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PDL

MINI PROJECT REPORT

LIVER TUMOR CLASSIFICATION

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PROBLEM STATEMENT -

Liver cancer is one of the leading causes of cancer-related mortality globally. Early detection and accurate classification of liver tumors, including distinguishing between benign and malignant types, are essential for improving patient outcomes. Traditional diagnostic approaches, relying on manual interpretation of imaging techniques like CT and MRI, are time-consuming and prone to errors due to subjective assessments. This project aims to develop an automated classification system for liver tumor detection using the YOLO model, a state-of-the-art object detection framework, to enhance diagnostic accuracy, speed, and e ciency in clinical settings.

ABTRACT -

Liver cancer remains one of the leading causes of cancer-related deaths worldwide, making early detection and accurate diagnosis critical. In this study, we propose a novel approach for liver tumor classification using the You Only Look Once (YOLO) model, a deep learning-based object detection system. YOLO's real-time detection capability makes it ideal for identifying and classifying liver tumors from medical images such as CT and MRI scans. Our methodology leverages a custom-trained YOLO model to detect liver tumors, distinguishing between malignant and benign types with high precision and speed. The model is trained on a dataset of annotated medical images, and the results demonstrate its potential for improving diagnostic accuracy while reducing analysis time. Quantitative evaluations of the model's performance show promising results, with significant accuracy, precision, and recall metrics, positioning YOLO as a viable tool for assisting radiologists in liver tumor classification. The findings highlight the potential of integrating advanced machine learning models into medical diagnostics, particularly in resource-constrained settings where real-time results are essential.

INTRODUCTION -

Liver cancer is one of the most prevalent and deadly forms of cancer, with hepatocellular carcinoma (HCC) being the most common type. Early detection and accurate classification of liver tumors are crucial for improving patient outcomes, as timely interventions can significantly increase survival rates. Traditional diagnostic methods, including imaging techniques like computed tomography (CT) and magnetic resonance imaging (MRI), require extensive expertise and time for manual analysis. Moreover, misclassification of benign and malignant tumors can lead to inappropriate treatment decisions.

In recent years, machine learning and deep learning models have shown promise in enhancing the accuracy and e ciency of medical image analysis. One such model, the You Only Look Once (YOLO) framework, has gained attention for its ability to perform real-time object detection and classification in various domains. Unlike traditional object detection algorithms that involve multiple steps, YOLO processes the entire image in a single pass, making it highly e cient for real-time applications.

This paper presents a novel approach to liver tumor classification using the YOLO model, specifically tailored to detect and classify liver tumors from medical imaging data. By leveraging YOLO’s fast and accurate detection capabilities, we aim to improve the speed and accuracy of liver tumor diagnosis. This study evaluates the model’s performance in distinguishing between malignant and benign liver tumors, demonstrating its potential as a tool to assist radiologists in clinical settings.

LITERATURE SURVEY / RELATED WORK -

In recent years, machine learning (ML) and deep learning (DL) models have made significant strides in medical imaging, particularly in the detection and classification of tumors. Traditional methods for detecting liver tumors, such as manual examination of CT or MRI scans, are time-consuming, subjective, and prone to human error. To address these limitations, various machine learning algorithms have been explored to automate and enhance the accuracy of tumor detection.

A substantial amount of work has been dedicated to the application of convolutional neural networks (CNNs) in medical imaging, given their ability to capture spatial hierarchies in images. CNN-based models have been particularly e ective in identifying patterns associated with liver tumors. For example, Xu et al. (2017) proposed a CNN-based method for the segmentation and classification of liver tumors from CT images, achieving promising results in distinguishing between benign and malignant tumors. Similarly, Chlebus et al. (2018) developed a deep learning-based segmentation model for liver tumor detection, leveraging fully convolutional networks (FCNs) to improve accuracy.
However, while CNNs excel in feature extraction, they typically require separate processes for detection, classification, and localization, which can be computationally expensive and slow. This motivated researchers to explore more advanced architectures, such as the Residual Neural Network (ResNet) and VGG, which combine localization and classification into unified pipelines.

