IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.155129

HEPATOSCAN:AI BASED LIVER TUMOR SEGMENTATION SYSTEM

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Abstract: Liver cancer is one of the leading causes of cancer-related deaths worldwide, and early diagnosis plays a crucial role in improving treatment outcomes and patient survival. Traditional methods of analyzing CT scan images rely heavily on manual interpretation by radiologists, which can be time-consuming, labor-intensive, and prone to human error. To address these challenges, this project presents HepatoScan, an AI-based web application designed for automated liver and tumor segmentation using deep learning techniques.

The proposed system utilizes a U-Net–based convolutional neural network implemented using TensorFlow to perform accurate pixel-level segmentation of liver and tumor regions from CT scan images. Prior to segmentation, the images undergo preprocessing steps such as grayscale conversion, resizing, and normalization to ensure consistent input quality for the model. The trained model generates liver and tumor masks, enabling automated identification of affected regions. In addition to segmentation, the system performs tumor size estimation using pixel-based area calculation and provides a user-friendly web interface developed using Flask and web technologies.

The application also includes automated PDF medical report generation containing the uploaded CT image, segmentation outputs, and tumor size details. By integrating deep learning, medical image processing, and automated reporting into a single platform, HepatoScan aims to improve diagnostic efficiency, reduce manual effort, and support radiologists in clinical decision-making.

Keywords: Artificial Intelligence (AI), Deep Learning, Medical Image Segmentation, Liver Tumor Detection, U-Net Architecture, Convolutional Neural Network (CNN), TensorFlow, CT Scan Analysis, Flask Web Application, Tumor Size Estimation, Image Preprocessing, Medical Imaging, Computer Vision, Automated PDF Report Generation, Healthcare AI, Liver Cancer Diagnosis, Supervised Learning, Biomedical Image Analysis.

I. INTRODUCTION

Liver cancer, also known as hepatic cancer, is one of the leading causes of cancer related deaths worldwide. Early detection and accurate diagnosis are crucial for effective treatment and improved survival rates. Traditional methods of detecting liver cancer involve manual interpretation of medical images such as computed tomography (CT) scans or magnetic resonance imaging (MRI) by radiologists. This process is not only time-consuming but also subject to variability and error due to human factors.

Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have revolutionized the field of medical image analysis. These techniques have shown great promise in automating the detection and segmentation of various types of cancers, including liver cancer. Among the numerous CNN architectures, the U-Net has emerged as a leading model for biomedical image segmentation due to its unique structure that allows for precise localization and context preservation.

The U-Net architecture, introduced by Ranneberger et al. in 2015, consists of a symmetric encoder-decoder structure. The encoder path captures the context of the input image through a series of convolutional and pooling layers, while the decoder path reconstructs the image to its original resolution using up-sampling layers. Skip connections between corresponding layers in the encoder and decoder paths enable the model to retain spatial information, leading to more accurate segmentation results.

This study focuses on leveraging the U-Net architecture for the detection and segmentation of liver cancer from CT scans. By automating this process, we aim to reduce the burden on radiologists and enhance the accuracy and efficiency of liver

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cancer diagnosis. The research involves the collection and preprocessing of liver CT scan data, training the U-Net model on annotated datasets, and evaluating its performance in terms of accuracy, sensitivity, and specificity.

1.1 Project Description

HepatoScan is a web-based medical imaging application developed for automated liver tumor detection and analysis from CT scan images using deep learning. The system uses a U-Net–based convolutional neural network to perform accurate liver and tumor segmentation, reducing manual effort and improving diagnostic consistency.

Users can upload CT scan images through a simple web interface, where the system preprocesses the images using resizing, grayscale conversion, and normalization techniques before performing segmentation. The application generates liver and tumor masks, estimates tumor size using pixel-based calculations, and displays the results in real time.

Additionally, HepatoScan includes automated PDF report generation containing the original CT image, segmentation outputs, tumor size details, and optional patient information. Developed using TensorFlow, Flask, and web technologies, the system demonstrates the practical application of artificial intelligence in medical image analysis and diagnostic support.

