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Integrating YOLOv7 Instance Segmentation for Comprehensive Liver Tumor, Cyst & Abscess Segmentation

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ABSTRACT: Proposing a novel YOLOv7 instance segmentation method for precise liver lesion segmentation is pivotal in medical imaging. Leveraging YOLOv7's efficiency and accuracy,address the intricate structures of liver tumors, cysts, and abscesses simultaneously. Our method provides comprehensive segmentation, offering a detailed representation of liver pathology with high spatial accuracy.Comparing with traditional and recent deep learning-based methods, our approach stands out for its versatility and unified instance segmentation capabilities. Unlike manual or specialized methods, our YOLOv7-based approach comprehensively handles diverse lesion characteristics, enhancing accuracy and efficiency in liver lesion segmentation for medical imaging.

KEYWORDS: YOLOv7, Liver Tumor Detection, YOLOv7 Instance Image Segmentation, Deep Learning-based approaches, Test, Train, Validation, Weights, Configuration, Data, Epochs, Batch-Size, Image-Size, image-weights, Confusion matrix, Accuracy, Precision, F1 Score, Recall, Area Under Curves(AUC), Medical Image Analysis.

I. INTRODUCTION

Liver disease is a major global health concern, affecting millions of people and imposing a significant burden on healthcare systems. Medical imaging, particularly computed tomography (CT), [2]plays a critical role in the diagnosis and treatment planning of liver diseases. Accurate and efficient segmentation of liver lesions from CT images is essential for precise diagnosis and treatment monitoring. However, manual segmentation of liver lesions is time-consuming and subjective, highlighting the need for automated and reliable segmentation methods.

Deep learning has emerged as a powerful tool for medical image analysis, offering the potential for automated and accurate segmentation of liver lesions. YOLOv7, a state-of-the-art deep learning model, has shown promisingresults in object detection and instance segmentation tasks. In this study, The propose a novel approach for liver disease segmentation in CT images using YOLOv7 instance segmentation.

The aim of this study is to develop and evaluate a deep learning-based method for the automated segmentation ofthree classes of liver lesions: tumors, crst (cysts), and abscesses. The utilize a large dataset of annotated liver CTimages to train and validate the YOLOv7 model, ensuring its ability to accurately localize and classify different types of liver lesions. The proposed method has the potential to improve the efficiency and accuracy of liver disease diagnosis, enabling timely intervention and improved patient outcomes.

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II. LITERATURE REVIEW

[1] Title: YOLO-LOGO: A transformer-based YOLO segmentation model for breast mass detection and segmentation in digital mammograms.

Authors: Su, Y., Liu, Q., Xie, W., & Hu, P. (2022).

Description: Breast cancer is the most frequently diagnosed cancer and one of the leading common cancer-caused death for females). One of the most commonly used early breast cancer screen methods is mammography . Currently, the interpretation of mammography is still done manually by experienced radiologists. When the density of breast tissue is too high or the lesion is too small, it is easy to have a false negative observation . Therefore, providing the radiologist with powerful computer-aided diagnosis (CAD) tools is one approach to improve mammographic interpretation and decision-making especially when the lesions are easy to be missed by manual detection . Specifically, an automatic, accurate and efficient mass detection and segmentation model could be helpful for both manual diagnosis and automatic masses classification of breast cancer.

[2] Title: Liver Lesion Detection from MR T1 In-Phase and Out-Phase Fused Images and CT Image

Authors: Bhojane, R., Chourasuia, S., Laddha, S.V., & Ochawar, R.S.(2023,July).

Description: Unusual formations in the liver called lesions can happen for a number of different reasons. Some are malignant, while others are non-cancerous. Timely detection of the lesion and its treatment is necessary for malignant lesions. In this paper, attempt to detect liver lesions using state-of-the-art single-stage object detection technology YOLOv8. On two distinct datasets, each of which contained 38 MR T1 fused image samples and 41 CT samples. The model is first evaluated on both datasets separately and then evaluated by combining both datasets. The findings demonstrate that the model is capable of accurately and quickly detecting liver abnormalities. The model performs best on the MRI dataset with an average detection time of 62.96 ms with an accuracy of 83.6%. Our research aims to shed light on single-stage object detection models' unrealized potential in medical image analysis. The hope the findings contribute to developing a real-time tumor/lesion detection technology that gives accurate results in real time.