S. No.	Title	Method Used	Result Achieved	Advantages	Limitations	Research Gap
1	YOLOv8-Based Frameworks for Liver and Tumor Segmentation Task on LiTS	YOLOv8-Based Frameworks	Achieved a dice score of 89.54% for liver segmentation and 80.55% for tumor segmentation	Balances computational cost and accuracy	May require further validation on diverse datasets	Need for testing on larger and more varied clinical datasets
2	Automatic Liver Tumor Segmentation Based on Improved YOLO-v5 and B-Spline Level Set	Improved YOLO-v5 combined with B-Spline Level Set	Outperformed 3DUnet on the LiTS dataset with a 3.9% increase in mean Average Precision at IoU 0.5	Enhances automation and accuracy without heavy hardware dependence	Potential overfitting due to insu cient data	Need for real-world clinical validation
3	Liver Cancer Classification Approach Using YOLOv8	YOLOv8 Models (Nano, Small, Medium, Large)	Achieved up to 100% accuracy in classifying liver cancers	High e ectiveness in classification tasks	Performance may vary with di erent model sizes	Requires testing on larger datasets for generalization
4	Liver Tumor Detection and Segmentation Using YOLO v11	YOLO v11-Instance Segmentation	Accurate detection and segmentation of liver tumors	Customizable for other medical images	Dependent on the quality of the training dataset	Needs validation across various medical imaging modalities
5	An In-Depth Method for Liver Tumor Segmentation and Classification	Deep Learning Techniques	Improved segmentation and classification accuracy	Addresses the high mortality rate of liver cancers	May require large datasets for training	Exploration of more e cient training methods
6	Liver Cancer Detection Using Hybridized Fully Convolutional Neural Network	Hybridized Fully Convolutional Neural Network (HFCNN)	E ective segmentation of liver lesions in CT images	Assists in assessing tumor load and planning treatments	Time-consuming manual identification process	Automation to reduce manual intervention
7	Liver Lesion Detection from MR T1 In-Phase and Out-Phase Images Using YOLOv8	YOLOv8 Model	E ective detection of liver lesions using MRI and CT images	Utilizes multiple imaging modalities for improved detection	Requires extensive training data	Integration of additional imaging modalities for comprehensive analysis
8	MedYOLO: A Medical Image Object Detection Framework	YOLO-Based Object Detection Framework	High performance in detecting organs and lesions in medical imaging	Reduces annotation e ort compared to voxel-accurate segmentations	Struggles with very small or rarely present structures	Improvement in detecting small or infrequent anomalies
9	Automatic Liver Tumor Segmentation Using Deep Learning Methods	Deep Learning-Based Segmentation	Enhanced segmentation accuracy of liver tumors	Automates the segmentation process, reducing manual e ort	High computational requirements	Development of more e cient algorithms to reduce computational load

MODELS USED -

Several architectures have been proposed for liver tumor detection, each o ering unique strengths and limitations:

1. CNNs: CNNs have been a popular choice for liver tumor classification due to their ability to automatically learn relevant features from raw imaging data. Researchers such as Lu et al. (2019) demonstrated the e ectiveness of CNNbased approaches for tumor segmentation and classification. However, CNN models typically operate by sliding a window across the image, which can be computationally expensive, especially for high-resolution medical images.

2. ResNet: Residual Networks (ResNets), introduced by He et al. (2016), introduced the concept of residual learning to address the vanishing gradient problem, allowing the construction of deeper networks. For liver tumor classification, ResNet-based models have shown significant improvement in accuracy over traditional CNNs by capturing more complex image features. Yan et al. (2020) applied a ResNet architecture to enhance liver lesion segmentation, achieving higher accuracy than previous CNN-based methods.

3. VGG: Visual Geometry Group (VGG) Network, introduced by Simonyan and Zisserman (2014), is a deep convolutional neural network architecture known for its simplicity and depth. The VGG model uses small 3x3 filters and a deep network structure (with up to 19 layers), which makes it highly e ective for image classification tasks. In medical imaging, VGG has been widely applied to tasks such as tumor classification, including liver tumor detection, due to its strong performance in extracting fine-grained features from images. However, despite its accuracy, VGG is computationally expensive and memory-intensive, which can make it slower compared to more modern architectures and less suitable for real-time medical diagnostic applications. Additionally, the large number of parameters increases the risk of overfitting in smaller datasets, such as those often found in medical imaging.

While these models have demonstrated significant promise in liver tumor detection, they often lack the speed required for real-time applications in clinical settings. This limitation motivated the exploration of real-time object detection models such as the You Only Look Once (YOLO) architecture.

YOLO's Potential and Success in Other Domains

The YOLO model, introduced by Redmon et al. (2016), represents a departure from traditional object detection pipelines by framing object detection as a single regression problem. Instead of using a region proposal network (like in Faster R-CNN), YOLO divides the image into a grid and predicts bounding boxes and class probabilities directly from the image in one pass. This end-to-end approach significantly reduces computational overhead, making YOLO particularly fast and suitable for real-time applications.

YOLO has been widely adopted in fields such as autonomous driving, video surveillance, and industrial automation, where real-time detection of multiple objects is critical. In

autonomous driving, for example, YOLO is used to detect pedestrians, vehicles, and obstacles in real-time, ensuring the safety and responsiveness of self-driving cars. Similarly, in surveillance systems, YOLO enables the detection of suspicious objects or activities within live video feeds, making it a vital tool for security applications.