1.2 Motivation

The main motivation behind HepatoScan is to address the challenges involved in manual liver tumor detection and analysis from CT scan images. Traditional diagnosis methods require experienced radiologists to manually examine medical images, which can be time-consuming, labor-intensive, and prone to human error. Delayed or inaccurate detection of liver tumors can significantly affect treatment planning and patient outcomes. Existing approaches often focus only on segmentation without providing additional analytical features such as tumor size estimation and automated reporting. Therefore, HepatoScan was developed as an AI-based solution that combines automated liver and tumor segmentation, tumor size calculation, and PDF medical report generation within a single web-based system. The project aims to improve diagnostic efficiency, reduce manual effort, provide consistent analysis, and demonstrate the practical application of deep learning in healthcare and medical imaging.

II. RELATED WORK

Reference	Year	Authors	Data Parameters	Methodology	Result	Limitation
U-Net: Convolutional Networks for Biomedical Image Segmentation	2015	Ronneberger et al.	Biomedical images, segmentation masks	U-Net architecture, CNN, encoder–decoder network	High segmentation accuracy in medical imaging	Requires annotated datasets
Automatic Liver and Tumor Segmentation of CT and MRI Volumes	2017	Christ et al.	Liver CT and MRI scans	Cascaded Fully Convolutional Networks (FCN)	Accurate liver and tumor segmentation	High computational complexity
Liver Tumor Segmentation Benchmark (LiTS)	2019	Bilic et al.	CT liver scan datasets	Deep learning segmentation models	Improved benchmarking and segmentation performance	Dataset variability affects consistency
Deep Learning in Medical Image Analysis	2017	Litjens et al.	Medical imaging datasets	CNN, deep learning techniques	Enhanced diagnostic accuracy	Requires large-scale training data
AI-Based Liver Tumor Analysis System	2023	Various Researchers	Annotated liver CT datasets	Deep learning, tumor segmentation, feature extraction	Improved diagnostic support and efficiency	Requires high-performance hardware

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III. METHODOLOGY

The HepatoScan system follows a structured methodology to perform automated liver and tumor segmentation from CT scan images using Deep Learning techniques.

[1] 1. CT Image Collection

Liver CT scan images along with liver and tumor masks are collected from medical imaging datasets for supervised learning.

[2] 2. Image Preprocessing

The collected CT images are preprocessed to improve model performance. Preprocessing steps include:

- Grayscale conversion
- Image resizing (252 × 252)
- Pixel normalization

These steps ensure uniform input and stable training.

[3] 3. Liver and Tumor Segmentation

A U-Net–based convolutional neural network is used to segment liver and tumor regions from CT scan images. The model performs pixel-level segmentation for accurate boundary detection.

[4] 4. Model Training

The U-Net model is trained using TensorFlow on annotated CT scan datasets. Binary cross-entropy loss and Adam optimizer are used to improve segmentation accuracy.

[5] 5. Tumor Size Estimation

After segmentation, the tumor mask is analyzed using pixel-based calculations to estimate the approximate tumor size.

[6] 6. Web Application Integration

The trained model is integrated with a Flask-based web application where users can upload CT scan images and obtain real-time segmentation results.

[7] 7. PDF Report Generation

The system automatically generates downloadable PDF reports containing:

- Original CT image
- Liver mask
- Tumor mask
- Tumor size details

[8] 8. Result Display

Finally, the segmentation outputs and tumor size results are displayed through a simple and user-friendly web interface.

IV. SYSTEM DESIGN

HepatoScan is a web-based client–server system developed using Flask and deep learning technologies for automated medical image analysis.

1. User Interface Layer

- A web-based interface developed using HTML, CSS, and JavaScript to ensure platform independence and ease of access.
- Provides an intuitive and user-friendly environment for interacting with the system.
- Provides clear labels, buttons, and on-screen instructions to guide users through each step of the workflow.

