Liver cancer classification approach using Yolov8

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Abstract. Liver cancer is a common and often fatal disorder that is becoming more commonplace worldwide. An accurate and timely diagnosis is necessary for both effective treatment and patient survival. In machine learning techniques, particularly deep learning, obtaining a large and diverse dataset is still a challenge for deep neural network training, particularly in the medical industry. This paper presents a classification of circulating tumor cells based on the YOLOv8 algorithm. Tumor cell identification and classification can be achieved by utilizing the algorithm's multi-layer high-level stacking, weight sharing, local connection, and pooling characteristics. The goal is to design a liver cancer classification system that makes it easier and increases the efficiency of doctors in analyzing the results of liver cancer. The models show the absolute the accuracy is 100%,100%,98%,96% to Yolov8n, Yolov8s, Yolov8m, and Yolov8l respectively.

Keywords: Liver cancer classification, Deep Learning, YOLO, Yolov8, Liver CT.

1 Introduction

Computed Tomography (CT) scan image of the liver together with clinical symptoms and laboratory test results provide unbiased, trustworthy evidence for liver diseases that can be thoroughly examined. CT, Magnetic Resonance Imaging (MRI), and ultrasound are commonly used imaging modalities and are considered imaging examination mainstays Nevertheless, the images are assessed using the expert judgment of radiologists, which has low sensitivity and likely displays observer bias. It also takes a lot of effort and time to visually examine so many medical imaging. To solve this issue, Computer-Aided Diagnostic (CAD) systems incorporating computer vision (CV) and deep learning have been successfully created in recent years (1). These methods make imaging interpretation easier than manual segmentation and detection of the images. Compared to manual image classification and detection, these techniques facilitate imaging interpretation. Unlike traditional machines, the DL algorithm—the fundamental building block of artificial intelligence—is progressively applied in CAD, eliminating the need for manual modification. Learning techniques are usually not ideal for particular tasks and are mainly reliant on manually generated visual descriptors. To assist medical practitioners in diagnosing and treating a wide

range of medical disorders, accurate and effective classification algorithms are crucial. You Only Look Once (YOLO) is one such algorithm that has drawn a lot of interest (2). The computer vision community has given YOLO, an innovative, real-time, end-to-end classification and object recognition technique, a lot of attention. It employs a single neural network to estimate the objects' bounding boxes and class probabilities in an image. Because of this, YOLO speeds and can run in real-time on even a low-end GPU (3). In this study, we propose an end-to-end system that is based on the YOLO-based model to simultaneously detect and classify liver lesions into mass tumors or calcification. Below is a summary of the most important contributions of this study:

1. To use a new set of data from Baghdad Medical City's Radiology Institute in Iraq.
2. To employ four Yolov8 models, such as Yolov8n, Yolov8s, Yolov8m and Yolov8l, along with modifications to parameters models, to enhance results and accuracy.
3. To solve the problem of Classification and identification of liver cancer.

2 Related Works

This section reviews the literature that addressed the medical images classification based on YOLO. N. Baranwal et al in (4) have used a method that begins with the selection of the Region of Interest (ROI) in medical images using YOLOv7. This methodology integrates advanced computer vision, chaos theory, and data compression techniques to develop a comprehensive approach for securing and compressing medical images while ensuring efficient reconstruction. They obtained a mAP of 76.9%, F1 of 73.2%, Precision of 78.1%, and Recall of 68.5%. One of the challenges with this research is the robustness of the proposed method to variations in medical images, such as different modalities (e.g., X-ray, MRI, CT scans) and image qualities, is not extensively discussed. The research methodology in 2023 (5) involved the use of advanced techniques such as object detection algorithms and transfer learning to address the challenges associated with the early detection and diagnosis of lung cancer nodules. The dataset was prepared according to the YOLO v7 format, and three different types of input were used to check their influence on nodule detection results for Precision, Recall, and mAP@50, respectively: 74.20%, 74.78%, and 80.22% for YOLO v5, 82.68%, 74.72%, and 81.28% for YOLO v7, and 80.9%, 70.4%, and 78.3% for YOLO v8. The limitation of the research is that the dataset may not fully capture the diversity of lung nodules encountered in clinical practice. The study in (6) introduced the architecture of the YOLO-based model, the authors discussed the suggested fusion models approach, which likely involves combining the outputs of multiple models to improve the overall detection and classification performance. The obtained results showed that the detection accuracy rates on mass lesions were 95.7%, 98.1%, and 98%, and on calcification lesions, they were 74.4%, 71.8%, and 73.2%. G. Hamed al et al (7) has been demonstrated that using anchors in YOLO-V3 on both the original and enhanced versions of the data improves detection accuracy, particularly when k-means clustering is employed to create anchors that match the dataset