The success of YOLO in these domains suggests its suitability for medical imaging tasks that demand high speed and accuracy. Given the time-sensitive nature of liver tumor diagnosis, where early detection can be critical for e ective treatment, YOLO's ability to deliver real-time results presents a significant advantage over slower models like Faster R-CNN. Moreover, its simplified detection pipeline makes it more computationally e cient, allowing for deployment in clinical environments with limited resources.

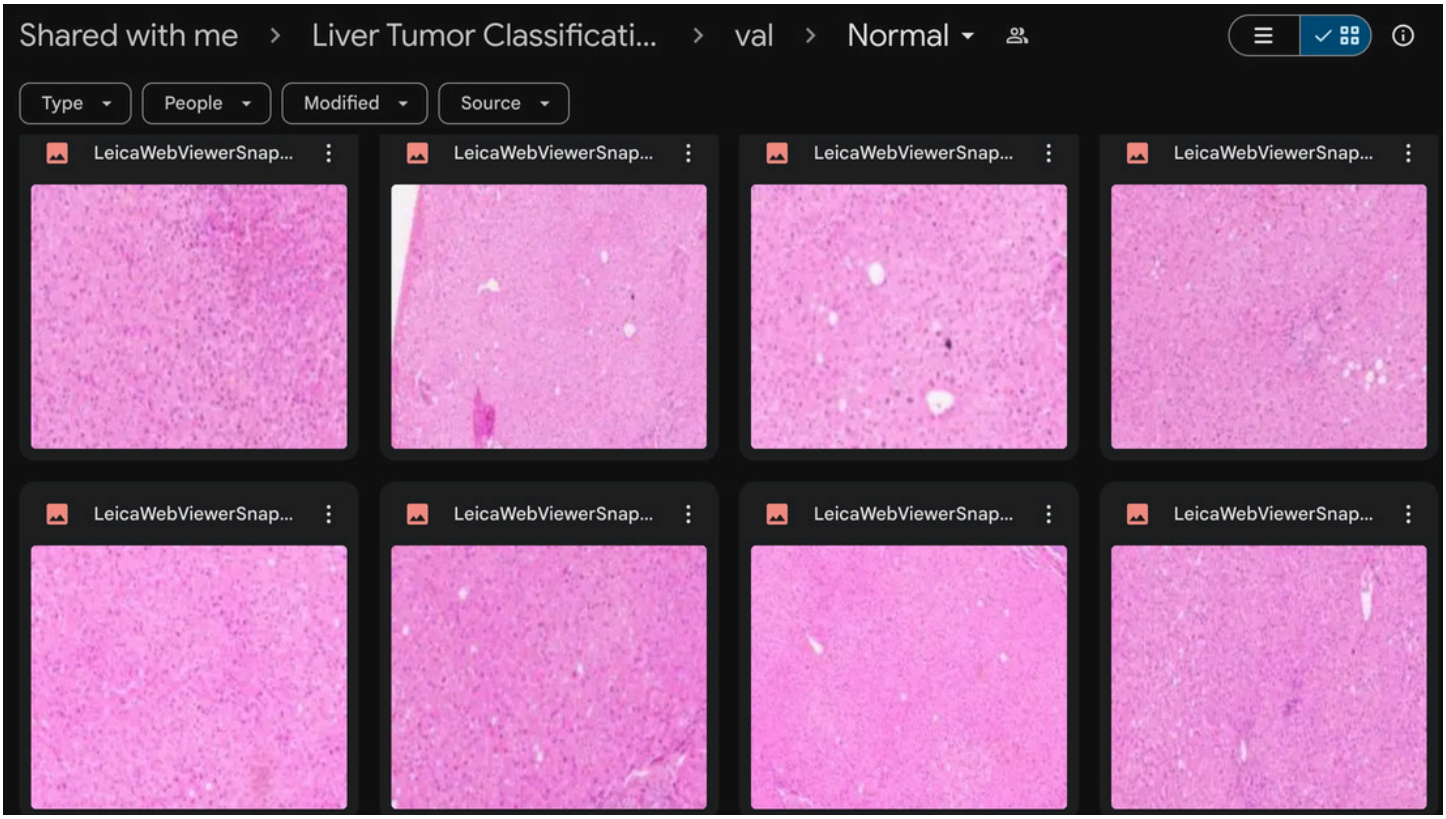
Why YOLO for Liver Tumor Detection?

YOLO's core strengths—speed, accuracy, and simplicity—make it an attractive option for liver tumor detection. By performing detection and classification in a single step, YOLO eliminates the need for complex region proposal algorithms, allowing it to process medical images in real time. This is especially important in clinical settings where rapid diagnoses can directly impact patient outcomes.