2. Input Acquisition Layer

- Accepts liver CT scan images uploaded by the user through the web interface.
- Supports common image formats such as PNG and JPG for ease of use.
- Performs validation checks on image format, resolution, and file size before processing.

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3. Processing Layer

The processing layer is the core component of the Hepatoscan system, responsible for transforming raw input images into meaningful diagnostic outputs.

4. Output & Reporting Layer

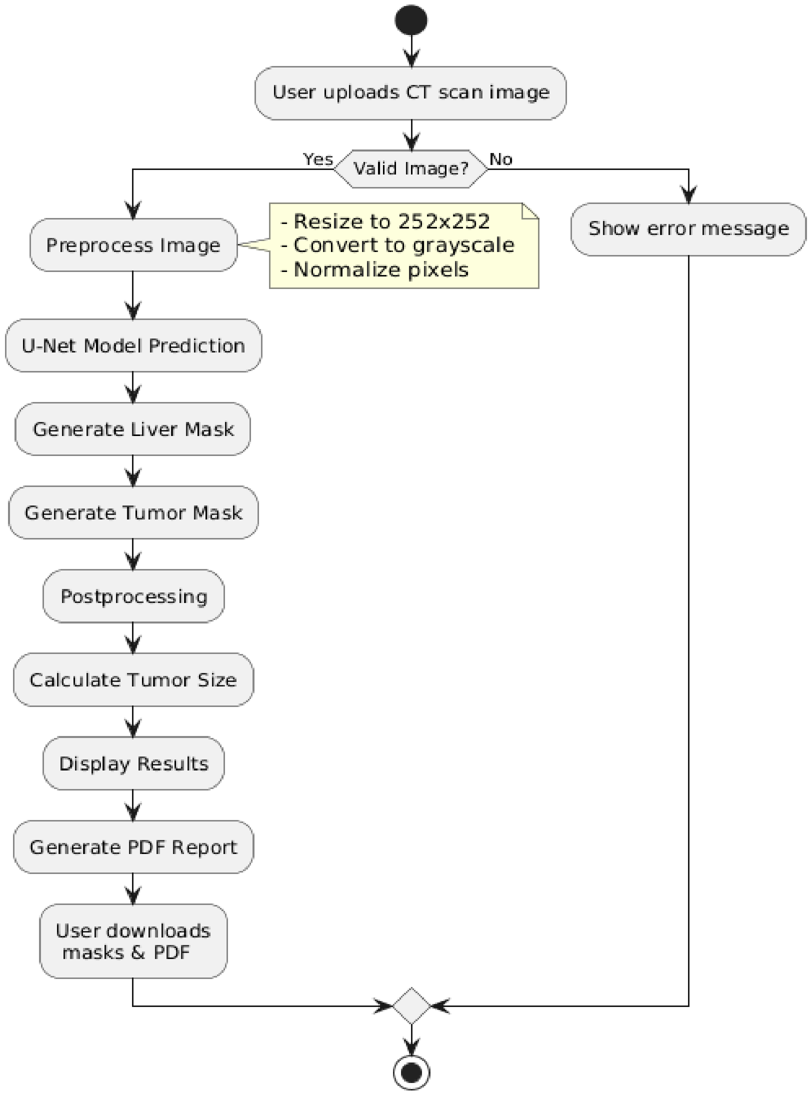
- Displays the segmented liver and tumor masks alongside the original CT image on the web interface.
- Clearly highlights the detected tumor region for easy interpretation.
- Shows the calculated tumor size in a readable and user-friendly format.

5. Backend Management Layer

- A Flask-based backend framework manages all server-side operations of the system.
- Implements robust error handling mechanisms to manage invalid inputs and processing failures.
- Facilitates secure and efficient data exchange between the frontend interface and the AI model.