being utilized. based on YOLO-V3, the best results are achieved when 89.4% of the masses in the INbreast mammograms are detected, with an average precision of 94.2% and 84.6% for benign and malignant mass classification, respectively. ResNet and InceptionV3 are used in place of YOLO's classification network to achieve overall accuracy of 91.0% and 95.5%, respectively.

3 Materials and Methods

This section describes the dataset and preparation techniques used to improve the performance of Yolov8 and deep learning classifiers for the classification of liver cancer.

3.1 Data Description

The dataset was produced by the researchers using an ethically approved CT scan images from the Radiology Institute in Baghdad Medical City, Iraq. There are 1000 PNG images in the collection, each with an average resolution of 500 by 500 pixels. Three categories are created from the images: malignant (286 images), benign (464 images), and normal (250 images). The benign kinds are: Simpol cyst, hemangioma, and hydatid cyst types include CE1, CE3a, CE4, and CE5. Figure 1 shows a sample from each class.

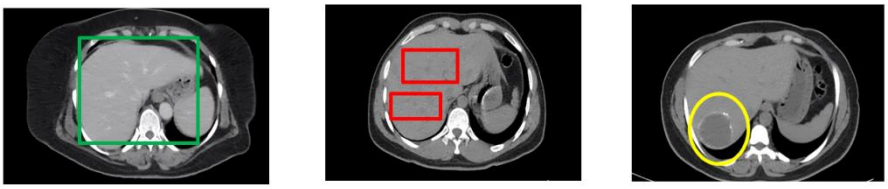

Fig. 1. (a) normal liver (b) malignant (c) benign(cyst)

3.2 Pre-processing

Image pre-processing is the first step toward displaying several significant image features for subsequent usage. The steps utilized in the first phase are described in depth in the following subsections:

- Augmentation

Increasing the dataset and altering the images in various ways is augmentation, sometimes referred to as data transformations, a common pre-processing technique that enables the network to recognize a wider variety of information. This method effectively grows the dataset by decreasing the likelihood of overfitting. Scaling, rotation, and other comparable modifications are commonly employed in Imagine (8). Through the expansion of datasets and the provision of multiple visual versions for neural networks, the augmentation technique increases the probability that the model will iden-

tify objects of any shape. It is also important to mention that the number of images before the operation increased from 1000 to 3125 consisting of malignant (1041 images), benign (1202 images), and normal (909 images).

- Normalization

It is one of the processes used for pre-treatment. The normalization process is necessary to make all sample values fall within the range of pixel (from 0 to 255), which is used for normalization purposes (9). Normalize (min, max) is used to achieve normalization purposes lightly on the data and prevent distortion of the data. The normalization process was performed using the following formula:

$$v = \frac{\text{vi} - \text{Min(vi)}}{\text{Max (vi)} - \text{Min (vi)}} \quad \text{i} = 1,2 \qquad (1)$$

Where Vi is a specific value of the v variable for the i^{th} instance. Max and min represent the Maximum and Minimum values of the column and row direction.

- Image Resize

This work involves reading each image as an RGB image with three channels, resizing each to the desired size (256 x 256), finding contours in the threshold image, selecting the largest one, finding the extreme points in the largest contour, cropping the image using the extreme points, and resizing it to the desired size.

- Non Local Mean filter

Non-local means is a technique used in image processing for image denoising. Unlike "local mean" filters that use the mean value of a collection of pixels surrounding a target pixel to smooth the image, non-local means filtering takes the mean of all the pixels in the image, weighted by how similar these pixels are to the target pixel.

