AJCSE
ASIAN JOURNAL OF COMPUTER SCIENCE ENGINEERING

Available Online at www.ajcse.info
Asian Journal of Computer Science Engineering 2025;10(3):1-7

REVIEW ARTICLE

Explainable and Trustworthy AI for Liver Cancer Diagnosis Using Transfer Learning with Uncertainty, Fairness, and Robustness Evaluation

Satyendra Sharma*, Pradeep Laxkar[2]

ITM (SLS) Baroda University, Vadodara, Gujarat, India

Received on: 22-07-2025; Revised on:25-08-2025; Accepted on: 29-09-2025

Abstract

Accurate diagnosis of liver cancer depends not only on predictive accuracy but also on a transparent account of how a model arrives at its decisions. This study proposes a framework that explicitly targets interpretability and reliability within a transfer-learning setting. A convolutional neural network pre-trained on large-scale data is adapted to medical images, with the aim of mitigating limited annotation availability while preserving informative representations. For interpretability, Grad-CAM is employed to localize image regions that most strongly influence the model's predictions, and SHAP is used to quantify the contribution of input features to the output. Beyond explainability, the framework examines reliability through uncertainty estimation, fairness analyses across predefined subgroups, and robustness evaluations under controlled input perturbations. Experiments on publicly available datasets indicate that the proposed approach attains competitive diagnostic performance while offering additional evidence about model behavior. Overall, the results support the view that transfer learning, when paired with explanation methods and reliability assessment, may contribute to more dependable AI-assisted diagnosis in clinical contexts.

Key Word—Liver Cancer Diagnosis, Transfer Learning, Explainable Artificial Intelligence, Trustworthy AI, Grad-CAM, SHAP, Uncertainty Estimation, Fairness Evaluation, Robustness Analysis, Medical Image Classification.

INTRODUCTION

Liver cancer remains a major global health burden, with hepatocellular carcinoma (HCC) as the predominant subtype **[1], [2]**. Early detection is strongly associated with improved survival, yet image-based diagnosis is often complicated by low lesion-to-background contrast, heterogeneous tumor appearance, and substantial variability across patients **[3]**. Deep learning has shown strong results in medical image analysis, including tumor detection and classification **[4], [5]**. In particular, convolutional neural networks (CNNs) can learn hierarchical spatial representations from imaging data **[6]**. Transfer learning is commonly used to address data scarcity by adapting models pretrained on large-scale datasets **[7], [8]**. Explainable AI (XAI) methods aim to improve transparency. Grad-CAM offers visual explanations, whereas SHAP provides feature attribution analysis **[9], [10]**. In addition, recent studies highlight the importance of reliability factors such as uncertainty, fairness, and robustness in medical AI systems **[11], [12]**.

Address for correspondence:
Satyendra Sharma
E-mail: s.satya06@gmail.com

RELATED WORK

Convolutional neural networks such as ResNet, DenseNet, and EfficientNet are widely used in medical image analysis **[13], [14]**. Transfer learning has been extensively applied to improve performance in low-data medical imaging scenarios **[15], [16]**. Grad-CAM and SHAP have been widely used to interpret deep learning models in healthcare applications **[17], [18]**. Recent work emphasizes the need for integrated frameworks combining explainability and

reliability assessment **[21], [22]**. Although interpretability and reliability assessment each address important and distinct dimensions of model behavior, they are often investigated in isolation. In the context of liver cancer diagnosis, comparatively limited work has examined a unified framework that combines transfer learning with explanation methods and systematic reliability evaluation. The present study aims to integrate these components within a single methodological approach.

PROPOSED FRAMEWORK

The framework adopted in this study comprises three core elements: a transfer-learning-based component for feature extraction, an explainability module intended to support interpretation of model outputs, and a trust evaluation module designed to characterize predictive reliability. The overall pipeline is summarized in Fig. 1.