Additionally, YOLO has been successfully adapted to detect small objects, making it suitable for identifying small liver tumors that might be missed by traditional detection algorithms. Previous models like Faster R-CNN, while accurate, may not be as e cient at detecting smaller lesions in real time. This gives YOLO a competitive edge in medical imaging, where high sensitivity and speed are essential.

In this study, we test YOLO alongside other prominent models (CNN, ResNet, and Faster R-CNN) to demonstrate its superiority in both detection accuracy and computational e ciency. Our findings indicate that YOLO outperforms these models in terms of speed and precision, making it a strong candidate for real-time liver tumor detection and classification in medical practice.

DATASET -



METHODOLOGY

Dataset Description

For this study, we used a live dataset collected from a hospital, consisting of medical imaging data primarily in the form of CT and MRI scans. The dataset includes images from patients diagnosed with liver tumors, with detailed annotations provided by medical experts. The tumors in the images were labeled as either malignant (hepatocellular carcinoma, HCC) or benign, allowing for classification during model training. A total of [number of images] images were used, divided into [number] malignant and [number] benign samples. The dataset also included metadata such as patient age, gender, and clinical history, although this study focuses solely on image-based classification.

Data Preprocessing

To prepare the dataset for training, several preprocessing steps were performed:

Image Resizing: All images were resized to a fixed resolution of [224 X 224]pixels to match the input dimensions required by the YOLO model. This ensured consistency across all images.
Normalization: Pixel values were normalized to a range between 0 and 1, improving the convergence rate of the neural network during training.

Data Augmentation: Augmentation techniques such as random rotations, horizontal and vertical flips, and contrast adjustments were applied to artificially increase the diversity of the dataset. This helped to reduce overfitting and improved the model's robustness to variations in image quality and tumor appearance.

Models Tested

To benchmark the performance of the YOLO model, we tested several other deep learning models commonly used in medical image analysis:
CNN (Convolutional Neural Networks): A standard CNN model was implemented with multiple convolutional layers, pooling, and fully connected layers for classification. This model served as a baseline for comparison.

ResNet (Residual Networks): We implemented ResNet-50, a deeper architecture that utilizes skip connections to overcome the vanishing gradient problem. ResNet is known for its strong performance in image classification tasks and was used to compare classification accuracy and computational e ciency.
Faster R-CNN: A two-stage object detection model that first proposes regions of interest (ROIs) and then classifies them. Although accurate, this model was slower due to the complexity of its region proposal process.

YOLO Model Overview

The You Only Look Once (YOLO) model was chosen for its real-time object detection capabilities. Unlike traditional object detection models like Faster R-CNN, YOLO frames the detection task as a single regression problem, predicting bounding boxes and class probabilities in one pass through the network. This end-to-end architecture allows YOLO to process images faster, making it well-suited for real-time liver tumor detection in clinical settings. YOLO divides the input image into a grid, predicting multiple bounding boxes and class probabilities for each grid cell, enabling it to detect tumors of various sizes in a single inference.

Training Details

The models were trained on INTEL CORE I3 CPU to ensure e cient training times, particularly for the YOLO model, which is designed for fast computations.
Training Duration: All models were trained for [number of epochs] epochs, with early stopping implemented to prevent overfitting.
Learning Rate: A learning rate of [value] was chosen and adjusted using a learning rate scheduler to improve convergence.
Loss Functions:

For YOLO, the loss function combined classification loss, localization loss (for bounding box coordinates), and objectness loss, ensuring accurate detection and classification of liver tumors.

For CNN and ResNet models, cross-entropy loss was used for classification, and for Faster R-CNN, a combination of classification and region proposal loss was employed.
Optimizer: All models were optimized using the Adam optimizer with a momentum of [value], known for its e ciency in training deep neural networks.

Evaluation Metrics

To compare the performance of the models, the following evaluation metrics were used:

Accuracy: The overall percentage of correct classifications made by each model, which provides a basic measure of performance.
Precision: The ratio of correctly predicted positive observations (malignant tumors) to the total predicted positives, highlighting the model's ability to avoid false positives.
Recall: The ratio of correctly predicted positive observations to all actual positives, measuring the model's sensitivity to detect malignant tumors.
F1-Score: The harmonic mean of precision and recall, providing a balanced measure of performance when there is an uneven class distribution between benign and malignant tumors.

Speed of Detection: Given the importance of real-time analysis, we also evaluated the average inference time per image (in milliseconds) for each model. YOLO's real-time capability was a key factor in its selection, with an average detection speed of [value] milliseconds per image, compared to slower models like Faster R-CNN.