Hardware Requirements:

- Standard computer or laptop
- Minimum **8 GB RAM** (recommended for model loading)
- CPU-based system (GPU optional for faster model inference)



- Adequate storage for datasets and model files

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Software Requirements:

- Operating System: Windows / macOS / Linux
- Programming Language: Python 3.8 or above
- Backend Framework: Flask
- Deep Learning Library: TensorFlow
- Frontend Environment: Web browser (Chrome / Firefox recommended)
- IDE: Visual Studio Code / PyCharm
- Additional Libraries: NumPy, PIL, Matplotlib, Report Lab

Software testing ensures that the HepatoScan system functions correctly across all modules, including image upload, preprocessing, deep learning–based segmentation, tumor size calculation, and PDF report generation. The testing strategy includes functional testing, integration testing, performance testing, and user acceptance testing to validate system reliability and accuracy

UNIT TESTING

Unit testing involves verifying individual components of the HepatoScan system independently to ensure each module functions correctly before full integration.

- **Individual Components Tested** – Functions related to image preprocessing, segmentation prediction, tumor size calculation, and PDF generation were tested separately to ensure correct functionality in isolation.
- **Model Prediction Accuracy** – The U-Net segmentation model was tested using sample CT scan images to verify proper liver and tumor mask generation.
- **Image Preprocessing Validation** – Preprocessing operations such as grayscale conversion, resizing, and normalization were tested to ensure consistent input preparation for the model.
- **Error Handling & Robustness** – The system was tested with invalid or corrupted image files to ensure proper error handling and prevent application crashes.

INTEGRATION TESTING

Integration testing verifies how different modules of the HepatoScan system work together, ensuring smooth interaction between the frontend, Flask backend, deep learning model, and PDF generation module.

- Ensured proper communication between the web interface, Flask backend, TensorFlow model, and report generation system.
- Validated the complete workflow: image upload → preprocessing → segmentation → tumor size calculation → result display → PDF generation.
- Verified that liver masks, tumor masks, and tumor size outputs were correctly displayed on the frontend after model prediction.
- Resolved issues related to image handling, frontend-backend communication, and PDF formatting during integration.

SYSTEM TESTING

System testing ensures the complete HepatoScan application works reliably and efficiently under real-world conditions by validating overall functionality, usability, and performance.

- Tested the end-to-end workflow on different devices and browsers to verify responsiveness and stable system performance.
- Validated real-time image upload, segmentation accuracy, tumor size estimation, and PDF report generation functionality.
- Tested system behavior with valid and invalid CT scan images to ensure reliable error handling and user-friendly responses.
- Confirmed that the application provides a smooth and intuitive user experience with accurate output visualization and report downloading capabilities.