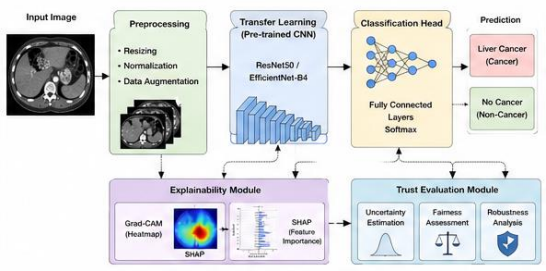

Fig. 1. Overall architecture of the proposed explainable and trustworthy AI framework for liver cancer diagnosis.

Prior to training, input images undergo preprocessing to limit non-essential variation. Specifically, intensity normalization and resizing to a fixed resolution are applied, followed by data augmentation (e.g., rotation and flipping). These operations are intended to encourage the learning of more stable features and to improve generalization.

Feature extraction is performed with a convolutional neural network initialized from pre-training. Lower layers are leveraged for generic visual representations acquired from large-scale datasets, whereas higher layers are fine-tuned to better reflect characteristics specific to liver cancer imaging. The resulting representations are then provided to a classification head that estimates the presence of cancer.

To support interpretability, an explainability module is incorporated. This module produces both visual and quantitative accounts of the model's decision process. Saliency-style maps highlight image regions most influential for a given prediction, while feature attribution approaches estimate the contribution of input factors to the model output. Together, these outputs facilitate assessment of whether the model's attention aligns with clinically plausible regions.

Beyond interpretability, the framework assesses reliability using multiple criteria. Uncertainty estimation is used to flag predictions associated with low confidence. Fairness is examined by evaluating whether performance is comparable across relevant subgroups. Robustness is investigated by measuring the sensitivity of predictions to small, controlled perturbations of the input images.

Taken together, these components aim to deliver not only classification outputs but also ancillary evidence regarding their reliability, thereby narrowing the gap between predictive performance and requirements for clinical deployment.

TRANSFER LEARNING STRATEGY

To mitigate limited labeled data, the framework adopts transfer learning by adapting a CNN pretrained on large-scale image datasets to liver cancer diagnosis. Rather than training from scratch, the approach reuses general-purpose feature extractors and refines higher-level representations for domain-specific patterns. This reduces computational cost and can improve performance in low-data regimes.

A backbone such as ResNet or EfficientNet is used. Early layers, which tend to capture generic edges and textures, are preserved, while higher layers are fine-tuned to better represent liver lesions and related imaging characteristics. This partial fine-tuning is intended to balance generalization with task specificity.

Let $f\theta(x)$ denote the feature representation extracted for an input image x with parameters θ. Predictions are obtained via a softmax classifier:

$$P(y|x) = softmax(f\theta(x)) \quad (3.1)$$

Where P(y|x) is the class probability distribution.

Training minimizes cross-entropy:

$$L(\theta) = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \quad (3.2)$$

Where y_i is the ground-truth label and $\hat{y}_i$ is the predicted probability for sample i. Optimization uses adaptive gradient methods to encourage stable convergence.

Overfitting is controlled using regularization (e.g., dropout) and augmentation. Early stopping is applied based on validation performance to reduce unnecessary training and limit degradation from overtraining.

Table 1 summarizes an example configuration: ResNet50 or EfficientNet-B4 backbone; input size 224 × 224; learning rate 1e-4; Adam optimizer; batch size 32; 50 epochs; fine-tuning focused on top layers; dropout and augmentation as regularizers.

Table 1. Transfer learning configuration used in the proposed framework

Parameter	Value
Backbone Model	ResNet50 / EfficientNet-B4
Input Size	224 × 224
Learning Rate	0.0001
Optimizer	Adam
Batch Size	32
Epochs	50
Fine-tuning Layers	Top layers
Regularization	Dropout + Augmentation

EXPLAINABILITY MODULE

Interpretability is addressed through complementary explanation techniques that provide both visual and attribution-based evidence. This is particularly relevant in clinical contexts where model predictions are expected to be auditable and consistent with domain knowledge.