3.3 Splitting data

Two sets of the dataset have been split: one for testing and the other for training. The model's efficacy is evaluated using the validation set of tests. Testing accounted for 30%, and training for 70%. The splitting ratio is the best value that is obtained by numerous ratio tests.

3.4 You Only Look Once (YOLO)

YOLOv8 is the most recently highly classified real-time model version for image categorization and object detection (10) (11). With unmatched speed and accuracy, YOLOv8 is based on state-of-the-art deep learning and computer vision developments. Figure 2 shows the yolov8s architecture that was used in this paper (12) (13).

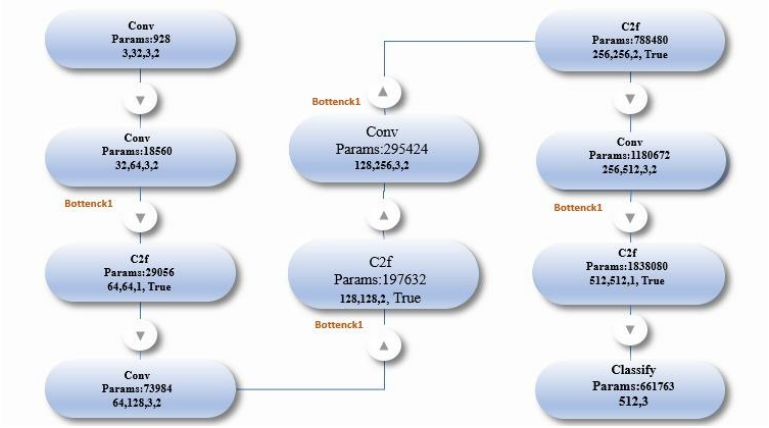

Fig. 2. Architecture Yolov8s (12)

4 Results

The YOLO for liver cancer disease diagnosis is assessed after each epoch. Four models were utilized to identify and classify the distinctive features in each liver image Yolov8 (Nano), Yolov8 (Small), Yolov8 (Medium), and Yolov8 (Large). Yolov8 has shown outstanding effectiveness in classifying liver cancers, as indicated by Table 1, which displays the details of each model and the accuracy attained. Figures 3,4,5 and 6 show the performance metrics for the Yolov8n (Nano), Yolov8s (small) Yolov8m (Medium) and Yolov8l (Large).

Table 1: The results of Yolov8

Models	Layers	Parameters	GFLOPs	Accuracy
Nano Model	99 layers	1442131 gradients	3.4 GFLOPs	100%
Small Model	99 layers	5084579 gradients	12.6 GFLOPs	100%
Medium Model	141 layers	15776179 gradients	41.9 GFLOPs	98%
Large model	183 layers	36203587 gradients	99.1 GFLOPs	96%

