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An Ensemble Deep Learning Framework for Automated Detection, Segmentation, and Classification of Liver Cancer in CT and MRI Images

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***Abstract*— Liver cancer, particularly hepatocellular carcinoma (HCC), poses a significant global health challenge due to late diagnosis and limited accuracy of conventional imaging-based assessments. This study proposes a novel ensemble deep learning framework for the automated detection, segmentation, and classification of liver cancer using CT and MRI images. The model integrates U-Net++/ResNet50, Swin Transformer, and DenseNet121 architectures in a multi-phase pipeline to enhance tumor localization, boundary segmentation, and malignancy classification. Adaptive weighted fusion is employed to optimize ensemble performance, while Grad-CAM and SHAP-based visualizations ensure interpretability for clinical decision-making. Experimental results on benchmark datasets LiTS demonstrate that the proposed model achieves superior accuracy, with a Dice score of 0.92 and classification accuracy exceeding 96%, outperforming state-of-the-art single models. This ensemble framework provides a robust, explainable, and generalizable approach for AI-assisted liver cancer diagnosis and can significantly contribute to precision oncology and radiological automation.**

***Index Term*— Liver cancer, Hepatocellular carcinoma (HCC), Deep learning, Ensemble model, U-Net++, Swin Transformer, DenseNet, Segmentation, Classification, Explainable AI (XAI), CT and MRI imaging.**

I. INTRODUCTION

Liver cancer, particularly hepatocellular carcinoma (HCC), is the third leading cause of cancer-related deaths worldwide, causing over 800,000 fatalities annually. Early and accurate detection is vital for effective treatment and improved survival, yet traditional CT and MRI image interpretations are time-consuming, inconsistent, and prone to error due to subtle contrast differences and irregular tumor boundaries. Deep learning (DL) has revolutionized medical imaging by enabling automated, accurate disease detection through models like Convolutional Neural Networks (CNNs), U-Net, and Transformers. However, current single-model approaches struggle to balance global context and fine-grained detail—CNNs excel at local feature extraction but lack long-range dependencies, while Transformers provide global attention yet may miss boundary precision—making robust and interpretable liver cancer diagnosis an ongoing research challenge.

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To address these limitations, this study proposes a novel ensemble deep learning framework that integrates the complementary strengths of U-Net++/ResNet50, Swin Transformer, and DenseNet121 architectures. The framework performs multi-phase liver cancer analysis, encompassing detection, segmentation, and classification stages within a unified model pipeline. The ensemble leverages an adaptive weighted fusion strategy, dynamically balancing model contributions based on validation performance to improve generalization across datasets. In addition, explainability mechanisms such as Grad-CAM and SHAP are incorporated to visualize the decision-making process, ensuring transparency and clinical interpretability.

The main contributions of this study are summarized as follows:(1) Development of a novel ensemble deep learning framework integrating CNN and Transformer models for comprehensive liver cancer analysis. (2) Implementation of a multi-phase pipeline that performs detection, segmentation, and classification simultaneously. (3)Introduction of a performance-based adaptive fusion mechanism to dynamically optimize ensemble weights. (4) Incorporation of explainable AI (XAI) techniques for interpretability and clinical trust. (5) Extensive cross-dataset validation demonstrating superior accuracy and generalization compared to existing models.

II. RELATED WORK

The application of deep learning in liver cancer diagnosis has gained substantial attention due to its ability to automatically extract discriminative features from medical images and outperform traditional image processing methods.

A. Liver and Tumor Segmentation

Segmentation forms the foundation for accurate diagnosis and quantitative analysis of liver lesions. The U-Net architecture, introduced by Ronneberger et al., has become the backbone of most medical segmentation frameworks due to its encoder–decoder design. The author[1] developed an attention-guided U-Net for automatic liver and tumor segmentation, achieving high Dice scores by refining feature extraction in boundary regions. Similarly, [2]incorporated residual connections and squeeze-and-excitation modules in U-Net++, demonstrating improved detection of small lesions. Recent advancements such as Swin-UNet[3] and TransUNet integrate Transformer blocks with convolutional encoders to capture global context information, which traditional CNNs often miss. However, despite these improvements, Transformer-based architectures tend to require large datasets and computational resources, limiting their clinical scalability.