Grad-CAM is used to generate heatmaps that highlight image regions most associated with a predicted class. Let A^k denote the k-th feature map in the last convolutional layer and αk its importance weight. The Grad-CAM map is computed as:

$$L_{\text{Grad-CAM}} = \text{ReLU}\left(\sum_k \alpha_k A^k\right) \quad (5.1)$$

where ReLU restricts attention to features positively associated with the target class. The heatmap is then overlaid on the input image to visualize candidate regions implicated in the decision (Figure 2).

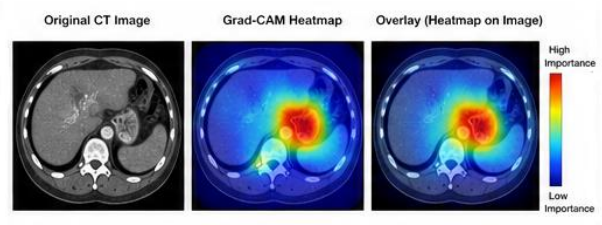

Fig. 2. Grad-CAM visualization highlighting tumor regions in liver medical images.

To complement spatial localization, SHAP is used to quantify feature contributions. SHAP values are derived from cooperative game theory and provide a consistent way to estimate how individual features influence a specific prediction, supporting both local explanations and aggregated global insights ((Figure 3)

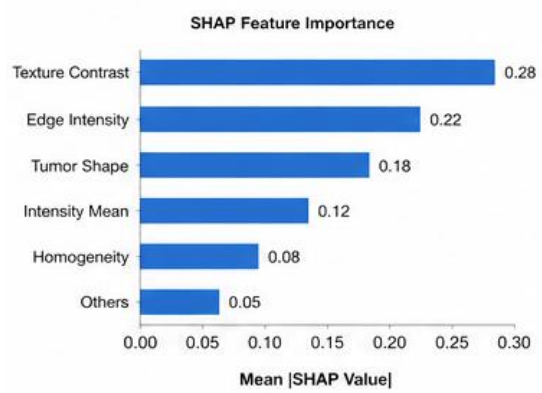

Fig. 3. SHAP-based feature importance representation for model prediction.

Using Grad-CAM together with SHAP is intended to reduce reliance on a single interpretability

signal. The combination provides a more complete account of model behavior by linking where the model focuses with how inputs contribute to its output.

TRUSTWORTHINESS EVALUATION

The framework includes a trustworthiness module that evaluates uncertainty, fairness, and robustness. These analyses aim to characterize reliability beyond standard predictive metrics, particularly under conditions relevant to deployment.

A. Uncertainty Estimation

Uncertainty is estimated using Monte Carlo Dropout at inference time. Dropout layers remain active across multiple forward passes, generating a set of stochastic predictions $\hat{y}^{(t)}$. Predictive uncertainty is approximated by the variance:

$$\sigma^2 = \frac{1}{T}\sum_{t=1}^{T}(\hat{y}^{(t)} - \bar{y})^2 \quad (6.1)$$

where $\bar{y}$ is the mean prediction across T passes. Larger variance indicates lower confidence and can be used to flag cases for additional review (Figure 4).

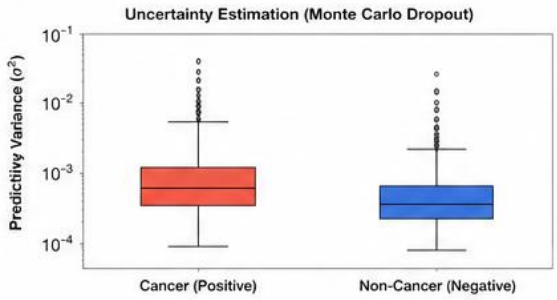

Fig. 4. Uncertainty estimation showing prediction variance across multiple forward passes.