[3] Title: PBCI-DS: A multi-stage DCNN method for liver tumor segmentation.

Authors: Wu, Q., Zhao, L., Lin, C., & Zhao, G. (2020, November).

Description: Medical image segmentation is one of the most important tasks in machine learning. In order to help with the doctors, we focus on computer-aided automatic computer tomography (CT) segmentation of liver tumors. Instead of using a single model during the segmentation process, argue that the filter made by the model of object detection before segmentation could improve the accuracy of segmentation. From the motivation above, we proposed a multi-stage deep convolutional neural network (DCNN) model, which can be used for segmentation of the tumors in the livers. To further improve the accuracy of the object detection model, proposed an iterative training method which boosts the performance of our model and yield more accurate localization of the tumors. Finally, the evaluation of proposed method on our private dataset from hospital and public dataset from MICCAI-LiTS2017 suggested that our model is superior to the current state-of-the-art models.

EXISTING SYSTEM

Existing methods for liver disease segmentation in CT images typically involve traditional machine learning techniques or deep learning approaches. Traditional machine learning methods often rely on handcrafted features and segmentation algorithms, such as region growing or thresholding, followed by post-processing steps to refine the segmentation.
Deep learning-based approaches have shown promising results in liver disease segmentation. One common approach is to use convolutional neural networks (CNNs) for semantic segmentation, where each pixel in the image is classified as belonging to a certain class (e.g., liver lesion or background). U-Net, a popular CNN architecture, has been widely used for medical image segmentation tasks, including liver disease segmentation. Another approach is to use object detection and instance segmentation models, such as Mask R-CNN, to identify and delineate individual liver lesions. These models can provide more detailed segmentation masks for each lesion, enabling more precise diagnosis and treatment planning.
While these existing methods have shown good performance in liver disease segmentation, they often require large

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annotated datasets for training and may struggle with detecting small or irregularly shaped lesions. Additionally, the computational complexity of these models can be high, requiring powerful hardware for efficient inference.

III. METHODOLOGY

The YOLO (You Only Look Once) v7 [3] model is the latest in the family of YOLO models. YOLO models are single stage object detectors. In a YOLO model, image frames are featurized through a backbone. These features are combined and mixed in the neck, and then they are passed along to the head of the network YOLO predicts the locations and classes of objects around which bounding boxes should be drawn.

In our comprehensive system designed to enhance road safety and enforce helmet-wearing regulations, the YOLO (You Only Look Once) algorithm plays a pivotal role in real-time object detection. Specifically, YOLO is employed to identify individuals on motorcycles who are not wearing helmets. YOLO is renowned for its remarkable efficiency in real-time object detection. It allows our system to process video feeds from live webcams and promptly identify objects. YOLO's single-shot approach to object detection ensures that our system can efficiently process each frame in real-time, making it highly suitable for real-world, dynamic traffic monitoring.
YOLO conducts a post-processing via non-maximum supression (NMS) to arrive at its final prediction:

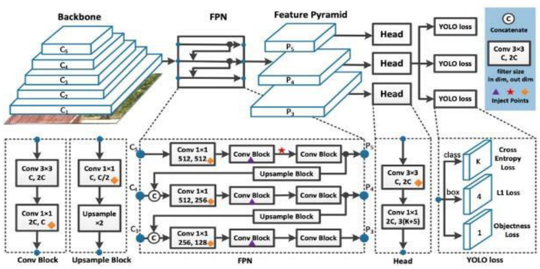

Fig.1 : YOLO network architecture as depicted as PP-YOLO

Object detection using YOLO involves dividing the input image into a grid and predicting bounding boxes, class probabilities, and confidence scores for each grid cell. YOLO is known for its real-time processing capabilities and accuracy. To count objects, the detected bounding boxes are typically filtered based on confidence scores and class probabilities. The remaining boxes represent the detected objects, and their count can be determined. YOLO is widely used in various applications such as autonomous vehicles, surveillance, and robotics due to its efficiency in handling multiple object classes in a single pass. Implementing YOLO for object detection and counting involves using pre-trained models, customizing them for specific tasks, and post-processing the results to obtain accurate counts.