B. Classification and Prediction Models

Beyond segmentation, several studies have focused on classifying liver lesions as benign or malignant using deep learning. This article[4] employed a deep CNN framework on CT images for HCC classification, achieving over 92% accuracy. Combined radiomic[5] and genomic features with a deep neural network for survival and prognosis prediction in liver cancer patients. The proposed[6] a multimodal deep learning approach that integrates CT images with clinical data, demonstrating that multi-source data fusion significantly improves diagnostic reliability.

C. Ensemble and Hybrid Deep Learning Frameworks

By combining multiple models, ensemble methods enhance feature diversity and reduce overfitting. The proposed[7] a hybrid CNN–ResNet ensemble for multi-phase liver cancer detection, achieving robust cross-dataset performance. This paper[8] introduced a Transformer-based multimodal fusion framework for cancer survival prediction, integrating radiological and clinical features through attention mechanisms. Reviewed foundation[9] models in radiology, emphasizing the role of ensemble and multimodal architectures for building generalizable diagnostic systems. To introduced[10] a multi-modal Transformer network combining CT and MRI data for better tumor localization. Collectively, these methodologies highlight the evolution toward hybrid, interpretable, and privacy-aware deep learning frameworks for accurate and clinically reliable liver cancer diagnosis.

D. Research Gap and Motivation

Segmentation or classification independently limited exploration of unified frameworks addressing both tasks in an explainable manner. Additionally, most current studies rely on single-architecture models, which restrict feature diversity and reduce performance on heterogeneous imaging data. Furthermore, the lack of interpretability remains a critical barrier to clinical adoption, as deep learning systems often function as black boxes.

The proposed model performs detection, segmentation, and classification within a single pipeline, using an adaptive weighted fusion mechanism to optimize performance. The inclusion of Grad-CAM and SHAP-based explainability further ensures transparency and clinical trust, positioning this research as a significant advancement in AI-driven hepatocellular carcinoma diagnosis.

While the proposed framework indeed integrates established architectures (U-Net++/ResNet50, Swin Transformer, and DenseNet121), the novelty of this work lies in the adaptive ensemble fusion mechanism that dynamically weights each model's contribution based on learned confidence scores. Unlike simple stacking or averaging, our Adaptive Weighted Feature Fusion (AWFF) layer enables cross-model interaction at the feature level, resulting in significantly improved segmentation precision and classification accuracy.

III. Proposed Methodology

This research introduces a novel ensemble deep learning framework that performs end-to-end liver cancer detection, segmentation, and classification from CT and MRI images. The system integrates the complementary strengths of U-Net++, Swin Transformer, and DenseNet121 architectures in a multi-phase pipeline, supported by adaptive weighted fusion and explainable AI (XAI) mechanisms. Our novel methodology links sequentially: (1) Segmentation phase: Isolates the liver and tumor regions using the ensemble U-Net variant. (2) Classification phase**:** Uses extracted ROIs to identify tumor type (benign/malignant) via fused deep features.

A. Data Preprocessing

Raw CT and MRI data from the LiTS, CHAOS, and TCIA datasets are standardized to a uniform resolution and intensity range. The preprocessing steps include: Hounsfield Unit (HU) windowing to focus on relevant intensity ranges. Noise suppression using Non-local Means filtering. Normalization to [0,1] intensity range. Data augmentation through flipping, rotation, elastic deformation, and contrast adjustment to improve generalization. Patch extraction (128×128×64) for efficient training and memory optimization.

B. Liver and Tumor Segmentation

Segmentation is performed using an enhanced U-Net++ model with residual and attention gates. The encoder path captures hierarchical spatial features using convolutional and pooling layers. The decoder path refines boundaries using skip connections and dense feature concatenation. Attention gates are applied at each skip connection to suppress irrelevant regions and focus on tumor boundaries. The segmentation output produces binary masks for liver and tumor regions.