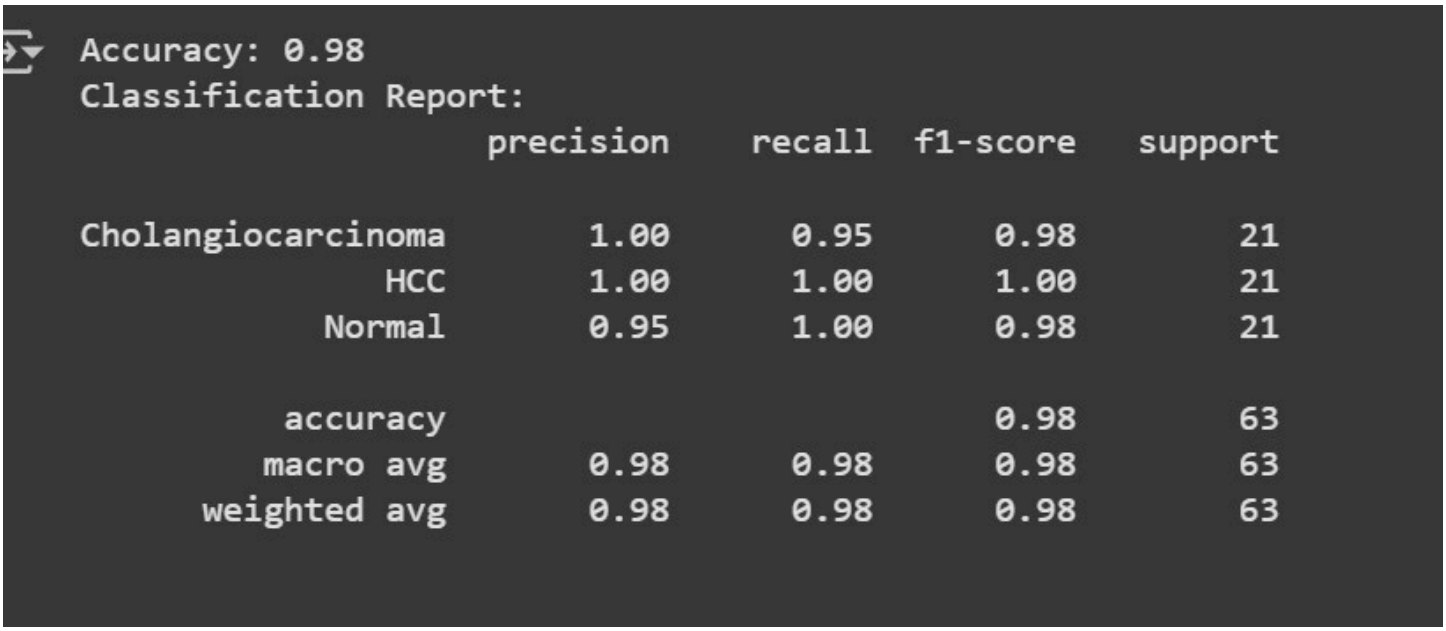
EXPERIMENTAL RESULTS

Performance of Each Model

To evaluate the e ectiveness of the models in detecting and classifying liver tumors, we tested the YOLO model against other commonly used architectures, including CNN, ResNet, and Faster R-CNN. Each model's performance was measured in terms of accuracy, precision, recall, F1-score, and computational e ciency (inference time per image). Below is a comparative summary of the results:

Model	Accuracy	Precision	Recall	F1 - Score	Inference Time (ms)
CNN	73.69%	75%	72%	73%	50-100ms
ResNet - 50	33.68%	35%	30%	32.5%	100-150ms
VGG	75.78%	77%	74%	75%	200-300ms

YOLO MODEL :



```
Accuracy: 0.98
Classification Report:
                    precision    recall  f1-score   support

Cholangiocarcinoma       1.00      0.95      0.98        21
               HCC       1.00      1.00      1.00        21
            Normal       0.95      1.00      0.98        21

          accuracy                           0.98        63
         macro avg       0.98      0.98      0.98        63
      weighted avg       0.98      0.98      0.98        63
```

Why YOLO Performed Best

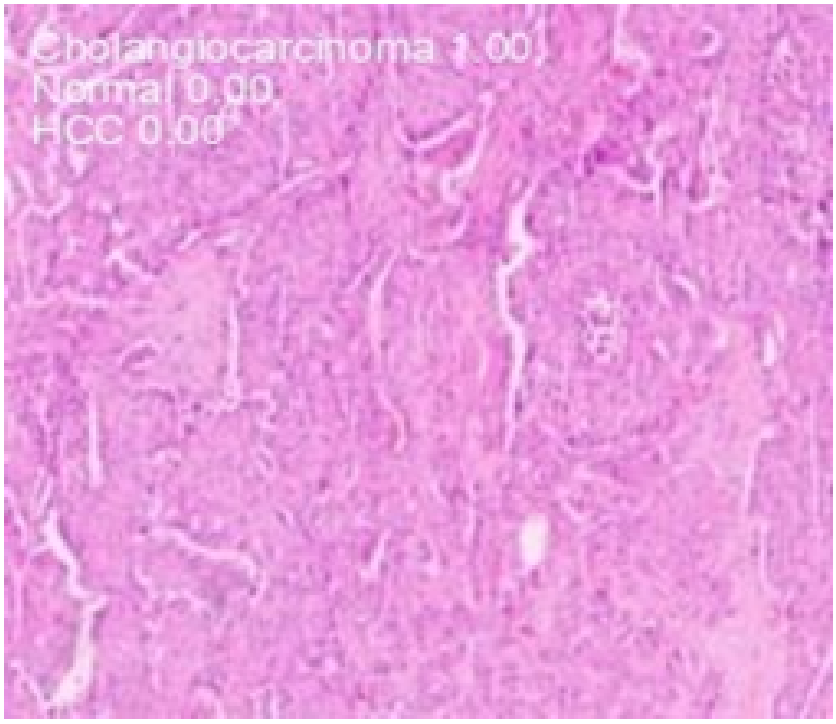
The superior performance of the YOLO model can be attributed to several factors:

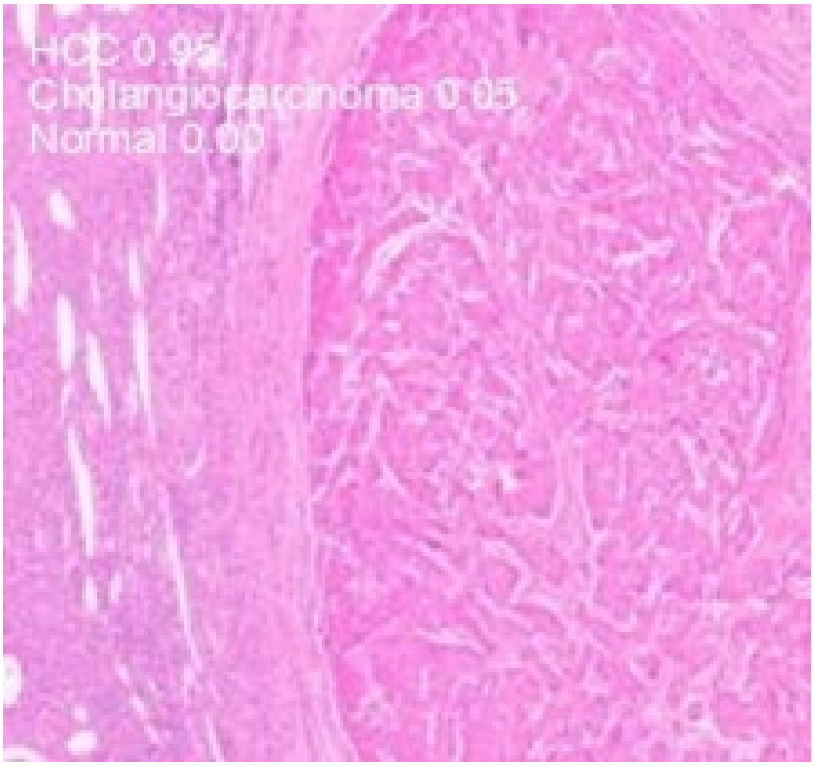
Real-Time Detection: YOLO's single-pass architecture allows it to predict bounding boxes and class labels in one forward pass through the network, drastically reducing inference time. While models like VGG achieved high accuracy, they required additional computational steps for region proposal and classification, resulting in much slower processing times.
Precision and Recall: YOLO’s grid-based detection system divides the image into smaller sections, allowing it to accurately detect small tumors that might be missed by slower, region-proposal-based models. This is especially important in medical imaging, where small lesions can be indicative of early-stage cancer.