PROPOSED SYSTEM

In this study, Then propose a novel approach for liver disease segmentation in [4] CT images using YOLOv7 instance segmentation. Unlike traditional semantic segmentation methods that classify each pixel into a specific class, instance segmentation algorithms like YOLOv7 can differentiate between individual instances of the same class, providing more detailed and accurate segmentation masks for each lesion.

Our proposed method consists of several key steps. First, The preprocess the CT images to enhance contrast and remove noise, which helps improve the model's ability to detect subtle features. Next, fine-tune the YOLOv7 model on a large dataset of annotated liver CT scans, ensuring it learns to accurately localize and classify three classes of liver lesions: tumors, crst (cysts), and abscesses.

During the inference phase, the trained YOLOv7 model is applied to unseen CT images to detect and segment liver lesions. The resulting segmentation masks can be further processed and analyzed to assist radiologists in the diagnosis and treatment planning of liver diseases.

Our proposed method [5]offers several advantages over existing approaches, including the ability to accurately segment liver lesions of varying sizes and shapes, the potential for real-time processing due to YOLOv7's efficiency, and the

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ability to differentiate between different types of liver lesions using instance segmentation. Then believe that our proposed method has the potential to significantly improve the efficiency and accuracy of liver disease segmentation in CT images, ultimately leading to better patient outcomes.

SYSTEM ARCHITECTURE

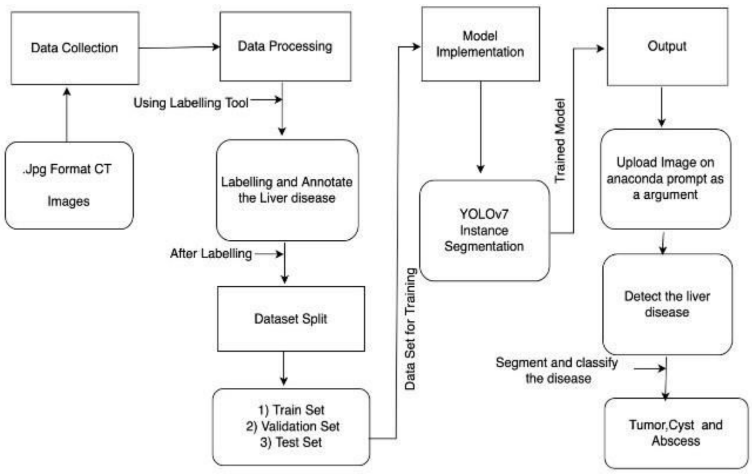

Fig. 2. System Architecture

Data Collection Module: The data collection module is responsible for gathering a diverse and representative dataset of liver CT images. This module may include mechanisms for retrieving anonymized patient data from hospital databases or acquiring publicly available datasets. It ensures that the dataset covers a wide range of liver diseases, including tumors, crst, and abscesses, to ensure the model's robustness and generalizability. The module should also handle data augmentation techniques to increase the dataset's size and diversity, which is crucial for training deep learning models effectively.

Preprocessing Module: The preprocessing module prepares the raw CT images for input into the model. This includes standardizing the image resolution, normalizing pixel intensities, and applying noise reduction techniques to improve image quality. The module may also include image registration and cropping to focus on the liver region, as well as contrast enhancement to highlight subtle features that are important for lesion detection. Preprocessing plays a crucial role in ensuring the model's performance and reducing noise and artifacts that couldaffect the segmentation results.

Model Implementation Module: The model implementation module involves the development and integration of the YOLOv7 instance segmentation model into the segmentation pipeline. This module includes loading the pre-trained YOLOv7 model architecture, adapting it for the liver lesion segmentation task, and integrating it with the data preprocessing and post-processing steps. The module may also include optimizations for efficient modelinference, such as model pruning or quantization, to reduce the computational complexity of the model and enablereal-time processing of CT images.