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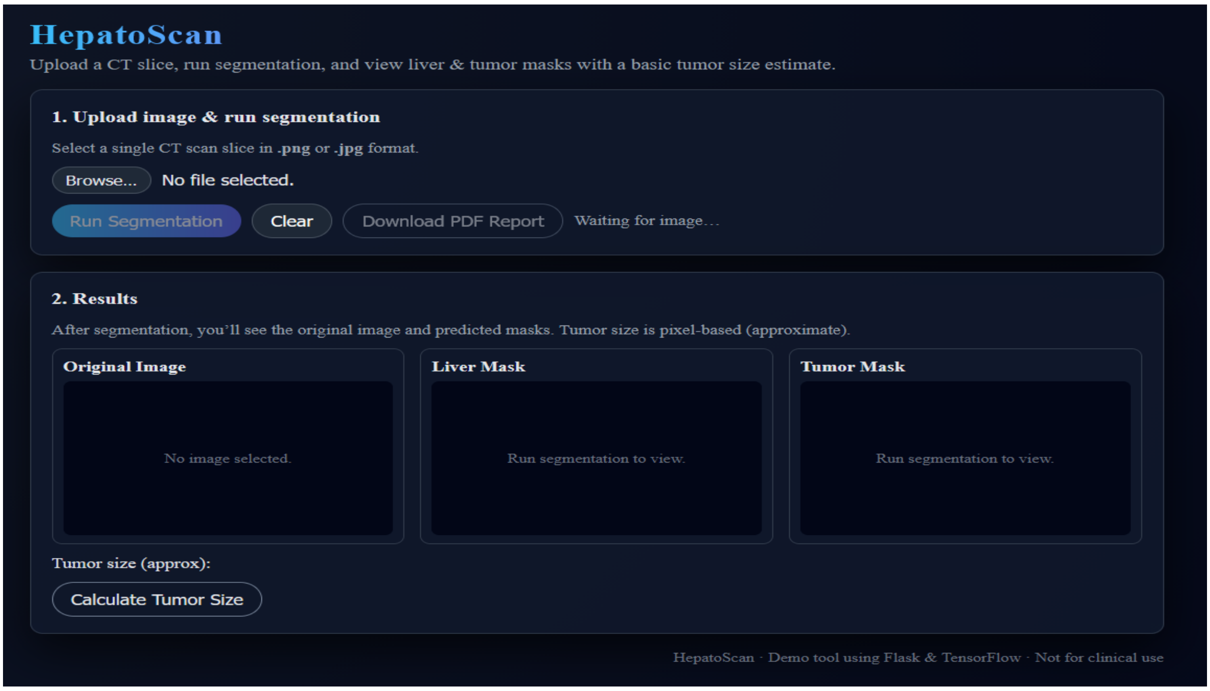

Figure 1: Welcome page of the website.

