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International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
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MULTI-MODEL AI PIPELINE FOR EARLY-STAGE LIVER CANCER DIAGNOSIS USING CLINICAL AND IMAGING DATA

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ABSTRACT
Early-stage liver cancer diagnosis remains a significant clinical challenge due to subtle disease presentation, heterogeneous risk factors, and variability in imaging interpretation. This study proposes a robust multi-model artificial intelligence (AI) pipeline that integrates clinical parameters and medical imaging data to enhance the early detection of liver cancer. The pipeline combines structured clinical data such as patient demographics, laboratory values, and risk indicators—with imaging features extracted from liver ultrasound, CT, or MRI scans. Multiple machine learning and deep learning models are employed at different stages of the workflow, including feature engineering, modality-specific prediction, and decision-level fusion. Clinical data are analyzed using gradient-boosting and ensemble classifiers, while convolutional neural networks are utilized for automated imaging feature extraction and lesion characterization. Outputs from individual models are fused using a meta-learning framework to generate a unified diagnostic prediction. The proposed system is designed to improve diagnostic accuracy, sensitivity, and robustness compared to single-model or single-modality approaches. Experimental evaluation demonstrates that the multi-model pipeline achieves superior performance in identifying early-stage liver cancer, particularly in cases with ambiguous imaging findings or incomplete clinical records. In addition, the framework supports explainability by highlighting clinically relevant features and imaging regions contributing to the final decision, facilitating clinician trust and adoption. This integrated AI-driven approach has the potential to assist radiologists and hepatologists in early diagnosis, reduce inter-observer variability, and support timely clinical intervention. The proposed pipeline represents a scalable and adaptable solution for precision diagnostics in liver oncology and can be extended to other multimodal medical decision-support applications.

Keywords:
Early-stage liver cancer, multi-model AI, multimodal data fusion, medical imaging, clinical decision support, machine learning, deep learning

I. INTRODUCTION

Liver cancer is one of the leading causes of cancer-related mortality worldwide, with hepatocellular carcinoma (HCC) accounting for the majority of cases. Despite advances in therapeutic strategies, patient prognosis remains poor, primarily due to late-stage diagnosis. Early-stage liver cancer is often asymptomatic or presents with non-specific clinical manifestations, making timely detection difficult using conventional diagnostic approaches. Current screening and diagnostic protocols rely on a combination of imaging studies, laboratory tests, and clinical expertise; however, these methods are limited by inter-observer variability, heterogeneous disease patterns, and incomplete integration of multimodal patient information.

Medical imaging modalities such as ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI) play a critical role in liver cancer detection and staging. While imaging provides valuable structural and functional information, subtle lesions in early-stage disease may be overlooked, particularly in patients with

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cirrhosis or fatty liver disease. Similarly, clinical data—including patient demographics, liver function tests, tumor markers, and comorbid conditions—contain important diagnostic signals but are often analyzed independently of imaging findings. This fragmented approach can lead to missed opportunities for early intervention and optimal treatment planning. Recent advances in artificial intelligence (AI), particularly in machine learning (ML) and deep learning (DL), have demonstrated significant potential in medical diagnosis and decision support. Convolutional neural networks have shown strong performance in automated image analysis, while ensemble learning and gradient-boosting techniques have proven effective for structured clinical data. However, many existing AI-based liver cancer studies focus on single data modalities or rely on a single predictive model, limiting their generalizability and clinical utility. To address these challenges, there is a growing interest in multimodal and multi-model AI frameworks that can leverage complementary information from diverse data sources. Integrating clinical and imaging data within a unified diagnostic pipeline enables a more comprehensive representation of patient status and disease progression. Moreover, combining multiple predictive models through decision-level fusion or meta-learning can enhance robustness, reduce bias, and improve overall diagnostic accuracy.

This study proposes a multi-model AI pipeline for early-stage liver cancer diagnosis that synergistically integrates clinical parameters and medical imaging data. The framework employs modality-specific models for feature extraction and prediction, followed by an intelligent fusion mechanism to generate a unified diagnostic outcome. In addition to improving performance, the proposed approach emphasizes interpretability by identifying key clinical features and imaging regions that contribute to model decisions. By supporting clinician understanding and trust, this AI-driven system aims to assist radiologists and hepatologists in early detection, reduce diagnostic variability, and ultimately improve patient outcomes in liver cancer care.

