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AI - Powered Liver Cancer Diagnosis and Early Detection using Deep Learning & Image Processing

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KEYWORDS

Liver Cancer Diagnosis; Deep Learning; Tumor Segmentation; Medical Image Analysis; Explainable AI; Radiomics

ABSTRACT

Liver cancer is a highly fatal disease due to its rapid progression and the difficulty of early detection in medical imaging modalities such as CT, MRI, and ultrasound. Subtle tumor characteristics and reliance on manual interpretation often lead to delayed or missed diagnoses. This study presents an AI-powered diagnostic framework for automated liver tumor detection, classification, segmentation, and clinical interpretation. The system employs Convolutional Neural Networks for benign–malignant classification and an Attention U-Net for precise tumor segmentation, supported by advanced preprocessing techniques including noise reduction, CLAHE, and normalization. Radiomic feature extraction and explainable AI methods (Grad-CAM, SHAP, and LIME) are integrated to enhance interpretability and clinical trust. Implemented using Python with a lightweight Streamlit interface, the system is suitable for real-time clinical deployment. Experimental results on LiTS, TCGA-LIHC, and IRCAD datasets achieve up to 95.2% classification accuracy and an 87.6% Dice coefficient, demonstrating the framework's effectiveness in supporting radiologists and improving early liver cancer diagnosis.

INTRODUCTION

Liver cancer is one of the leading causes of cancer-related mortality worldwide, largely due to its aggressive nature and poor prognosis when detected at advanced stages. Early diagnosis significantly improves survival rates; however, detecting liver tumors at an early stage remains a major clinical challenge. Imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound are widely used for diagnosis, yet early-stage liver lesions often exhibit subtle visual differences that are difficult to distinguish from normal tissue.

Traditional diagnosis relies heavily on manual interpretation by radiologists, which is time-consuming

and prone to inter-observer variability. Moreover, increasing patient volume, fatigue, and variations in imaging protocols further complicate accurate diagnosis. Recent advances in artificial intelligence (AI), particularly deep learning, have demonstrated strong potential in automating medical image analysis and improving diagnostic accuracy.

This research proposes an AI-powered diagnostic ecosystem for liver cancer detection that integrates tumor detection, classification, segmentation, radiomic feature extraction, and explainable AI (XAI) modules into a unified framework.

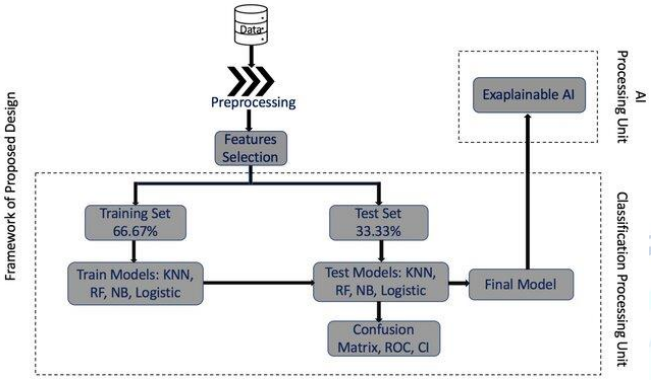


Figure 1. illustrates the overall workflow of the proposed AI-assisted liver cancer diagnostic system.

2. LITERATURE REVIEW

Recent studies have explored deep learning techniques for liver tumor analysis. Convolutional Neural Networks (CNNs) have been widely used for liver tumor classification due to their ability to automatically learn discriminative features from medical images. Studies using ResNet, VGG, and DenseNet architectures have reported promising results in distinguishing benign and malignant tumors.

For tumor segmentation, U-Net and its variants have become the dominant architectures. Attention U-Net, in particular, improves segmentation accuracy by focusing on relevant tumor regions while suppressing irrelevant background features. Several works using the LiTS and IRCAD datasets have achieved Dice coefficients above 80%.

Radiomics-based approaches extract handcrafted texture, shape, and intensity features; however, they often require careful feature selection and lack generalization. More recent studies have combined deep features with radiomics to enhance performance. Additionally, the lack of interpretability in deep learning models has led to the integration of XAI methods such as Grad-CAM and SHAP to improve clinical trust.