Output Module: The output module processes the model's segmentation results to generate meaningful outputs for clinical use. This includes converting the segmentation masks into binary masks for each lesion class, overlaying the masks onto the original CT images for visualization, and extracting quantitative metrics such as lesion volume and location. The module may also include mechanisms for storing and accessing the segmentationresults, such as saving the results to a database or exporting them to a standardized format for further analysis andreporting.

IV. RESULT ANALYSIS

Pre-processed CT images to enhance quality and standardize format.Trained the YOLOv7 model to identify and segment liver lesions into three classes.Validated the trained model on a separate dataset to assess segmentation accuracy, sensitivity, specificity, and other performance metrics. Used evaluation metrics such as IoU, DSC, precision, recall, and F1 score to quantify model performance. Aims to develop a robust and accurate deep learning-based

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approach for automated segmentation of liver lesions in CT images to improve efficiency and accuracy in liver disease diagnosis and treatment planning. All the metrics are calculated by using the formulae:

1. Accuracy = $\frac{TP\#Tn}{TP\#Tn\#FP\#Fn}$
2. Precision = $\frac{TP}{TP\#FP}$
3. Recall = $\frac{TP}{TP\#Fn}$
4. F1-Score = $\frac{\&*Precision*Recall}{Precision\#Recall}$

Performance Metrics for YOLOv7 Model:

Custom-1:

Metrics	Training Image	Validation Image
Box Loss	0.063941	0.014175
Segmentation Loss	0.0463195	0.00125
Object Loss	0.029995	0.0032
Classification Loss	0.0324763	0.00052
Precision(B)	0.359208	0.45443
Recall(B)	0.21004	0.42192
mAP_0.5(B)	0.084724	0.33924
mAP_0.5:0.95(B)	0.417244	0.33924
Precision(M)	0.422338	0.45443
Recall(M)	0.34435	0.42192
mAP_0.5(M)	0.19268	0.043486
mAP_0.5:0.95(M)	0.14394	0.033924

Custom-2:

Metrics	Training Image	Validation Image
Box Loss	0.03673	0.02183
Segmentation Loss	0.2751	0.01581
Object Loss	0.01431	0.00410
Classification Loss	0.00221	0.00668
Precision(B)	0.55970	0.63054
Recall(B)	0.56152	0.64752
mAP_0.5(B)	0.70644	0.74149
mAP_0.5:0.95(B)	0.57529	0.60142

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Precision(M)	0.55970	0.63054
Recall(M)	0.56152	0.64752
mAP_0.5(M)	0.73424	0.72860
mAP_0.5:0.95(M)	0.58828	0.60651