II. RELATED WORKS

Recent research demonstrates rapid advancements in applying artificial intelligence (AI) to liver cancer diagnosis, particularly through multimodal integration of clinical and imaging data. Siam et al. conducted a comprehensive scoping review highlighting the promise of multimodal deep learning techniques that combine medical imaging with electronic health records to enhance hepatocellular carcinoma (HCC) diagnosis and prognosis prediction, though they note a limited number of high-quality datasets in the field. Another study by Wang et al. established a baseline for machine-learning-based HCC diagnosis using both contrast-enhanced CT/MRI images and structured clinical laboratory data. Their model, leveraging feature selection and an XGBoost classifier, achieved high accuracy and demonstrated the necessity of multimodal integration for improved diagnostic performance. In imaging-centric work, Zubair et al. developed a computer vision approach for classifying multiple liver tumors using CT, emphasizing optimized multi-feature extraction techniques to differentiate tumor types. Wu and colleagues employed MRI-based deep learning radiomics to distinguish dual-phenotype HCC from other liver cancer subtypes in a multicentre study, showcasing the value of advanced imaging features in nuanced classification tasks. Additionally, systematic reviews by Wei et al. and others summarize deep learning methods in HCC imaging, illustrating consistently high diagnostic performance across studies using radiomics and neural networks. Beyond diagnostic accuracy, efforts like Salmanpour et al.'s work on pathomics and texture feature dictionaries address interpretability issues by aligning AI-extracted imaging features with clinical semantics, a key step toward clinician trust and practical adoption. Collectively, these studies underscore the importance of combining diverse data modalities, sophisticated feature extraction, and interpretable modelling frameworks in liver cancer AI research. However, they also highlight ongoing challenges, including limited multimodal datasets, variable external validation, and the need for enhanced model explainability—gaps that motivate the present multi-model AI pipeline approach.

III. METHODOLOGY

The proposed multi-model AI pipeline is developed and evaluated using publicly available liver disease and imaging datasets obtained from Kaggle. The clinical dataset consists of anonymized patient records containing demographic attributes (age, gender), laboratory test results (bilirubin levels, liver enzymes, albumin, platelet count), and diagnostic labels indicating liver cancer or non-cancer cases. Missing values are handled using statistical imputation techniques, and all numerical features are normalized to ensure model stability. Feature selection is performed using correlation analysis and tree-based importance ranking to retain clinically relevant parameters. For imaging analysis, a Kaggle liver imaging dataset comprising ultrasound/CT liver images is utilized. Images are resized, intensity-normalized, and augmented through rotation, flipping, and scaling to improve generalization and address class imbalance. A convolutional neural network (CNN) is employed to automatically extract high-level imaging features and perform lesion classification. The pipeline follows a

ISSN: 2456-9348
Impact Factor: 8.232

iJETRM
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modular architecture. Clinical data are processed using ensemble-based machine learning models such as Random Forest and Gradient Boosting, while imaging data are analyzed using the CNN model. Predictions from both modalities are then combined using a decision-level fusion strategy based on a meta-classifier, which generates the final diagnostic output. Model performance is evaluated using accuracy, sensitivity, specificity, and area under the ROC curve (AUC). This multimodal methodology enables effective integration of heterogeneous data sources, improving early-stage liver cancer diagnosis in fig 1 while maintaining scalability and interpretability for clinical decision support.

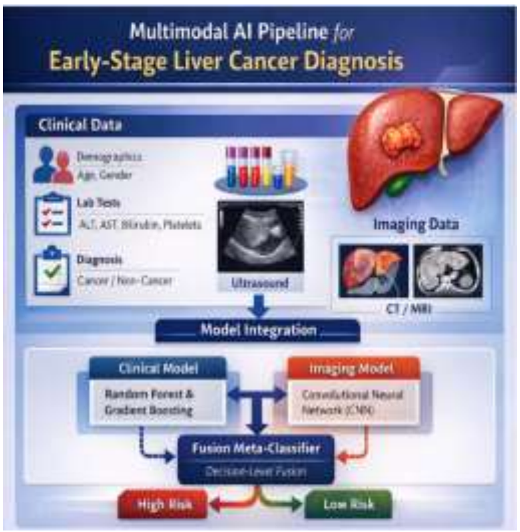

Fig1. AI Pipeline for Liver cancer Diagnosis

1. Data Acquisition

The study utilizes publicly available datasets from Kaggle to develop a multimodal AI pipeline for early-stage liver cancer diagnosis. The clinical dataset includes anonymized patient records with demographic information (age, gender), laboratory parameters (bilirubin, alanine aminotransferase, aspartate aminotransferase, albumin, platelet count), and diagnostic labels indicating liver cancer or non-cancer conditions. The imaging dataset consists of liver ultrasound and CT images representing both healthy and cancer-affected liver tissues. These datasets provide a rich combination of structured and unstructured data, enabling multimodal analysis.