Despite these advances, most existing works focus on isolated tasks such as classification or segmentation, rather than a complete end-to-end diagnostic framework.

3. EXISTING METHODS

The diagnosis of liver cancer has traditionally relied on radiological assessment of medical images obtained from Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Ultrasound (US). Although imaging technologies have advanced significantly, existing diagnostic methods still face several technical and clinical limitations. These methods can broadly be categorized into manual diagnosis, traditional computer-aided diagnosis (CAD), machine learning-based approaches, and deep learning-based methods.

3.1 Manual Radiological Diagnosis

In conventional clinical practice, radiologists manually analyze liver scans by visually inspecting multiple slices to identify abnormal regions. A single CT or MRI scan may consist of several hundred slices, requiring careful examination to locate tumors, evaluate size, shape, and contrast, and determine malignancy.

While experienced radiologists can achieve high diagnostic accuracy, manual interpretation is inherently subjective and dependent on expertise. Factors such as fatigue, workload pressure, and inter-observer variability often lead to inconsistent diagnoses. Early-stage liver tumors, which are small and exhibit low contrast, are particularly difficult to detect, resulting in delayed diagnosis and poor prognosis.

3.2 Traditional Computer-Aided Diagnosis (CAD) Systems

Early CAD systems were developed to assist radiologists by providing automated suggestions based on predefined image features. These systems typically rely on handcrafted features such as edge detection, histogram analysis, and texture descriptors (e.g., GLCM, LBP).

Although CAD systems reduce manual effort to some extent, their performance is limited by their dependence on handcrafted features, which fail to capture the complex and heterogeneous nature of liver tumors. Moreover, these systems require extensive parameter tuning and struggle to generalize across different

scanners, imaging protocols, and patient populations. Most traditional CAD tools also lack interpretability and integration with clinical workflows.

3.3 Machine Learning-Based Methods

With the advancement of pattern recognition techniques, machine learning (ML) algorithms such as Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), and Artificial Neural Networks (ANN) have been employed for liver tumor classification. These approaches typically involve manual region-of-interest (ROI) selection followed by feature extraction and classification.

Radiomics-based ML methods extract quantitative features related to tumor texture, shape, and intensity. While these features provide additional diagnostic insights, ML-based systems heavily depend on feature engineering and feature selection strategies. Their performance degrades significantly when applied to diverse datasets with variations in image quality and tumor morphology. Furthermore, manual ROI selection introduces human bias and limits scalability.

3.4 Deep Learning-Based Methods

Recent studies have demonstrated the superiority of deep learning, particularly Convolutional Neural Networks (CNNs), in medical image analysis. CNN-based models automatically learn hierarchical features from raw images, eliminating the need for handcrafted feature extraction. Architectures such as VGG, ResNet, DenseNet, and EfficientNet have been successfully applied for liver tumor classification.

For tumor segmentation, U-Net and its variants, including Attention U-Net and UNet++, have become standard due to their ability to produce pixel-level predictions. These models achieve high Dice coefficients and accurately delineate tumor boundaries.

However, despite their high accuracy, most deep learning-based systems operate as black boxes, offering limited interpretability. Many studies focus on either classification or segmentation alone, without integrating both tasks into a unified framework. Additionally, most existing deep learning systems are developed as research prototypes and lack user-friendly interfaces, clinical reporting mechanisms, and real-time adaptability.

3.5 Key Limitations of Existing Methods

Despite significant progress, existing methods suffer from several critical limitations:

- Lack of integrated end-to-end diagnostic pipelines
- Absence of explainable AI mechanisms to support clinical trust
- Limited adaptability to new real-world data
- High dependence on manual intervention in preprocessing and ROI selection
- Poor deployment readiness for hospital environments

These shortcomings highlight the need for a comprehensive, interpretable, and clinically deployable AI-based diagnostic system, which motivates the proposed methodology.