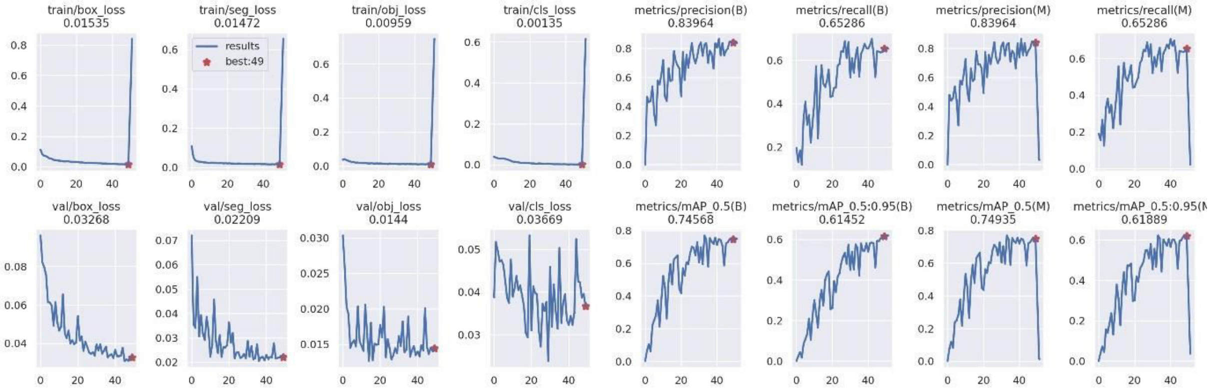

Fig.3. Results

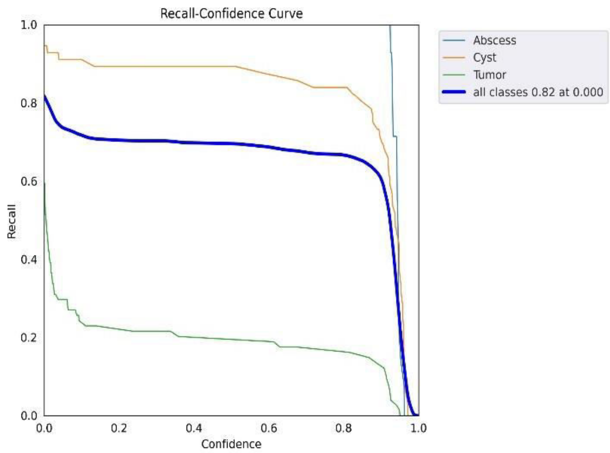

Fig.4.Recall-Confidence Curve

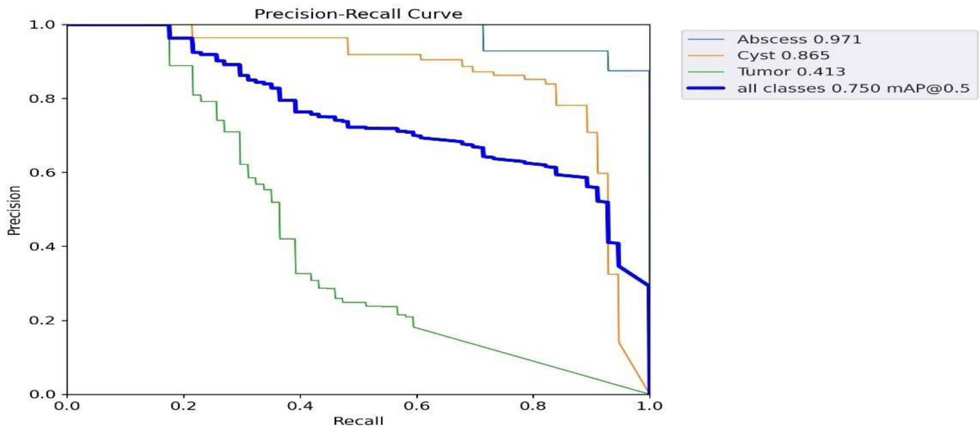

Fig.5. Precision- Recall Curve

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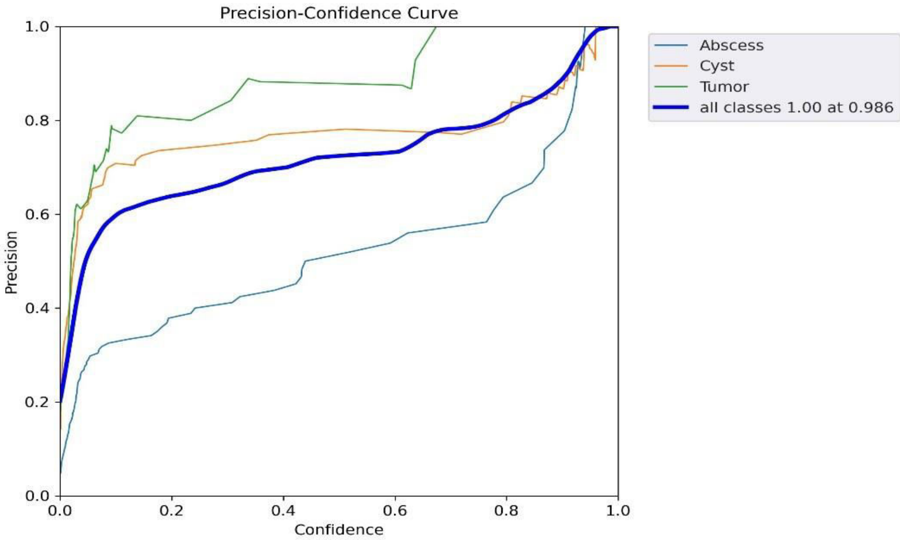