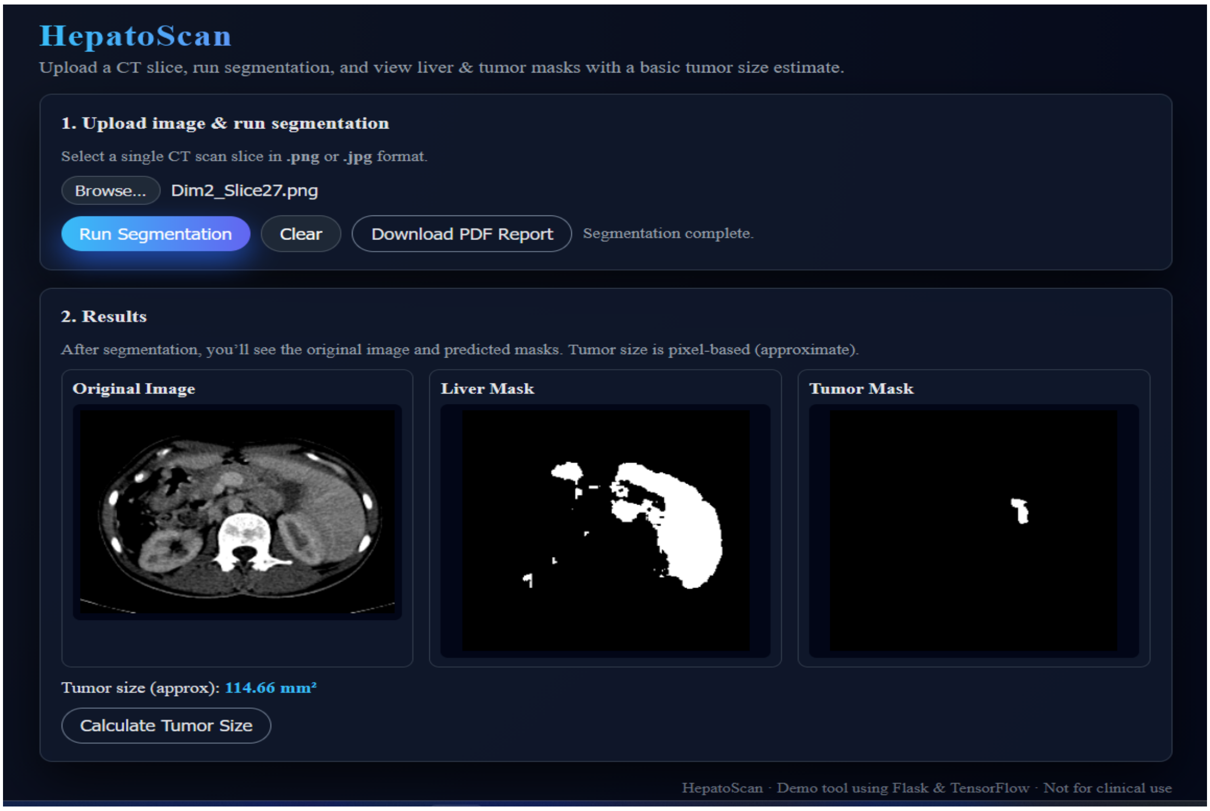

Figure 2: Image upload

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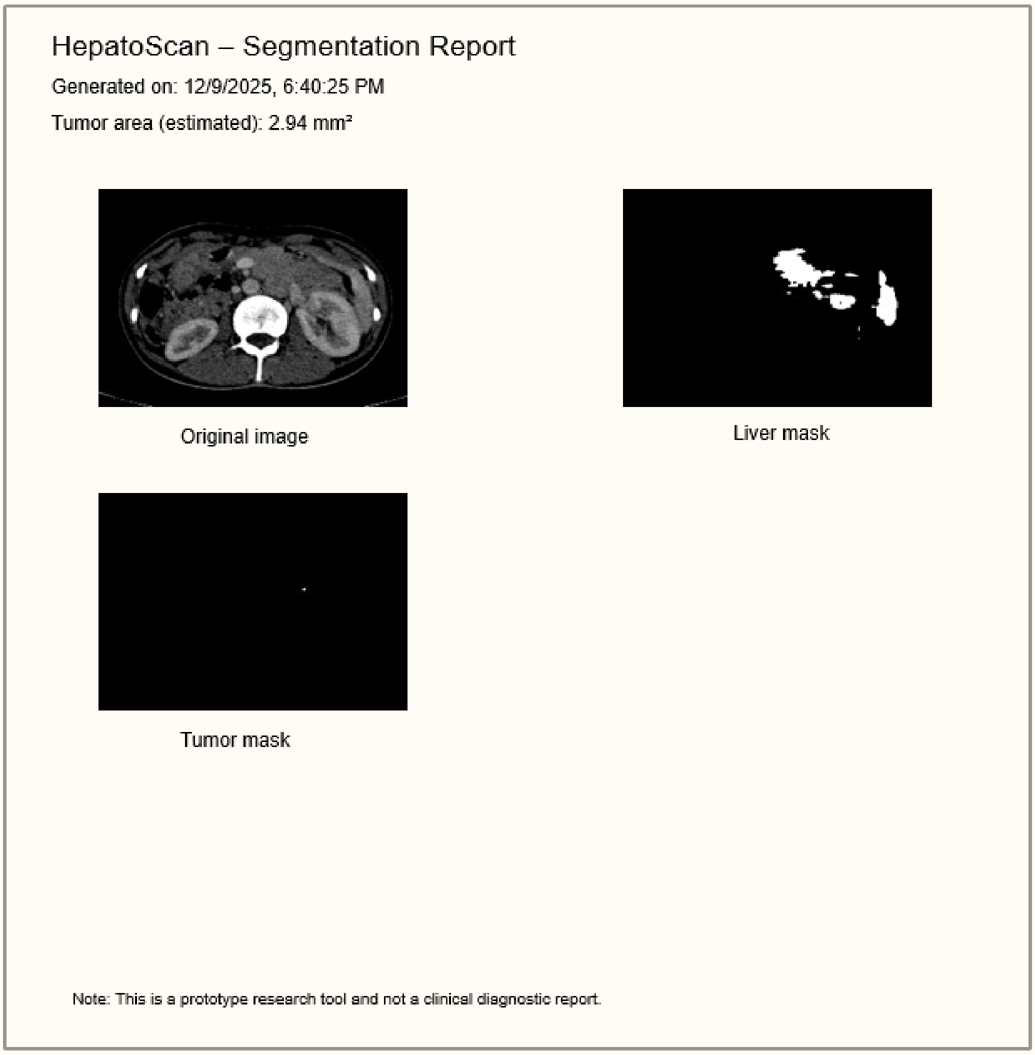