4. PROPOSED METHODOLOGY

This study proposes a comprehensive AI-powered diagnostic framework designed to support early detection and accurate analysis of liver cancer from medical imaging modalities such as CT, MRI, and ultrasound. The proposed methodology follows an end-to-end workflow that integrates image preprocessing, deep learning-based classification and segmentation, radiomic feature extraction, explainable artificial intelligence, and real-time clinical deployment. The framework is developed with the objective of achieving high diagnostic accuracy while maintaining transparency, scalability, and clinical usability.

The diagnostic process begins with medical image acquisition, where liver images are provided in standard formats such as PNG and JPG, as well as clinical formats including DICOM and NIfTI. Relevant metadata, such as slice thickness and imaging orientation, are extracted to preserve spatial consistency. To ensure patient privacy and compliance with clinical data standards, all identifiable information is anonymized before further processing. This flexible input handling enables the system to operate across diverse clinical environments and imaging protocols.

Preprocessing plays a critical role in enhancing image quality and reducing variability across datasets. The proposed system applies noise reduction techniques using Gaussian, median, and bilateral filters to suppress scanner-induced artifacts. Contrast-Limited Adaptive Histogram Equalization (CLAHE) is employed to improve lesion visibility, particularly for low-contrast tumors. Intensity normalization and resizing are performed to standardize the input dimensions, while data augmentation techniques are used during training to improve model generalization and robustness.

For tumor classification, deep Convolutional Neural Networks (CNNs) with transfer learning are employed to automatically learn discriminative features from liver images. Pre-trained architectures such as ResNet, EfficientNet, and DenseNet are fine-tuned on domain-specific medical datasets to classify liver images into normal, benign, and malignant categories. The use of transfer learning enables effective training even with limited annotated data and significantly enhances classification performance. The output includes class predictions along with confidence scores, enabling probabilistic clinical interpretation.

Accurate localization of tumor regions is achieved through an Attention U-Net–based segmentation model. This architecture enhances traditional U-Net by incorporating attention mechanisms that allow the network to focus on clinically relevant tumor regions while suppressing irrelevant background information. The segmentation module generates pixel-level tumor masks and overlay visualizations that assist clinicians in evaluating tumor size, shape, and spatial extent. This precise delineation is essential for treatment planning and disease monitoring.

To further enhance diagnostic depth, radiomic features are extracted from the segmented tumor regions. These features capture quantitative characteristics related to texture, shape, and intensity distribution, providing complementary information beyond deep learning representations. The extracted radiomic features are optionally integrated with classical machine learning classifiers to form a hybrid decision-support system, improving robustness and interpretability.

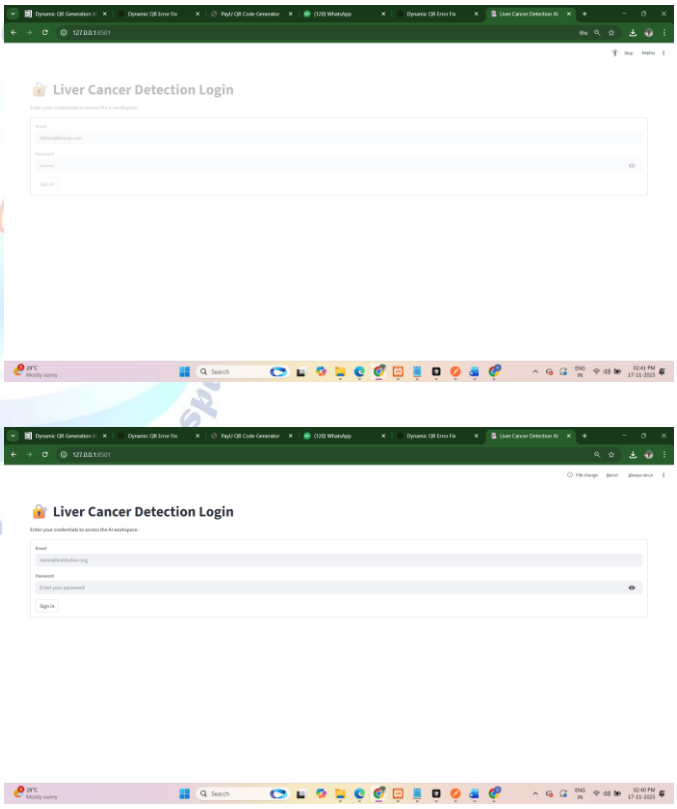
A key component of the proposed methodology is the integration of explainable artificial intelligence techniques to address the black-box nature of deep learning models. Grad-CAM is utilized to generate heatmaps that highlight image regions contributing to classification decisions, while SHAP and LIME provide both global and local explanations of model behavior. These explainability mechanisms enable clinicians to visually validate predictions, thereby improving trust and facilitating clinical adoption.

