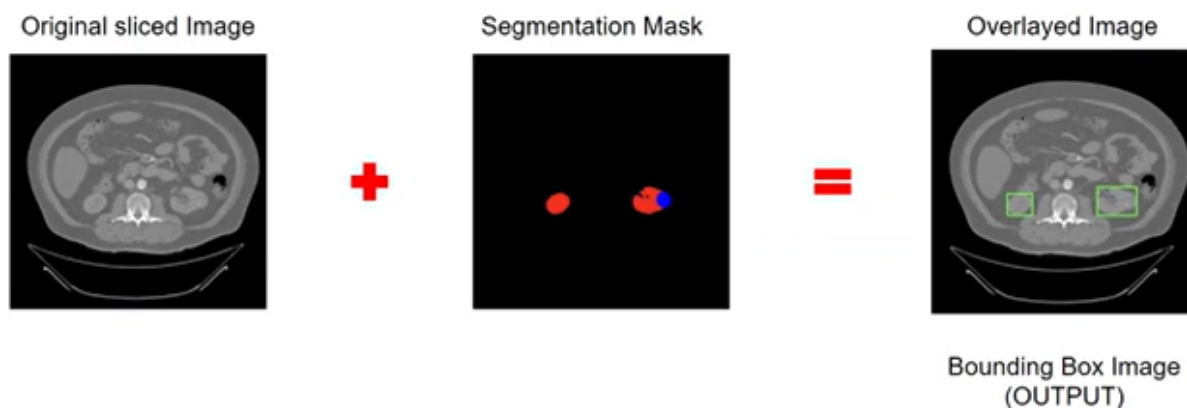

Fig. 7: Data Visualization

C. Data Generation

Fig. 8: Data Generation

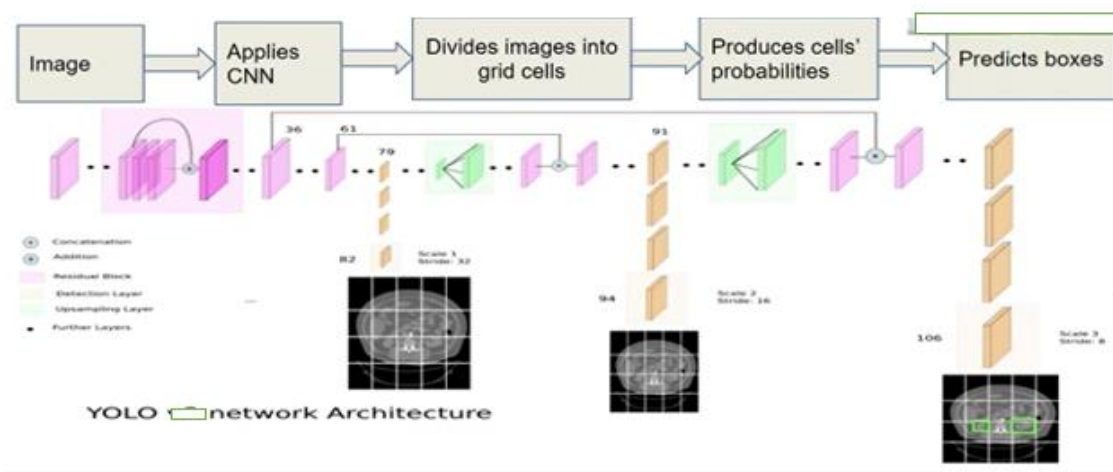*D. Base Line model Description*

Fig. 9: baseline model description

IV. CONCLUSION

From the study results, we have demonstrated efficacy of yolo deep learning algorithm kidney tumor cancer detection. Using the proposed algorithms, we have run the circuit for different parameters and optimized it for the accurate detection of kidney tumor cancer. Kidney Tumor cancer is difficult to detect and can be difficult for doctors to detect, the growth of abnormal in some may lead to cancer or may get worse in another way which can affect daily activity. This research will be solution to efficacy of yolo deep learning algorithm kidney tumor cancer detection,model that will facilitate the way used to efficacy the kidney tumor cancer which used to take long to get a patient's results and not much trusted and low accuracy which can lead to serious cancer, research will provide efficacy of kidney tumor cancer detection, diagnosis with effective and high accuracy ,time saving , treatment information that offers new hope to the lives of kidney cancer patients.

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