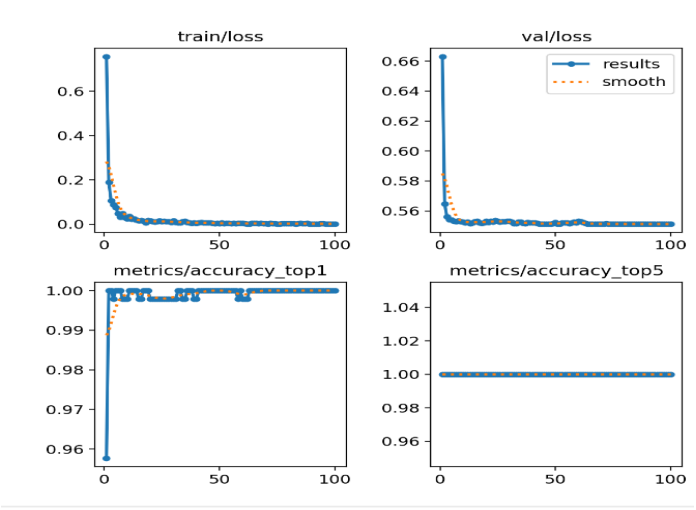

Fig. 3. The Yolov8n Performance Metrics

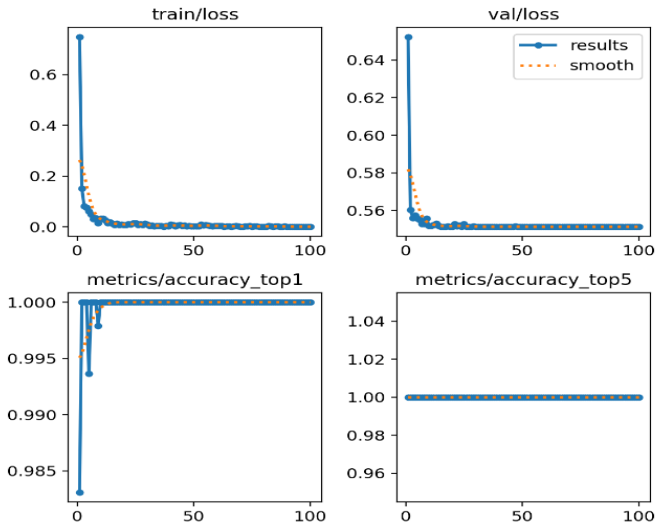

Fig. 4. The Yolov8s Performance Metrics

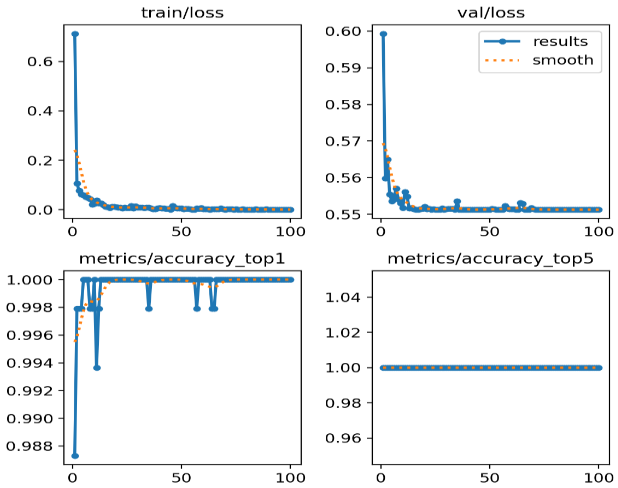

Fig. 5. The Yolov8m Performance Metrics

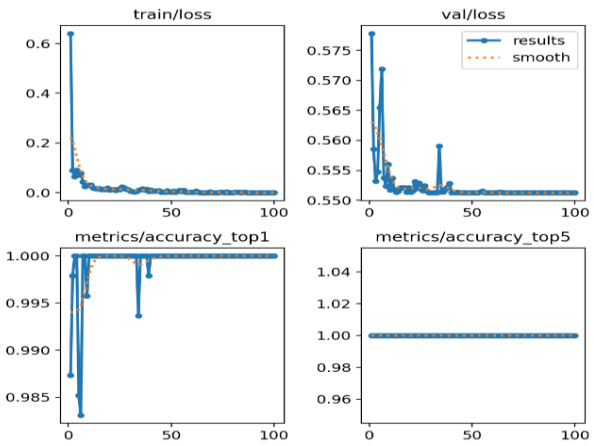

Fig. 6. The Yolov8l Performance Metrics

5 Comparing the YOLO8 algorithm with fuzzy logic approaches and other works

The results of the suggested methodology have been compared with the related works, as shown in Table 2, proving the effectiveness of the methods used. In terms of accuracy, Nano Model achieved 100%, while the Small Model achieved 100%, the Medium Model achieved 98%, and finally, the large model achieved 96%.

