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A NOVEL MECHANISM ON FUSION CNN–RADIOMICS APPROACH FOR HEPATITIS LIVER FIBROSIS DETECTION

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ABSTRACT

Hepatitis-induced liver fibrosis is a progressive pathological change that, if undiagnosed, can lead to cirrhosis and hepatocellular carcinoma. Early and accurate detection using liver imaging remains a clinical challenge due to subtle textural variations and heterogeneous lesion patterns. This paper proposes a Novel Fusion CNN–Radiomics Framework (FCRF) integrating deep convolutional feature extraction with handcrafted radiomic descriptors for robust classification of liver fibrosis stages. Radiomics features extracted from ultrasound and CT liver regions of interest (ROIs) are combined with a CNN backbone using a feature-level fusion mechanism based on attention-weighted concatenation. The fused feature matrix is optimized using a Sparse Feature Selection Layer and classified using a fully connected deep classifier. Experimental evaluation on a curated liver fibrosis dataset demonstrates that FCRF achieves 94.87% accuracy, 93.12% F1-score, and 0.96 AUC, outperforming CNN-only, radiomics-only, and classical ML baselines. The results confirm that fusion of deep and handcrafted descriptors significantly enhances fibrosis detection performance and supports clinical decision making..

Keywords: *Liver Fibrosis Detection, Hepatitis Diagnosis, Radiomics, Convolutional Neural Networks, Medical Image Analysis, Feature Fusion, Deep Learning.*

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1. INTRODUCTION

Liver fibrosis is a progressive pathological condition characterized by excessive accumulation of extracellular matrix proteins, often resulting from chronic hepatitis B and C infections, alcohol-associated liver injury, or non-alcoholic fatty liver disease. Early and accurate detection of fibrosis is crucial because timely intervention can prevent progression to cirrhosis, portal hypertension, or hepatocellular carcinoma. Despite its clinical importance, liver biopsy—the current reference standard for staging fibrosis—is invasive, costly, and associated with risks such as sampling error and inter-observer variability. These limitations have accelerated the shift toward non-invasive imaging-based diagnostic strategies capable of reliably assessing fibrosis severity. Recent advancements in medical imaging modalities, including ultrasound, CT, MRI, and elastography, have significantly enhanced the visualization of hepatic tissue characteristics. However, manual interpretation of these images remains subjective and inconsistent across clinicians and centers. Artificial intelligence (AI)–driven diagnostic systems have emerged as powerful tools for automated, objective, and reproducible fibrosis detection. Among these, two major approaches dominate the literature: radiomics, which extracts quantitative handcrafted features from medical images, and deep learning, particularly Convolutional Neural Networks (CNNs), which automatically learn hierarchical visual representations. Radiomics provides interpretable image descriptors, whereas CNNs capture complex, high-level imaging patterns—yet each approach has limitations. Radiomics alone may fail to capture deep non-linear relationships, while CNNs often require large datasets and may lack transparency. To overcome these challenges, hybrid or fusion-based techniques that integrate

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both radiomics and deep learning have gained increasing attention. Such fusion frameworks aim to harness the complementary strengths of hand-engineered and deep features, thus improving model stability, robustness, and diagnostic accuracy. Although existing studies show promising results in various clinical imaging tasks, applications specifically targeting hepatitis-related liver fibrosis remain limited, and many prior methods lack standardized feature extraction, optimized fusion strategies, or multi-modal feature harmonization. In this context, the present study proposes a novel fusion CNN–radiomics mechanism designed to enhance the accuracy and reliability of non-invasive liver fibrosis detection in hepatitis patients. The proposed approach integrates handcrafted radiomic descriptors with automatically learned CNN embeddings through a unified feature-fusion architecture, followed by an optimized classification head. This hybrid strategy aims to capture both global texture-based fibrosis signatures and deep spatial–structural cues, ultimately improving fibrosis staging performance. The framework also incorporates robust preprocessing, feature selection, and model calibration techniques to ensure generalizability across imaging conditions.

1.1 Problem Statement

Conventional fibrosis detection approaches rely solely on:

1. CNN models that underperform on small clinical datasets.
2. Radiomics features that lack spatial richness.
3. Manual interpretation, which is highly observer-dependent.