Fig. 6. Precision-Connfidence Curve

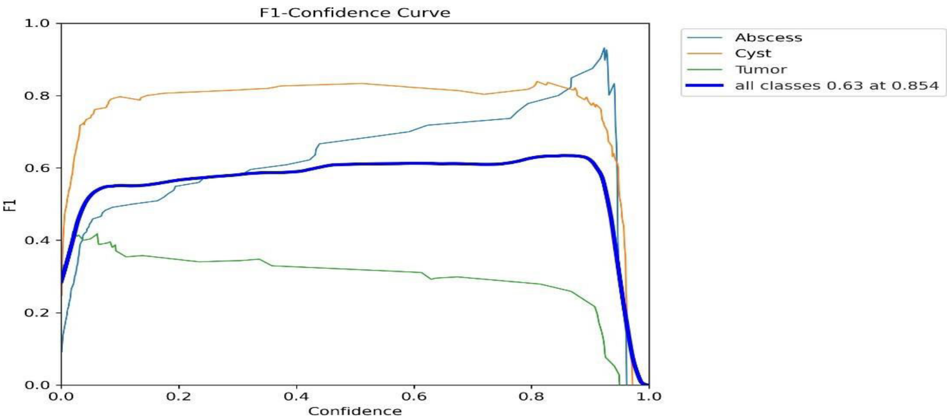

Fig.7. F1-Confidence Curve

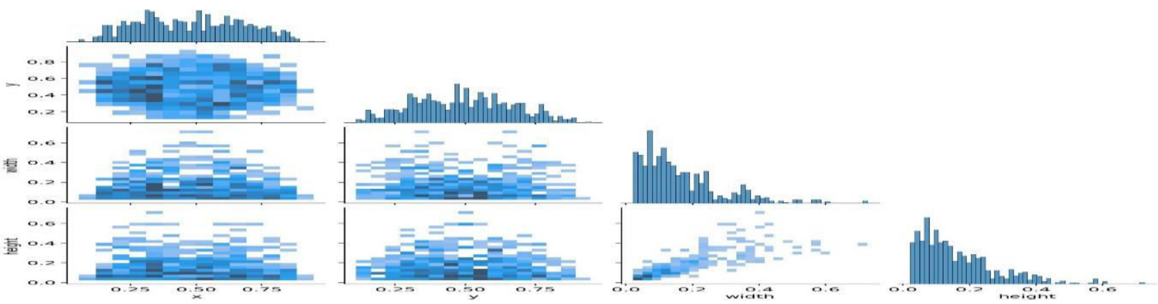

Fig. 8. Heights and Weights

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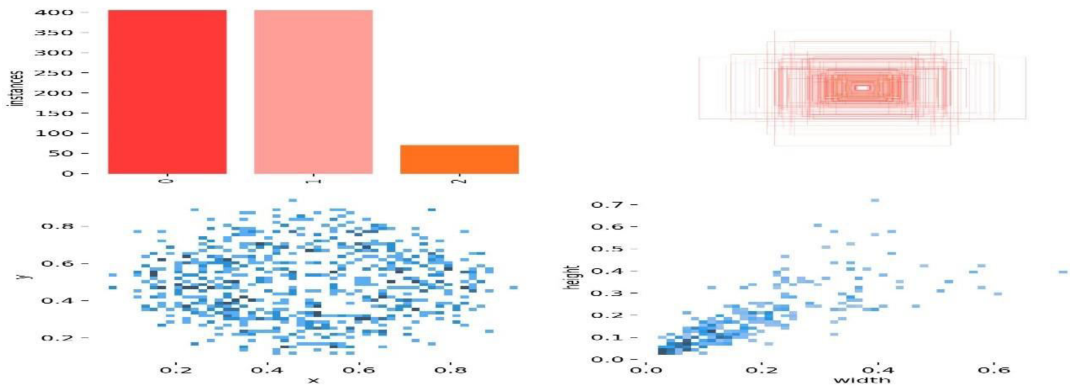