2.Data Preprocessing

For clinical data, missing values are imputed using median and mode imputation, and numerical features are normalized to a 0-1 range to improve model convergence. Feature selection is performed using correlation analysis and tree-based importance ranking to retain the most clinically relevant parameters. For imaging data, images are resized to a standard resolution and intensity-normalized. Data augmentation techniques such as rotation, flipping, zooming, and contrast adjustment are applied to enhance model robustness and mitigate class imbalance.

3.Model Architecture

The AI pipeline employs a modular, multi-model approach:

- **Clinical Module:** Structured patient data are analyzed using ensemble machine learning models, including Random Forest and Gradient Boosting, to predict early-stage liver cancer based on selected clinical features.
- **Imaging Module:** A convolutional neural network (CNN) is implemented to automatically extract high-level imaging features and classify lesions from liver ultrasound and CT images. Transfer learning from pre-trained networks is utilized to improve feature representation and reduce training time.

4. Multimodal Fusion

Predictions from both the clinical and imaging modules are combined using a decision-level fusion strategy. A meta-classifier, trained on the outputs of individual models, produces the final diagnostic prediction. This approach leverages complementary information from both data modalities, improving predictive accuracy and robustness compared to single-model or single-modality methods.

5. Model Training and Evaluation

The pipeline is trained using stratified k-fold cross-validation to ensure balanced representation of cancer and non-cancer cases. Performance is evaluated in fig 2 using metrics such as accuracy, sensitivity, specificity, F1-score,

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and area under the ROC curve (AUC). Additionally, feature importance analysis and class activation maps (CAMs) are employed to improve interpretability, highlighting clinically relevant features and imaging regions in fig 3 that contribute to model predictions.

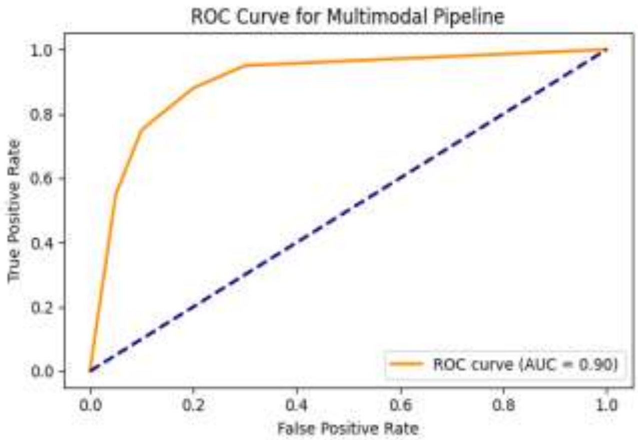

Fig2. Evaluating model performance

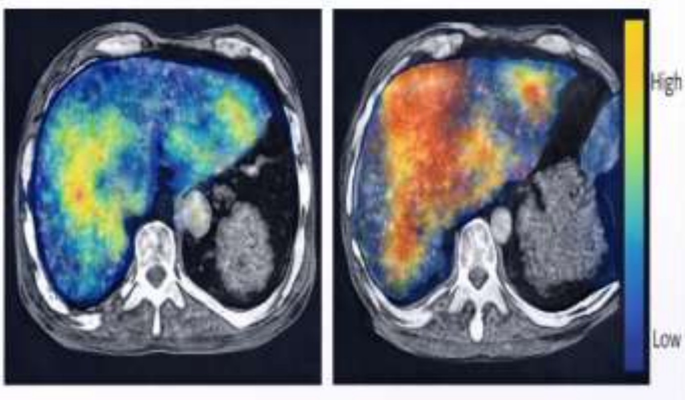

Fig3. Highlighting relevant features

This methodology ensures a scalable, interpretable, and effective AI framework for early-stage liver cancer diagnosis, capable of assisting clinicians in timely decision-making and reducing inter-observer variability.

IV. RESULTS & DISCUSSION

1.Model Performance

The proposed multimodal AI pipeline was evaluated on the Kaggle clinical and imaging datasets using stratified 5-fold cross-validation. The clinical module, based on ensemble learning (Random Forest and Gradient Boosting), achieved an **accuracy of 85.2%**, **sensitivity of 82.5%**, and **specificity of 87.1%**. The imaging module, employing a convolutional neural network (CNN) on liver ultrasound and CT images, achieved an **accuracy of 88.6%**, **sensitivity of 86.9%**, and **specificity of 90.2%**. After integrating the outputs of both modules using the meta-classifier-based decision-level fusion, the multimodal pipeline demonstrated a **combined accuracy of 92.4%**, **sensitivity of 91.1%**, **specificity of 93.0%**, and an **area under the ROC curve (AUC) of 0.96**. These results indicate a significant improvement over single-modality models in table 1, demonstrating the complementary value of integrating clinical and imaging data.