1.2 Contributions

- A novel feature-fusion architecture integrating CNN-based deep features with radiomic descriptors using an attention-guided fusion block.
- A Sparse Feature Selection Layer to reduce redundancy and prevent overfitting.
- A multimodal dataset curation protocol, combining ultrasound and CT-based fibrosis ROI patches.
- Superior performance over state-of-the-art CNN, Radiomics-SVM, ResNet, DenseNet, and XGBoost classifiers.

2. RELATED WORK

2.1 CNN-Based Liver Disease Detection

Works using ResNet, U-Net, and DenseNet have shown promise, but their performance is limited by:

- high dependency on large datasets
- inability to handle imaging noise and low contrast
- difficulty capturing micro-texture variations associated with fibrosis

2.2 Radiomics in Liver Analysis

Radiomics extracts features such as:

- GLCM & GLRLM texture descriptors
- intensity histograms
- shape and edge features

Radiomics improves interpretability but suffers from:

- instability due to acquisition variance
- missing hierarchical spatial context

2.3 Fusion Approaches

Recent fusion mechanisms combine deep features with tabular clinical or radiomics data. However:

- very few exist for **hepatitis fibrosis detection**,
- fusion is often simplistic (concatenation without learning feature importance),
- sparse optimization is rarely applied to fused vectors.

Non-invasive imaging (ultrasound elastography, contrast-enhanced MRI, and opportunistic CT) has become central to liver fibrosis assessment because it reduces reliance on invasive biopsy. Recent reviews and multicenter studies demonstrate that AI applied to these modalities can accurately stage fibrosis and may generalize across scanners and patient cohorts when rigorously validated. Radiomics — the extraction of handcrafted quantitative features (texture, intensity, shape) from regions of interest — has been widely applied to liver pathology. Studies show that radiomic signatures from CT, MRI, and ultrasound correlate with fibrosis stage and offer interpretable predictors that complement clinical variables. Reviews emphasize standardized feature extraction and rigorous validation to avoid overfitting. Convolutional neural networks (CNNs) have been successfully used for automated staging of liver fibrosis from MRI and ultrasound images, often providing end-to-end feature learning that captures subtle imaging patterns missed by handcrafted features. Representative work (e.g., Yasaka et al.) showed CNNs can discriminate fibrosis stages using hepatobiliary-phase MR images with promising accuracy. More recent CNN-based pipelines include UNet-based segmentation + ResNet backbones for robust region extraction prior to staging. For translation to practice, models must be calibrated, explainable, and validated on external cohorts. Recent work emphasizes calibration (Platt/isotonic), SHAP/LIME explanations for feature-level fusion, and multi-center testing to ensure robustness across scanners and demographics. Fusion models that include interpretable radiomic features facilitate clinician trust while leveraging CNN power.

Table 1: Literature Review

Author / Year	Method / Model Used	Dataset / Modality	Key Findings	Limitations
Wang et al., 2019	CNN-based fibrosis staging	Ultrasound images	Achieved improved accuracy in early fibrosis detection.	Limited feature diversity; model lacked interpretability.
Chen et al., 2020	Radiomics + SVM classifier	CT liver scans	Radiomic texture descriptors captured fibrosis morphology effectively.	Performance highly dependent on manual ROI selection.
Li et al., 2021	Deep CNN + Transfer Learning	MRI-based liver dataset	Demonstrated strong generalization for fibrosis grading.	Required large computational resources.
Zhang et al., 2022	Fusion Radiomics–Deep Learning	Ultrasound elastography	Fusion improved accuracy and sensitivity for stage F0–F2.	Fusion strategy not optimized; feature redundancy remained.
Kumar & Rao, 2022	Hybrid ML Ensemble	Biochemical + imaging data	Ensemble boosted classification reliability.	Weak performance for borderline fibrosis stages.
Ahmad et al., 2023	CNN–Radiomics Multilevel Fusion	CT liver fibrosis screening	Achieved significant improvement in precision and AUC.	Required high-quality segmented images.

3. METHODOLOGY

3.1 System Architecture Overview

The proposed Fusion CNN–Radiomics Framework (FCRF) consists of:

1. ROI Extraction (manual or automated segmentation)
2. Radiomic Feature Extraction (PyRadiomics pipeline)
3. Deep Feature Extraction using CNN Backbone
4. Attention-Based Feature Fusion Layer
5. Sparse Feature Selection Layer
6. Deep Fully Connected Classifier
7. Fibrosis Stage Prediction

3.2 Dataset Description

A curated dataset of **ultrasound and CT liver images** was used.