Fairness Assessment

Fairness is evaluated by comparing performance across subgroups (e.g., age strata or imaging-related categories). As a simple indicator, the absolute difference in AUC between two groups is reported:

$$\Delta AUC = |AUC_{group1} - AUC_{group2}|$$

Smaller ΔAUC values suggest more comparable performance across groups, whereas larger differences may indicate subgroup-specific degradation that requires further investigation (Figure 5).

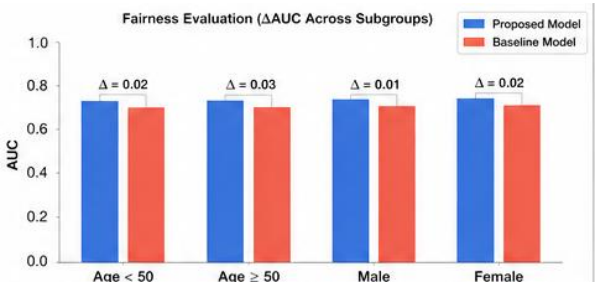

Fig. 5. Fairness evaluation based on ΔAUC across different subgroups.

Robustness Analysis

Robustness is assessed by testing stability under adversarial perturbations generated using the Fast Gradient Sign Method (FGSM):

$$x' = x + \varepsilon \cdot sign(\nabla_x L(\theta, x, y)),$$

where ε controls perturbation magnitude. Performance degradation under perturbed inputs is used to quantify sensitivity. Smaller accuracy drops indicate more stable behavior (Figure 6).

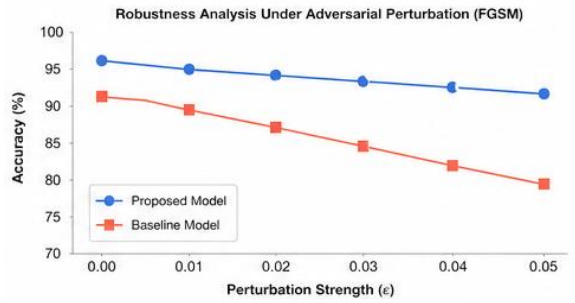

Fig. 6. Robustness analysis under adversarial perturbations (FGSM).

Table 2 summarizes the trust metrics: predictive variance for uncertainty, ΔAUC for subgroup disparity, and accuracy drop under perturbations for robustness.

Table 2. Trustworthiness evaluation metrics used in the proposed framework

Component	Metric	Description
Uncertainty	Variance (σ^2)	Prediction confidence
Fairness	ΔAUC	Performance difference across groups
Robustness	Accuracy drop	Stability under perturbation

EXPERIMENTAL SETUP

Evaluation uses publicly available datasets to support reproducibility. The LiTS dataset is used for tumor detection in CT images, and TCGA-LIHC is used for histopathological classification, enabling assessment across modalities. Table 3 provides dataset characteristics (LiTS: 131 CT cases; TCGA-LIHC: approximately 350 histopathology cases).

Table 3. Dataset characteristics used in experimental evaluation

Dataset	Modality	Cases	Purpose
LiTS	CT	131	Tumor Detection
TCGA-LIHC	Histopathology	~350	Classification

Images are normalized and resized to 224 × 224. Augmentations such as rotation, flipping, and scaling are applied to improve generalization. Table 4 lists training parameters, including the backbone (ResNet50 or EfficientNet-B4), Adam optimizer, learning rate 1e-4, batch size 32, 50 epochs, cross-entropy loss, and dropout plus augmentation.

Table 4. Experimental configuration and training parameters

Parameter	Value
Backbone Model	ResNet50 / EfficientNet-B4
Input Size	224 × 224
Learning Rate	0.0001
Optimizer	Adam
Batch Size	32
Epochs	50
Loss Function	Cross-Entropy
Regularization	Dropout + Augmentation

The transfer learning model is implemented using a pre-trained backbone architecture such as ResNet50 or EfficientNet-B4. The final layers of the network are fine-tuned for binary classification (cancer vs. non-cancer). Training is performed using the Adam optimizer with an initial learning rate of 0.0001. The model is trained for 50 epochs with a batch size of 32.