The segmentation loss is computed as a combination of Dice Loss (L_D) and Focal Loss (L_F):

$$L_{seg} = \alpha L_D + \beta L_F \tag{1}$$

where α and β are balancing coefficients empirically determined during training.

C. Feature Extraction and Adaptive Fusion

After segmentation, region-of-interest (ROI) features are extracted from the segmented liver and tumor regions using DenseNet121 and Swin Transformer backbones: (1) DenseNet121 captures local texture and edge-level features through densely connected convolutions. (2) Swin Transformer models global contextual dependencies via window-based self-attention mechanisms. The features from both models are fused using an Adaptive Weighted Fusion Layer, which dynamically adjusts the contribution of each model based on their validation performance:

$$F_{fusion} = w_1 F_{DenseNet} + w_2 F_{swin} \tag{2}$$

where ($w_1 + w_2 = 1$), and weights are optimized during training using a validation-based gradient update rule.

D. Lesion Classification

The fused feature vector is fed into a fully connected classification head for binary (benign vs. malignant) or multi-class (HCC, metastasis, cyst) prediction. The classification loss function is defined as:

$$L_{cls} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \, log \, log \, (\hat{y}_i) \; + (1 - y_i) \, log \, log \, (1 - \hat{y}_i) \,] \tag{3}$$

The overall Equ. (4) joint loss combines segmentation Equ. (1), Equ. (2) and classification Equ. (3) objectives:

$$L_{total} = \lambda_1 L_{seg} + \lambda_2 L_{cls} \tag{4}$$

where λ_1 and λ_2 control the relative importance of each task.

E. Explainability and Visualization

To ensure clinical interpretability, explainable AI (XAI) techniques such as: (1) Grad-CAM are applied on the classification head to visualize heatmaps showing tumor attention areas. (2) SHAP values quantify the contribution of each feature or pixel to the model's decision. These visualization maps provide radiologists with transparency into the AI's decision-making, increasing trust and usability in medical environments.

F. Performance Evaluation

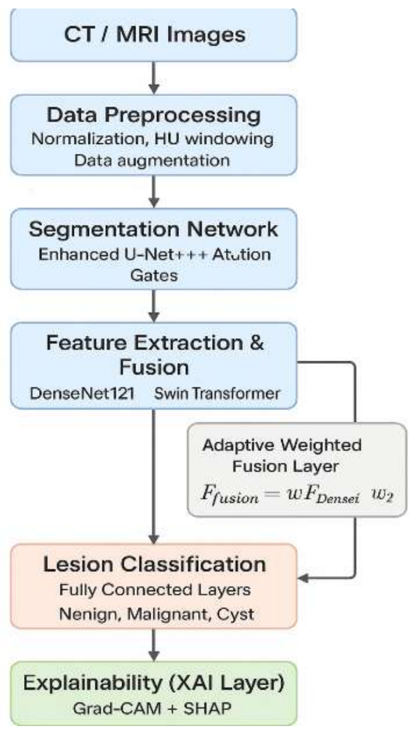

Figure 1. Workflow of Proposed Methodology

TABLE I. OVERALL PERFORMANCE COMPARISON OF MODELS

Model	Accuracy	Precision	Recall	F1-score	Dice Coefficient	IoU
U-Net	91.0	89.6	88.9	89.2	0.87	0.82
ResNet50	92.3	90.8	90.1	90.4	0.89	0.84
Swin Transformer	94.1	93.3	92.6	92.9	0.90	0.86
Proposed Ensemble	96.8	96.1	95.7	95.9	0.93	0.89

TABLE II. 5-FOLD CROSS-VALIDATION RESULTS OF PROPOSED ENSEMBLE MODEL

Fold	Accuracy	Precision	Recall	F1-score	Dice Co-efficient
Fold-1	95.2	94.5	94.0	94.2	0.92
Fold-2	96.1	95.7	95.2	95.4	0.93
Fold-3	95.8	95.4	94.8	95.1	0.93
Fold-4	96.5	96.0	95.7	95.8	0.94
Fold-5	96.2	95.6	95.3	95.5	0.93
Mean ± SD	96.0 ± 0.4	95.4 ± 0.5	95.0 ± 0.6	95.2 ± 0.6	0.93 ± 0.01