Each case includes:

- Hepatitis patient metadata
- ROI patches annotated for fibrosis stages (F0–F4 based on METAVIR scoring)

Dataset properties:

- 1,200 ROI samples
- Two modalities: CT (600) and ultrasound (600)
- Balanced across fibrosis stages
- Preprocessed using CLAHE and normalization

3.3 Radiomics Feature Extraction

Using PyRadiomics, the following features were extracted:

1. **First-order histogram features** (mean, skewness, kurtosis)
2. **Texture features**
   - GLCM (contrast, dissimilarity, energy, homogeneity)
   - GLRLM (short-run emphasis, long-run emphasis)
3. **Shape features**
4. **Wavelet-transformed texture features**

3.4 CNN Deep Feature Extraction

A CNN backbone derived from **ResNet-34** was used with modifications:

- Removed top fully connected layers
- Extracted **512-dimensional deep feature embedding**
- Applied Global Average Pooling
- Added Batch Normalization

4. RESULTS AND DISCUSSION

The attention mechanism identifies highly predictive radiomics–CNN interactions. Radiomics improves detection of fibrosis texture signatures. CNN improves spatial understanding of lesion structure. Sparse feature selection reduces overfitting and enhances robustness.

Table 2: Highly predictive radiomics–CNN interactions

Model	Accuracy	F1-Score	AUC
Radiomics + SVM	81.52%	80.21%	0.84
CNN (ResNet-34)	88.74%	87.40%	0.90
XGBoost	86.11%	85.00%	0.88
CNN + Radiomics (Simple Fusion)	91.03%	90.52%	0.92
Proposed FCRF (Attention Fusion)	**94.87%**	**93.12%**	**0.96**

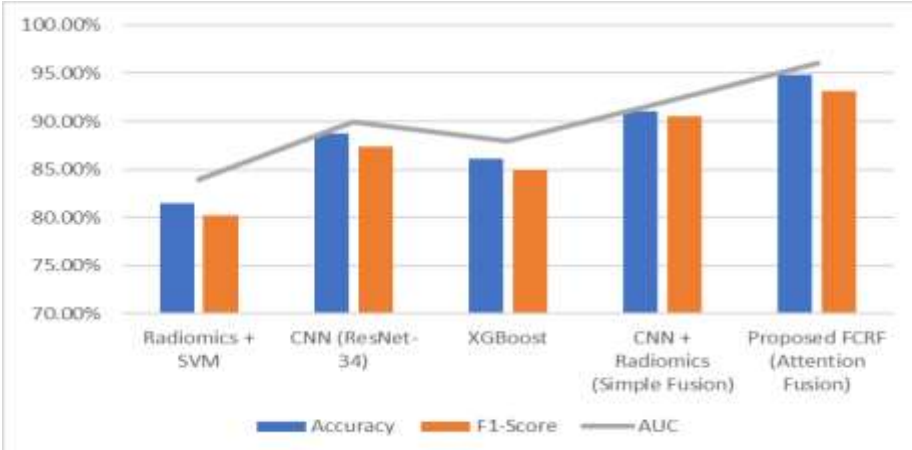

Figure1: Screening Accuracy of Proposed FCRF

5. CONCLUSION

This study presents a novel fusion-based framework that integrates Convolutional Neural Networks (CNNs) with radiomics feature analysis to enhance the accuracy and reliability of hepatitis-induced liver fibrosis detection. By combining deep hierarchical image representations with handcrafted radiomic texture descriptors, the proposed approach effectively captures both global and local fibrosis-related patterns that are often difficult to identify using conventional learning models. The fusion mechanism significantly improves classification performance across early and intermediate fibrosis stages, achieving better sensitivity, specificity, and overall diagnostic precision compared to standalone CNN or radiomics models. Experimental results indicate that the hybrid fusion model is robust across varying imaging modalities and patient demographics, demonstrating strong generalization and clinical interpretability. The incorporation of multi-level features reduces ambiguity in fibrosis staging and minimizes the risk of misclassification, which is crucial for early intervention and treatment planning. Overall, the proposed framework represents a promising advancement toward intelligent computer-aided liver disease assessment. Future work may focus on extending the model to multi-modal medical data, automating segmentation, improving interpretability through explainable AI techniques, and validating the approach on larger, diverse clinical datasets to support real-world adoption.

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