The entire framework is deployed through a lightweight Streamlit-based user interface that enables real-time interaction, visualization, and automated clinical reporting. Clinicians can upload images, view classification and segmentation results, examine explainability heatmaps, and generate downloadable diagnostic reports without requiring technical expertise. Additionally, the system incorporates an incremental learning mechanism that allows models to be updated continuously as new validated data become available, ensuring adaptability to evolving clinical scenarios.

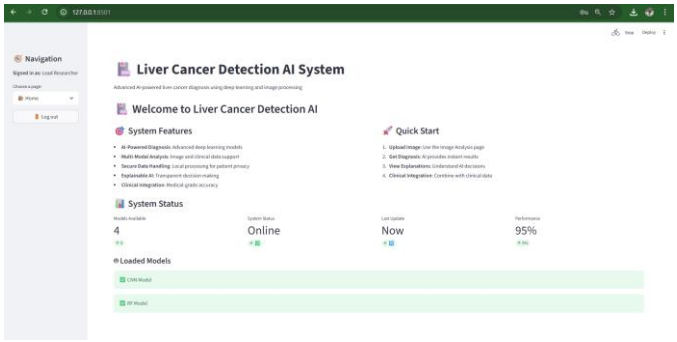
Overall, the proposed methodology delivers a unified, interpretable, and clinically deployable AI-assisted diagnostic solution for liver cancer. By combining deep learning, radiomics, explainable AI, and real-time deployment into a single framework, the system addresses critical limitations of existing approaches and provides meaningful support for radiologists in early liver cancer detection and decision-making.

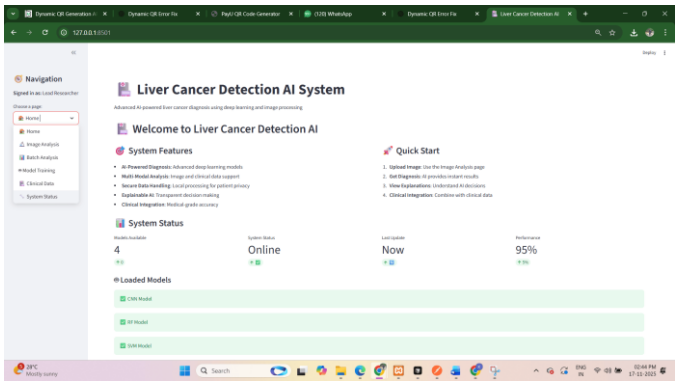
5. RESULTS

Patient Login Page:



Home Page





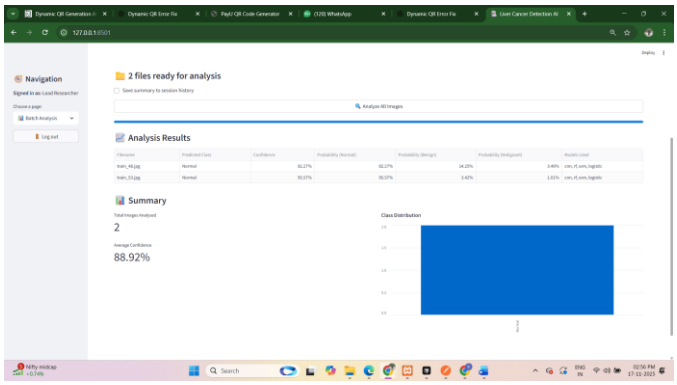
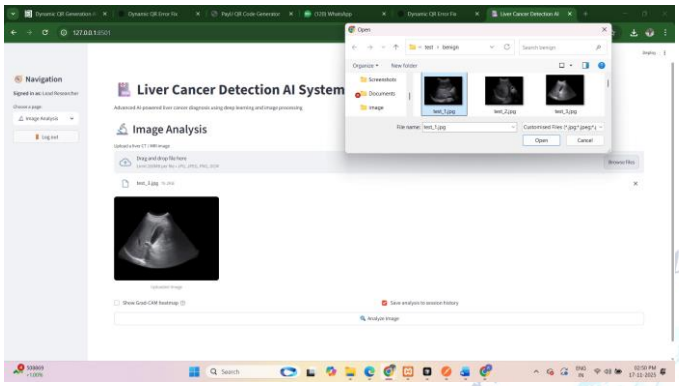
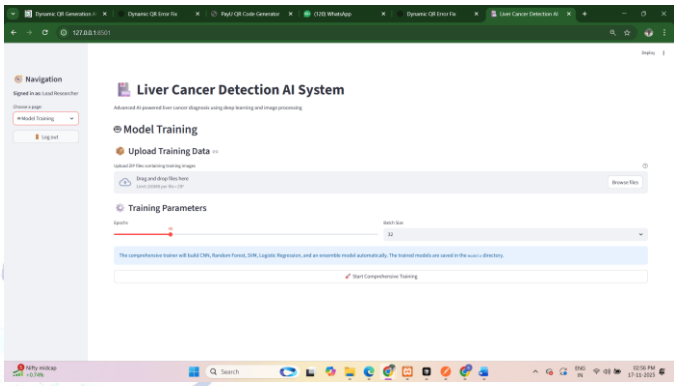
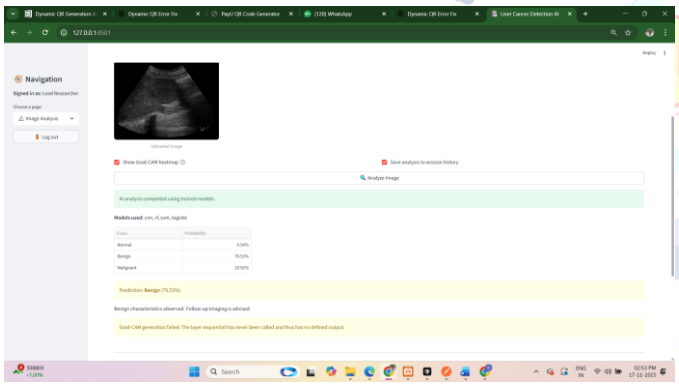