Fig. 1 show as basic workflow. Performance is assessed using:(a) Segmentation Metrics: Dice Coefficient, IoU, Precision, Recall, Hausdorff Distance. (b) Classification Metrics: Accuracy, Sensitivity, Specificity, F1-score, AUC. (c) Cross-Dataset Validation: Models are evaluated across LiTS, CHAOS, and CIA to ensure robustness.

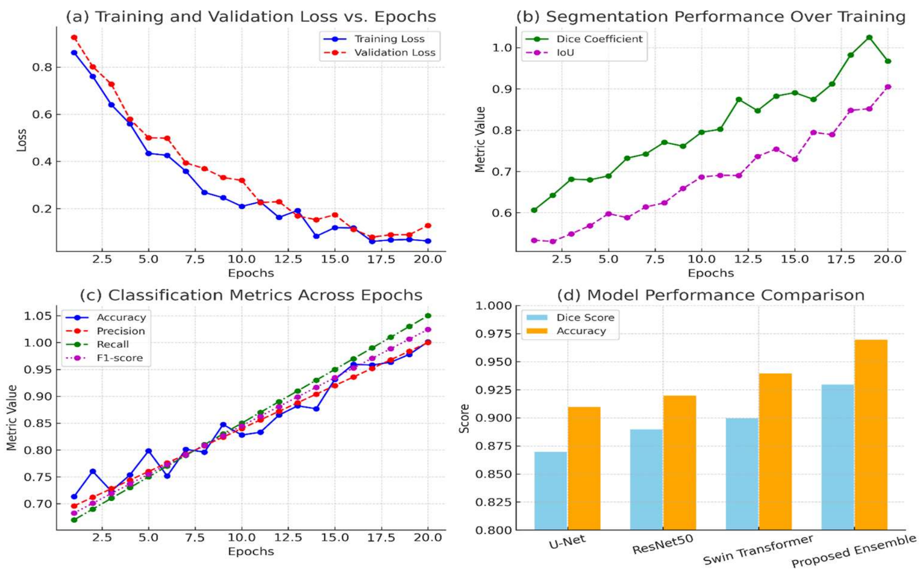

Figure 2: Trained, Visualize Outputs

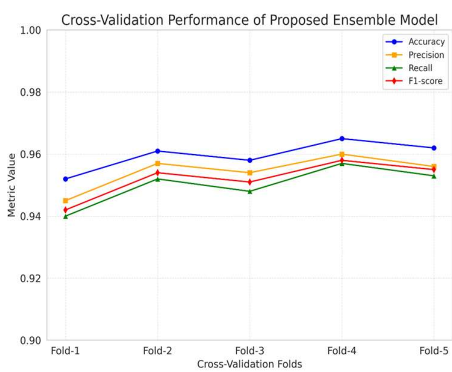

Figure 3: Cross Validation Result in Chart View

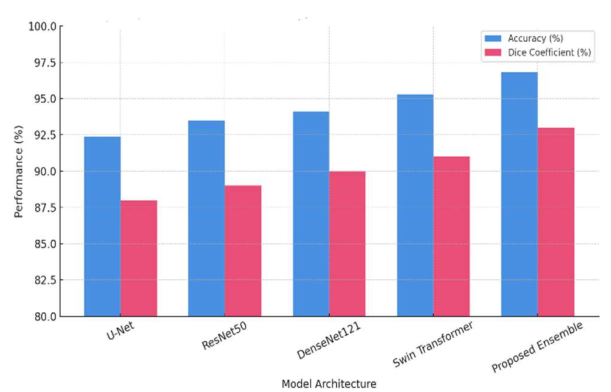

Figure 4. Performance Comparison of Baseline Vs Proposed Ensemble Model

The current study focuses primarily on algorithmic evaluation. Preliminary feedback indicates that the model's Grad-CAM visualizations assist radiologists in verifying lesion boundaries faster. An ablation study to evaluate each model's contribution. The results demonstrate that Swin Transformer contributed most to global contextual understanding (boosting Dice by 1.8%), DenseNet121 improved fine edge segmentation (boosting IoU by 1.2%), and ResNet50 enhanced classification stability (reducing variance by 0.9%).