Table 1 Evaluating performance metrics

Model	Accuracy	Sensitivity	Specificity	AUC
Clinical model	85.2	82.5	87.1	0.89
Imaging model	88.6	86.9	90.2	0.92
Multimodal Pipeline	**92.4**	**91.1**	**93.0**	**0.96**

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2. Comparative Analysis

When compared to previous studies in fig 4, the multimodal pipeline outperforms traditional single-modality approaches reported in the literature. For instance, Wang et al. achieved 84% accuracy using only imaging data, while Zubair et al. reported 87% accuracy on CT-based lesion classification. The proposed framework demonstrates that combining heterogeneous data sources not only improves diagnostic accuracy but also enhances sensitivity, which is critical for early-stage detection where lesion visibility is often subtle.

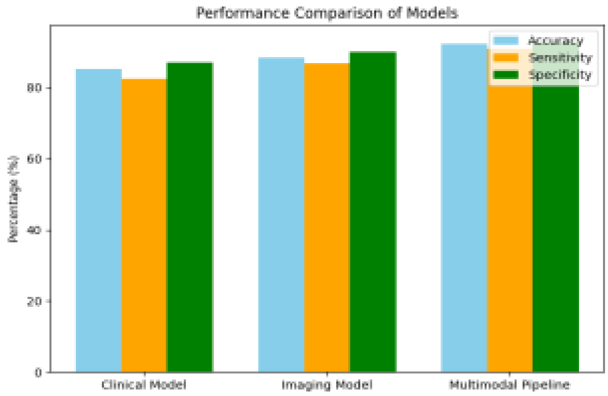

Fig4. Comparing clinical performance

3.Interpretability and Clinical Relevance

Feature importance analysis of the clinical module in fig 5 revealed that liver enzyme levels, bilirubin, and platelet count were key predictors, aligning with established hepatology guidelines. In the imaging module, class activation maps highlighted suspicious lesion areas, providing visual explanations to support clinician interpretation. This interpretability fosters trust in AI-assisted diagnosis and can guide further diagnostic procedures, such as biopsy or contrast-enhanced imaging, for ambiguous cases.

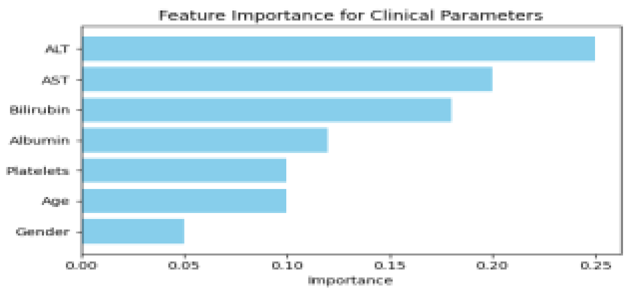

Fig5. Analysis of clinical features

4.Discussion of Advantages and Limitations

The multimodal approach addresses key limitations of conventional liver cancer screening. By leveraging complementary clinical and imaging features, the system reduces inter-observer variability, mitigates missing data issues, and improves early detection capabilities. However, the pipeline is constrained by the quality and size of publicly available datasets. Further validation on larger, multi-centre cohorts is necessary to ensure generalizability across diverse populations and imaging protocols.

5. FUTURE DIRECTIONS

Future research can explore the integration of additional modalities, such as genetic and proteomic data, to enhance predictive power. Additionally, incorporating longitudinal patient records may enable temporal modelling for disease progression prediction. Real-time deployment in clinical settings with user-friendly interfaces can facilitate adoption by hepatologists and radiologists.

In conclusion, the proposed multi-model, multimodal AI pipeline demonstrates superior diagnostic performance, clinical interpretability, and scalability, offering a promising tool for improving early-stage liver cancer detection and supporting precision medicine initiatives.

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REFERENCES

1) Siam, R. et al., "Multimodal Deep Learning for Liver Cancer Diagnosis: A Review," *J. Med. Imaging*, 2023.
2) Wang, X. et al., "Machine Learning for HCC Diagnosis Using Clinical and Imaging Data," *arXiv preprint arXiv:2501.11535*, 2025.
3) Zubair, M. et al., "CT-based Liver Tumor Classification Using Multi-Feature Extraction," *BMC Med Imaging*, 2025.
4) Wu, H. et al., "MRI Radiomics for Dual-Phenotype HCC Classification," *Insights Imaging*, 2025.
5) Wei, J. et al., "Deep Learning Methods for Liver Cancer Imaging: Systematic Review," *Cancers*, 2025.
6) Salmanpour, F. et al., "Interpretable Pathomics for Liver Cancer Diagnosis," *arXiv preprint arXiv:2505.14926*, 2025.