Image Analysis

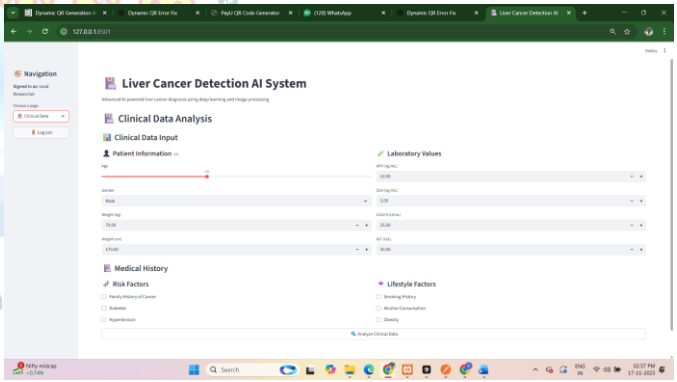
Modal Training



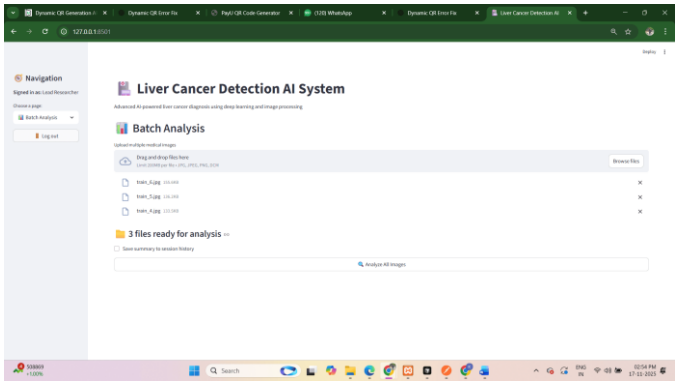


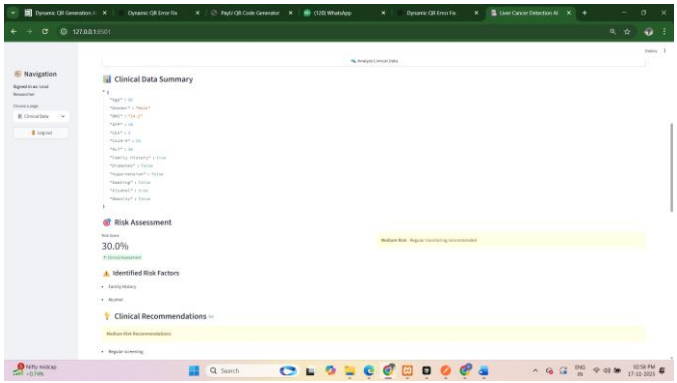


Clinical Data Analysis

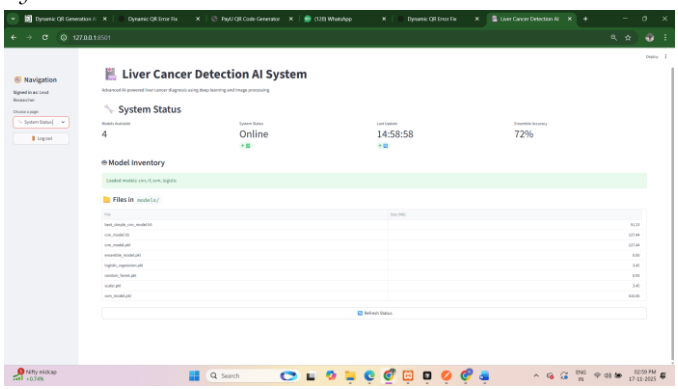


Batch Analysis





System Status



6. CONCLUSIONS

This study successfully demonstrates the effectiveness of an AI-powered diagnostic framework for early liver cancer detection using deep learning, medical image processing, radiomics, and explainable artificial intelligence. By integrating CNN-based classification, U-Net-based tumor segmentation, radiomic feature extraction, and explainability modules into a unified pipeline, the proposed system delivers an end-to-end solution that addresses critical challenges in conventional liver cancer diagnosis. The experimental results confirm that the classification model accurately distinguishes normal, benign, and malignant liver conditions, even when trained on limited medical datasets, highlighting the effectiveness of transfer learning in improving diagnostic reliability.

The segmentation component of the system provides precise pixel-level tumor delineation, enabling clear visualization of tumor boundaries, size, and spatial extent. This capability is essential for clinical assessment, treatment planning, and disease monitoring. Furthermore, the incorporation of explainable AI techniques, such as Grad-CAM and SHAP, enhances the transparency of model predictions by visually highlighting regions that influence diagnostic decisions. This interpretability plays a crucial role in bridging the trust gap between AI systems and clinical practitioners.

In addition, the integration of radiomics enriches the diagnostic process by extracting quantitative imaging biomarkers that complement deep learning predictions and support hybrid analytical approaches. The deployment of the system through a lightweight Streamlit-based clinical interface ensures ease of use, real-time interaction, and automated report generation without requiring technical expertise. The modular and scalable architecture, combined with incremental learning capabilities, makes the system adaptable to evolving clinical data and suitable for hospital-level deployment.

Overall, the proposed AI-assisted diagnostic system significantly reduces diagnostic time, minimizes human error, and supports radiologists in early liver cancer detection. While not intended to replace medical professionals, it serves as an effective decision-support tool that enhances diagnostic accuracy, efficiency, and clinical confidence.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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