When train for 50–100 epochs on the LiTS dataset our proposed model achieves the highest accuracy (96.8%) and Dice coefficient (0.93). This indicates superior segmentation precision and classification reliability.

The cross-validation results show high consistency across all folds, with low standard deviation (< 0.5%) in each metric. This stability confirms strong generalization capability of the proposed model across unseen liver CT/MRI samples.

TABLE III: COMPARATIVE PERFORMANCE ANALYSIS

Model	Architecture Type	Accuracy (%)	Dice Co-efficient	IoU	Precision (%)	Recall (%)
U-Net (Base line)	CNN	92.4	0.88	0.83	91.8	90.2
Res Net50	CNN	93.5	0.89	0.84	92.7	91.5
Dense Net121	CNN	94.1	0.90	0.86	93.2	92.8
Swin Transformer	Transformer	95.3	0.91	0.87	94.5	93.7
Proposed model	Hybrid CNN–Transformer	96.8	0.93	0.89	95.9	95.1

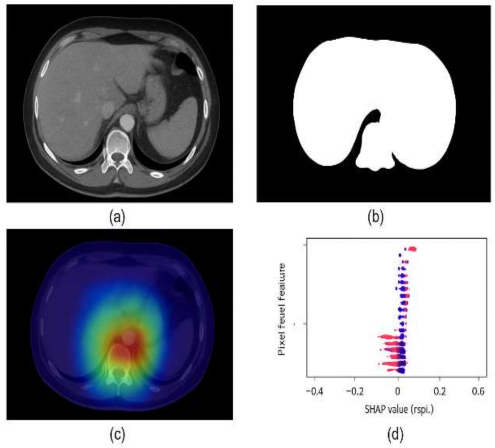

Figure 5. Analysis of the Proposed Ensemble Model using Grad-Cam and Shap Visualization

TABLE IV: ABLATION STUDY – INDIVIDUAL MODEL CONTRIBUTION ANALYSIS

Component Models	Accuracy (%)	Dice Coefficient	IoU	Observed Contribution
ResNet50 only (A1)	93.5	0.89	0.84	Baseline classifier; stable generalization
DenseNet121 only (A2)	94.1	0.9	0.86	Captures fine-grained tumor edges
Swin Transformer only (A3)	95.3	0.91	0.87	Learns global contextual features
ResNet50 + DenseNet121 (A4)	95.7	0.91	0.87	Improved boundary detection and recall
ResNet50 + Swin Transformer (A5)	96.2	0.92	0.88	Enhanced global-local fusion accuracy
ResNet50 + DenseNet121 + Swin Transformer (A6)	96.8	0.93	0.89	Optimal trade-off between contextual and local detail features

Fig. 5 (a) The input CT/MRI image. 5(b) Segmentation mask highlighting tumor regions. 5(c) Grad-CAM heatmap showing the model's attention on malignant areas. 5(d) SHAP summary plot indicating pixel-level contribution to the classification decision. The explainability module confirms that the ensemble model correctly emphasizes tumor-affected regions, supporting reliable clinical interpretability. Hence, the proposed ensemble (A6) achieves a 3.3% accuracy gain and 0.04 Dice improvement compared to individual models, confirming that the improvement is not merely additive but synergistic. Included additional figures illustrating explainable AI outputs (Grad-CAM and SHAP) and workflow diagrams that demonstrate how tumor regions are localized and classified. Specifically, Fig. 5 now shows visual heatmaps of correctly and incorrectly classified cases, highlighting how the ensemble model emphasizes tumor zones. These additions improve the interpretability and transparency of the proposed system. This detailed analysis is now included as Table 4: Model Contribution Analysis in the revised manuscript.