Table 2: Comparing the YOLO8 algorithm with fuzzy logic approaches and other works

Model	Accuracy
Fuzzy expert system (FES) (14)	89.93%
Fuzzy-GA (15)	93.82%
Neural network (16)	83.50%
Fuzzy-DE (17)	99.24%
Proposed Nano Model	100%
Proposed Small Model	100%
Proposed Medium Model	98%
Proposed Large Model	96%

6 Conclusions and future work

A lot of lives could be saved by medical assistance made possible by deep learning and computer vision. This motivation led to the use of Yolov8 in deep learning in this paper for the investigation of the liver cancer. This paper employs a collection of procedures to identify liver cancer by assessing the effectiveness of YOLO in deep learning using Yolov8n, Yolov8s, Yolov8m, and Yolov8l. The proposed models using transfer learning (Yolov8n, Yolov8s, Yolov8m, and Yolov8l) obtained an accuracy of 100%, 100% and 98%, 96%, as it turns out modern research techniques can successfully handle diagnosing issues for physicians. Data augmentation improved the number of training data that was available throughout the training phase, which helped the suggested model to avoid the overfitting issue. For future work and based on what we have observed in the outcomes of prior studies and our own discoveries, we are trying to implement continuous deep learning, a novel and significant area of research for medical diagnosis, because it allows data to be updated continually without forgetting the previous datasets.

References

1. Selma, M Mohamed, A et al.: Early detection and diagnosis of lung cancer using YOLO v7, and transfer learning. Multimedia Tools and Applications (2023): 1-16
2. Asma, B Begonya Garcia, Z et al.: Breast Lesions Detection and Classification via YOLO-Based Fusion Models. Computers, Materials & Continua (2021): 69.1.

3. Fatimah I. Abdulsahib, Belal Al-Khateeb et al. A transfer learning approach for the classification of liver cancer Journal of Intelligent Systems 2023; 32: 20230119 (2023).
4. Hasna, F Hilal, H et al.: Real Time-based Skin Cancer Detection System using Convolutional Neural Network and YOLO. International Conference on Computer and Informatics Engineering (IC2IE) (2021): (pp. 152-157). IEEE.
5. Qureshi, Rizwan, et al.: A Comprehensive Systematic Review of YOLO for Medical Object Detection (2018 to 2023)." Authorea Preprints (2023).
6. Ghada, H Mohammed, M et al. YOLO based breast masses detection and classification in full-field digital mammograms. Computer methods and programs in biomedicine (2021): 105823.
7. Yongye, S Qian, L et al.: YOLO-LOGO: A transformer-based YOLO segmentation model for breast mass detection and segmentation in digital mammograms. Computer Methods and Programs in Biomedicine (2022): Jun 1; 221:106903.
8. Cubuk, E. D., Zoph, B., Mane, D., Autoaugment: Learning augmentation strategies from data. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (2019): (pp. 113-123).
9. Lima, F. T., Souza, V. M. (2023). A large comparison of normalization methods on time series. Big Data Research (2023): 34, 100407.
10. Maryam, H Denis, F et al.: Cycle GAN-based data augmentation for multi-organ detection in CT images via Yolo. IEEE international conference on image processing (ICIP) (2020): p. 390-393.
11. L, Xin et al. Learning an Improved Object Detection Approach Based on the YOLO Algorithm to Identify Circulating Tumor Cells. (2022).
12. Bader, A Farzeen, A et al. Yolo-based deep learning model for pressure ulcer detection and classification. Healthcare. MDPI, (2023): p. 1222.
13. Ma, Mingyang, and Huanli Pang. "Sp-yolov8s: An improved yolov8s model for remote sensing image tiny object detection." *Applied Sciences* 13, no. 14 (2023): 8161.
14. AmirHosseini B, Hosseini R, Mazinani M . A hybrid fuzzy GA approach applied to an expert system for diagnosis of liver tumor. J Soft Comput Inform (2017) 5:45–52.
15. Amirhosseini B, Hosseeini R, Mzinani M An MLP neural network andfuzzyinferecence system fordiagnosis ofmetastasis in liver, first international conference on new research achievements in electrical and computer engineering, (2016) 1–10.
16. Si T, Hazra S, Jana ND Artificial neural network training using differential evolutionary algorithm for classification. Adv Intell Soft Comput (2012) 132:769–778
17. AmirHosseini, B., & Hosseini, R. An improved fuzzy-differential evolution approach applied to classification of tumors in liver CT scan images. *Medical & Biological Engineering & Computing*, (2019) *57*(10), 2277-2287.