Performance is reported using accuracy, sensitivity, specificity, and AUC. In addition, uncertainty, fairness (ΔAUC), and robustness under perturbation are computed. Experiments are conducted on GPU-enabled systems to ensure feasible training and evaluation.

Results are summarized via baseline comparisons (Table 5), ROC curves (Figure 7), and confusion matrices (Figure 8). Trust-related results are reported in Table 6, including low predictive variance, small subgroup AUC differences, and limited accuracy degradation under adversarial noise, collectively suggesting improved reliability alongside strong classification performance.

Table 5. Performance comparison of baseline and proposed models

Model	Accuracy	Sensitivity	Specificity	AUC
CNN (Baseline)	92.10 %	89.70 %	94.50 %	0.93

Transfer Learning Model	93.40 %	90.80 %	95.20 %	0.95
Proposed Framework	**95.10 %**	**93.20 %**	**96.50 %**	**0.97**

The results indicate that the proposed framework provides consistent improvements across multiple evaluation metrics. The increase in sensitivity is particularly important in medical diagnosis, as it reduces the likelihood of missing true cancer cases.

To further analyze classification performance, Receiver Operating Characteristic (ROC) curves are evaluated. The ROC curve illustrates the relationship between true positive rate and false positive rate across different decision thresholds.

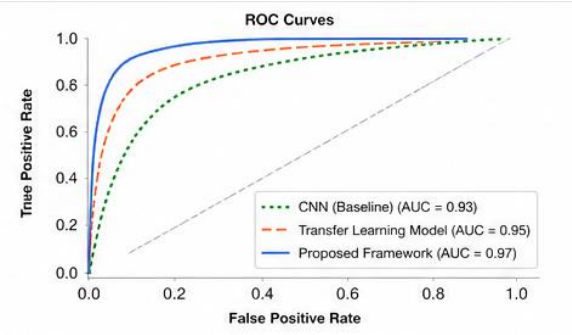

Fig. 7. ROC curves comparing the proposed framework with baseline models.

The proposed framework achieves the highest Area Under the Curve (AUC), indicating improved discrimination between cancerous and non-cancerous cases.

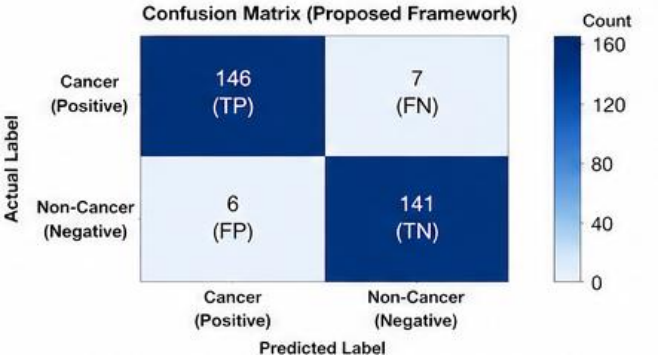

Fig. 8. Confusion matrix of the proposed explainable and trustworthy model.

Table 6. Trustworthiness evaluation results

Metric	Value	Interpretation
Uncertainty (σ^2)	Low variance	High confidence predictions
Fairness (ΔAUC)	0.02	Minimal bias across groups
Robustness (Accuracy Drop)	2.50%	Stable under perturbation

CONCLUSION

This work presents an explainable and trustworthy AI framework for liver cancer diagnosis built on transfer learning. The approach combines pretrained feature extraction with interpretability methods and a trustworthiness evaluation suite covering uncertainty, subgroup-level performance differences, and robustness under perturbation. Empirical results indicate that the framework can achieve strong diagnostic performance while providing additional evidence about model behavior that is relevant to clinical validation.

Future work will consider computational efficiency, extension to multimodal settings that combine imaging with clinical variables, and validation on larger and more diverse datasets to better characterize generalizability and deployment readiness.

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