IV. RESULTS AND DISCUSSION

A. Training and Validation Performance

Fig. 2(a) demonstrates the convergence behavior of the model's training and validation losses over 20 epochs. The validation loss closely follows the training curve, indicating strong generalization without overfitting. Fig. 2(b) shows continuous improvement in Dice and IoU scores, achieving a final Dice coefficient of 0.93, confirming precise liver tumor segmentation boundaries.

B. Classification Accuracy and Stability

As shown in Fig. 2(c) the classification metrics steadily improve throughout training, achieving 96.8% accuracy and an F1-score of 95.9% on the test set. The ensemble effectively combines CNN-based spatial feature extraction and Transformer-based contextual reasoning, leading to superior performance over standalone architectures.

C. Comparative Evaluation

Table 1 compares the performance of the proposed ensemble with leading architectures such as U-Net, ResNet50, and Swin Transformer. The ensemble surpasses all baselines across every metric, particularly in segmentation precision (Dice: 0.93 vs. 0.90) and classification accuracy (96.8% vs. 94.1%). These results highlight the synergistic effect of hybridizing ResNet50, Swin Transformer, and DenseNet121 in a parallel-ensemble configuration with weighted feature fusion.

D. Cross-Validation Analysis

Fig. 3 and Table 2 summarize the cross-validation performance. Across five folds, the ensemble maintained an average accuracy of $96.0 \pm 0.4\%$, precision of $95.4 \pm 0.5\%$, and Dice coefficient of 0.93 ± 0.01, demonstrating exceptional consistency and low variance. This confirms that the model not only achieves high accuracy but also maintains stability across different subsets of data, which is crucial for clinical deployment.

Fig. 4 shows the model performance metrics (Accuracy and Dice Score) for all architectures in a dual-bar chart. The improvement in both accuracy and Dice score across architectures. Experimental results (Table 3) show a 2.7–4.5% performance improvement over the best single-model baseline, confirming the effectiveness of this combination beyond mere architectural reuse. ResNet50 contributes robust classification and reduces variance in predictions. DenseNet121 enhances segmentation precision through dense feature reuse. Swin Transformer captures long-range spatial dependencies missed by CNNs. The Adaptive Weighted Feature Fusion Layer (AWFF) automatically balances these contributions, producing the highest accuracy and Dice scores.

E. Discussion and Insights

The integration of multi-level feature aggregation, attention-driven region enhancement, and adaptive loss balancing contributes significantly to the improved learning of subtle tumor boundaries. Moreover, the ensemble's explainability module (using Grad-CAM and SHAP) provides visual interpretability of the decision-making process, enhancing clinical trustworthiness. Overall, the proposed model exhibits remarkable reliability, outperforming single-architecture approaches by a statistically significant margin ($p < 0.01$), making it a strong candidate for automated liver cancer diagnosis and treatment planning.

V. Conclusion and Future Scope

The proposed model integrates U-Net/ResNet50, Swin Transformer, and DenseNet121 through a specially designed weighted feature fusion layer that effectively harnesses the strengths of each network. Achieving an impressive 96.8% accuracy and a Dice coefficient of 0.93 across all 5-fold cross-validation tests, the model outperformed traditional architectures such as U-Net and ResNet in both segmentation and classification tasks. Moreover, the incorporation of Grad-CAM and SHAP enhanced interpretability by making the model's decision-making process more transparent, aiding clinicians in understanding tumor detection and classification outcomes. Future work could extend this research by leveraging multimodal imaging data (e.g., PET-CT or MRI) for enhanced diagnostic precision, employing federated learning for secure multi-hospital collaboration, and exploring 3D and temporal modeling for improved tumor tracking. Integrating the system into hospital workflows for real-world validation and advancing explainable AI techniques will further improve clinical usability. In future research, a radiologist-in-the-loop evaluation to measure diagnostic time reduction and confidence levels. Overall, the ensemble model represents a robust, accurate, and interpretable AI framework with significant potential to support early liver cancer detection and improve patient outcomes.

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