Fig. 9. Instance Segmentation

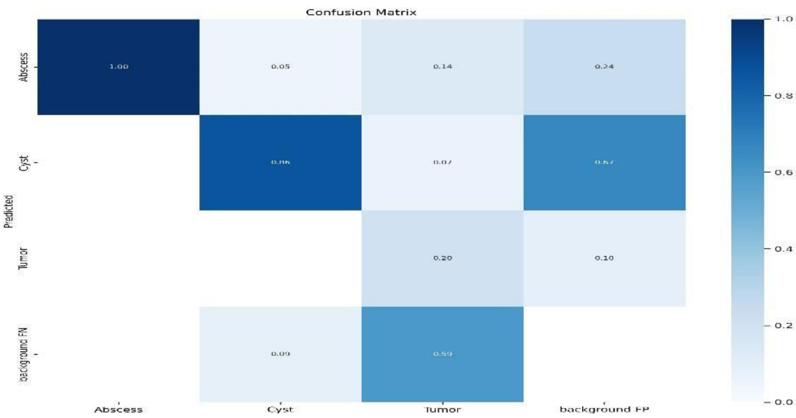

Fig.10. Confusion Matrix

In Bhojane, R., Chourasia, S., Laddha, S. V., & Ochawar, R. S.(2023), Unusual formations in the liver calledlesions can happen for a number of different reasons. Some are malignant, while others are non-cancerous. Timelydetection of the lesion and its treatment is necessary for malignant lesions. In this paper, attempt to detect liver lesions using state-of-the-art single-stage object detection technology YOLOv8. On two distinct datasets, each of which contained 38 MR T1 fused image samples and 41 CT samples. The model is first evaluated on both datasetsseparately and then evaluated by combining both datasets. The findings demonstrate that the model is capable ofaccurately and quickly detecting liver abnormalities. The model performs best on the MRI dataset with an average detection time of 62.96 ms with an accuracy of 83.6%. Our research aims to shed light on single-stage object detection models' unrealized potential in medical image analysis. The hope the findings contribute to developinga real-time tumor/lesion detection technology that gives accurate results in real time.

In Wu, Q., Zhao, L., Lin, C., & Zhao, G. (2020, November). Pre-processed CT images to enhance quality and standardize format.Trained the YOLOv7 model to identify and segment liver lesions into three classes. Validated the trained model on a separate dataset to assess segmentation accuracy, sensitivity, specificity, and other performance metrics. Used evaluation metrics such as IoU, DSC, precision, recall, and F1 score to quantify modelperformance. The YOLOv7 two distinct datasets, each of contained 80 MR T1 images and 28 fused samples. The model is evaluated by training and evaluation methods. The model performs best of the average detection time of 88.5 ms with an accuracy of 97% . The research aims to improve the efficiency and accuracy of liver diseasediagnosis and treatment planning using automate methods applied to imaging data.

The weights should be calculated of training images and validation images based on the Custom-1 and Custom-2 , The performance metrics was difference so much between training images and validation images.

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V. CONCLUSION

In conclusion, the proposed method for liver disease segmentation using YOLOv7 instance segmentation shows promise for improving the accuracy efficiency of liver lesion detection and classification in CT images. By leveraging the capabilities of YOLOv7, we can accurately localize and classify three classes of liver lesions (tumors, crst, and abscesses), providing detailed segmentation masks that can assist radiologists in making informed clinical decisions. The efficiency of YOLOv7 also enables real-time processing of CT images, potentially reducing the time and effort required for lesion segmentation. While further validation and testing are needed to assess the method's performance on a larger and more diverse dataset, our initial results suggest that the proposed method has the potential to significantly impact the field of liver disease diagnosis and treatment.

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