Figure 3: Generated report

V. CONCLUSION

The application of U-Net for liver cancer detection marks a significant advancement in medical imaging. By leveraging deep learning, U-Net offers precise and reliable segmentation of liver tumors, crucial for early diagnosis and effective treatment. This improvement in diagnostic accuracy reduces misdiagnosis and enhances the reliability of medical analyses. Automating the image analysis process decreases the workload on radiologists, minimizing human error and increasing efficiency.

Early detection enabled by U-Net significantly improves patient outcomes by allowing timely intervention. The integration of U-Net models into various clinical settings, including resource-limited environments, makes advanced diagnostic tools more accessible. This automated segmentation aids radiologists by providing preliminary analyses, allowing them to focus on more complex cases.

In conclusion, U-Net enhances the precision and efficiency of liver cancer diagnosis, supporting better patient care through early detection and treatment. This integration of advanced deep learning models into medical practice highlights the transformative potential of artificial intelligence in healthcare, promising improved diagnostic capabilities and patient outcomes.

In addition to accurate segmentation, this project extends the U-Net framework by incorporating tumor size estimation and automated PDF report generation within a web-based application. The ability to quantify tumor size provides valuable clinical insight for monitoring disease progression and treatment planning. Furthermore, the integration of a Flask-based interface enables easy access to the system without specialized software, making the solution practical for real-world clinical and academic use. These enhancements transform the model from a research-oriented segmentation tool into a complete diagnostic support system.

VI. FUTURE WORK

Although HepatoScan provides reliable liver and tumor segmentation results in its current form, several future enhancements can further improve its accuracy, scalability, and real-world clinical applicability:

- **Advanced U-Net Architectures:** Improve segmentation performance by adopting advanced architectures such as UNet++, Attention U-Net, or Transformer-based segmentation models for better feature extraction and boundary detection.
- **3D CT Scan Segmentation:** Extend the system from 2D slice-based segmentation to full 3D volumetric analysis, enabling more accurate tumor localization and tumor volume estimation.
- **Real-Time Clinical Deployment:** Deploy the system on cloud platforms with GPU acceleration to support real-time analysis for multiple users in hospitals and diagnostic centers.
- **Integration with Hospital Databases:** Integrate the system with PACS (Picture Archiving and Communication Systems) and Electronic Medical Records (EMR) for secure storage and retrieval of patient imaging data.
- **Multi-Disease Liver Analysis:** Expand the system to detect and analyze additional liver conditions such as cirrhosis, fatty liver disease, liver cysts, and benign tumors.
- **Explainable AI Integration:** Incorporate Explainable AI (XAI) techniques such as Grad-CAM to visually highlight the regions influencing model predictions, improving transparency and clinician trust.
- **Tumor Progression Monitoring:** Add functionality to compare historical CT scans and track tumor growth or reduction over time to support treatment monitoring and follow-up analysis.
- **Support for Multiple Imaging Modalities:** Extend compatibility to MRI and ultrasound images to increase the system's applicability across different medical imaging techniques.
- **Mobile and Edge Deployment:** Optimize the trained model using TensorFlow Lite for deployment on portable and edge devices, enabling lightweight medical imaging support in remote healthcare environments.
- **Automated Clinical Recommendation System:** Integrate intelligent recommendation modules that provide preliminary diagnostic insights and treatment suggestions based on segmentation and tumor analysis results.

These future enhancements can transform HepatoScan from a research-oriented prototype into a scalable, intelligent, and clinically valuable medical imaging support system for advanced liver cancer diagnosis and healthcare applications

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