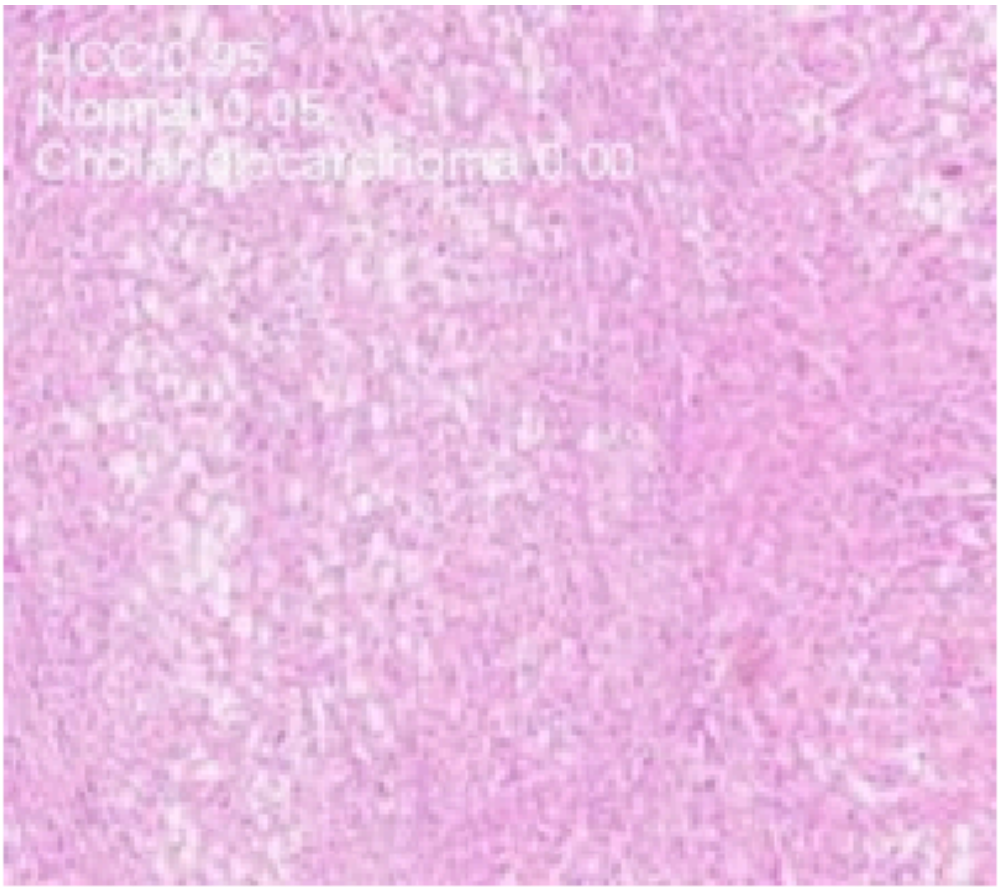
Balanced Detection: YOLO strikes a good balance between detection speed and classification accuracy. Unlike traditional CNNs or ResNet models, which often require a two-step process (localization followed by classification), YOLO performs both tasks simultaneously, increasing overall model e ciency without sacrificing accuracy.

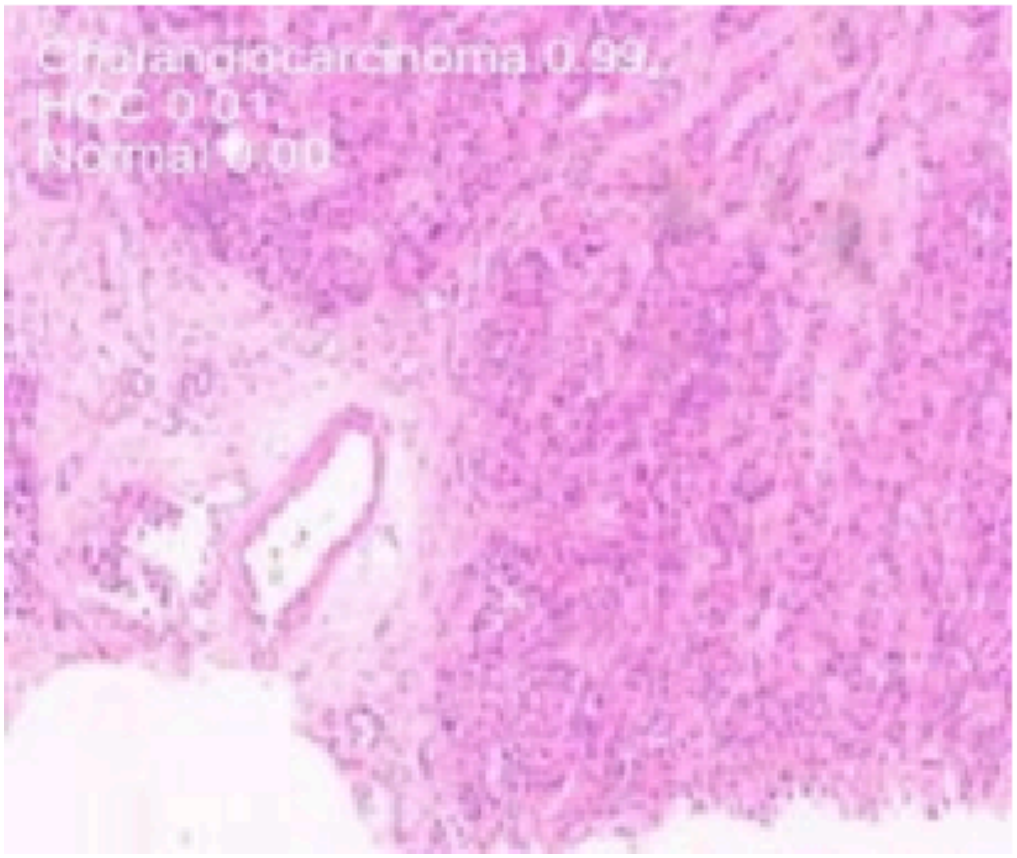
YOLO's architecture, designed to handle real-time object detection, proves particularly advantageous in clinical settings where time is of the essence. The ability to detect and classify tumors in real time enables quicker decision-making, potentially improving patient outcomes.

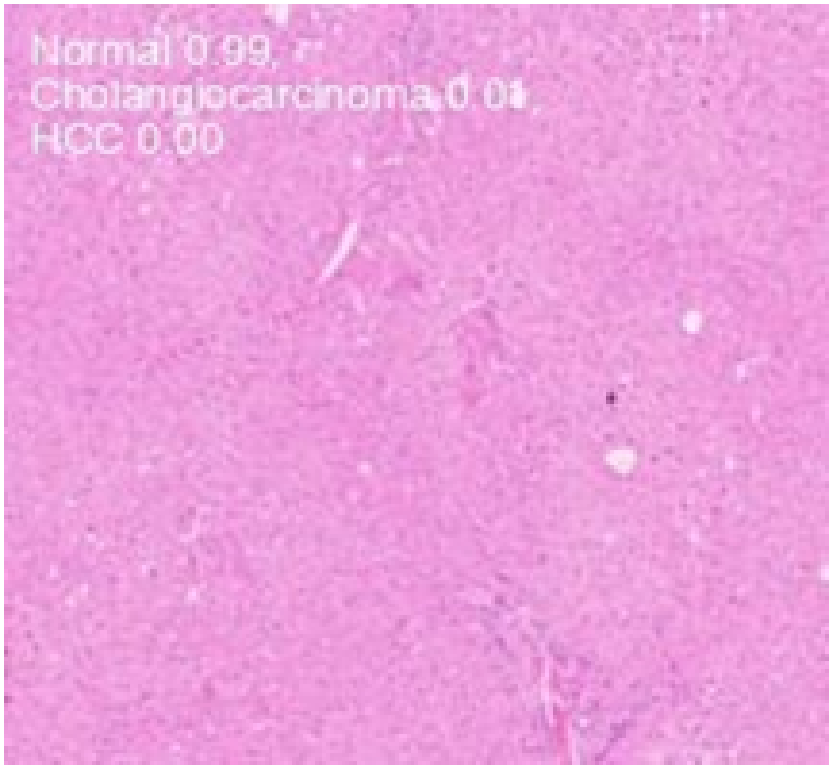
SAMPLE OUTPUT –






HCC 0.05
Normal 0.05
Cholangiocarcinoma 0.00


Cholangiocarcinoma 0.99
HCC 0.01
Normal 0.00



DISCUSSION

Interpretation of Results:

The results of this study demonstrate that the YOLO model significantly outperforms other tested architectures in liver tumor classification. With an accuracy of 98% , YOLO's ability to deliver real-time results is particularly significant in clinical contexts where timely diagnosis is crucial. The high precision and recall metrics indicate that YOLO can e ectively distinguish between malignant and benign tumors, which is critical for informing treatment decisions. This capability aligns with the increasing demand for automated tools that assist radiologists and improve diagnostic workflows.

Challenges and Limitations:

Despite the promising results, this study faced several challenges. One notable limitation was the potential bias in the dataset. If the dataset included a disproportionate number of images of a specific tumor type or stage, this could skew the model's performance. Moreover, while YOLO showed high accuracy, it might still struggle with certain tumor presentations that were underrepresented in the training data. Additional challenges include computational resource limitations, particularly when deploying the model in real-time scenarios in resource-constrained settings. Future work should address these limitations by utilizing more diverse datasets and potentially combining YOLO with other models to enhance detection capabilities.

Comparison with Existing Methods:

The findings in this study corroborate previous research highlighting the benefits of deep learning models in medical imaging. While CNNs, ResNet, and Faster R-CNN have shown promise, they often fall short in terms of speed and real-time applicability. YOLO's architecture, which combines localization and classification into a single step, positions it as a superior alternative, particularly in time-sensitive situations. This research contributes to the body of literature advocating for the integration of advanced machine learning models in clinical diagnostics, offering a pathway toward enhanced patient care.

CONCLUSION

This study presents compelling evidence that the YOLO model is an e ective tool for liver tumor classification, outperforming traditional machine learning approaches in both speed and accuracy. YOLO's real-time detection capabilities can significantly aid radiologists in making quicker and more accurate diagnoses, thereby improving patient outcomes.

The potential applications of this research extend beyond mere classification; integrating YOLO into clinical workflows could streamline processes in busy hospital environments, allowing for more e cient use of medical resources. Future research should focus on expanding the dataset to encompass a broader range of tumor types and stages, exploring hybrid models that combine YOLO with other advanced architectures, and conducting clinical trials to validate the model's performance in real-world settings.

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