Computer-Aided Diagnosis of Hepatic Tumors Using Radiomics in Multi-Phase CT Images.

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Abstract : Hepatic tumors pose significant diagnostic challenges due to their diverse biological behaviors and the inherent limitations of traditional imaging methods. These limitations often result in delayed or imprecise diagnoses, especially in resource-limited settings where advanced tools are not readily available. This study investigates the application of radiomics and Machine Learning (ML) to address these challenges, focusing on the classification of hepatic tumors and the prediction of early recurrence in Hepatocellular Carcinoma (HCC). Radiomic features were extracted from multi-phase CT images and used to train machine learning models, achieving an accuracy of 80% in tumor classification and 71% in HCC recurrence prediction. To ensure clinical relevance and usability, the models were integrated into a user-friendly web application. This integration emphasizes the feasibility of applying advanced machine learning techniques in practical, real-world medical contexts, highlighting their potential to enhance diagnostic precision, especially in resource-constrained environments.

Keywords : Machine learning, Diagnostic Images, Hepatocellular Carcinoma, Hepatic tumors.

1. Introduction

Hepatic tumors, encompassing both benign forms (e.g., Hemangiomas, Cysts) and malignant varieties (e.g., Hepatocellular Carcinoma, Metastases), are among the most complex conditions to diagnose due to their heterogeneous presentations. These conditions often overlap in their radiological appearances, adding to the difficulty of accurate diagnosis. Traditional diagnostic tools such as ultrasound, CT, and MRI scans are indispensable in clinical practice, providing structural and functional insights. However, these modalities frequently lack the specificity needed to differentiate among tumor types confidently. For example, cirrhotic changes in the liver can obscure imaging findings, further complicating the diagnostic process.

The gold standard for hepatic tumor diagnosis remains biopsy. While effective, it is invasive and carries associated risks such as bleeding, infection, and sampling errors. Additionally, in regions with limited healthcare infrastructure, access to experienced radiologists or advanced imaging tools can be scarce, leading to delayed diagnoses and poor clinical outcomes. Consequently, there is an urgent need for innovative approaches to improve diagnostic workflows and outcomes.

Radiomics, an emerging field in medical imaging, has shown great promise in addressing these diagnostic gaps [1]. Radiomics extracts a high-dimensional set of features from imaging data, capturing patterns and nuances invisible to human interpretation. When coupled with machine learning models, these features can enable accurate, automated tumor classification and prognostic prediction. This study aims to leverage radiomics and machine learning for hepatic tumor classification and HCC early recurrence prediction, providing a practical, resource-efficient framework applicable even in constrained environments.

2. Methodology

This study utilized two datasets to develop and validate machine learning models. For hepatic tumor classification, a multi-phase hepatic tumor (MPHT) dataset comprising 2D CT scans of five tumor types (cysts, metastases, focal nodular hyperplasia, hepatocellular carcinoma, and hemangiomas) was split into 80% training and 20% testing subsets. For HCC early recurrence prediction, a labeled dataset of 2D CT scans from a local hospital underwent a similar 80:20 division [7]. Radiomic features, including shape descriptors, intensity metrics, and texture features, were extracted using Pyradiomics, with early feature fusion integrating data from multiple CT phases (non-contrast, arterial, and portal venous). Feature selection employed LASSO regression and L1-regularized SVM to reduce dimensionality and focus on clinically relevant features. Classification tasks were carried out using Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), chosen for their suitability in handling high-dimensional data and optimized for performance through hyperparameter tuning. This process is well illustrated in Figure 2 below

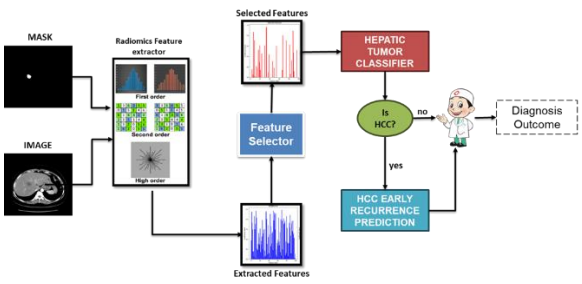

Figure 2.1 Simple Neural Network architecture for Hepatic tumor Classification

2.1 Data Acquisition

This study utilized two datasets with one for the Hepatic Tumor classification and one for HCC early recurrence prediction. For Hepatic Tumor Classification, this study utilized a carefully curated in-house Multi-Phase Hepatic Tumor (MPHT) dataset with 121 2D CT scans representing five hepatic tumor types: cystic lesions, metastases, focal nodular hyperplasia, hepatocellular carcinoma, and hemangiomas. Multi-phase CT imaging, a key diagnostic tool, involves capturing images across four contrast-enhanced phases—Non-Contrast (NC), Arterial (ART), Portal Venous (PV), and Delayed. Each phase provides distinct insights: NC highlights calcifications and hemorrhages; ART identifies hypervascular tumors like HCC; PV emphasizes liver parenchyma and portal structures, crucial for detecting metastases; and Delayed assesses lesion washout, ensuring accurate tumor characterization and staging.

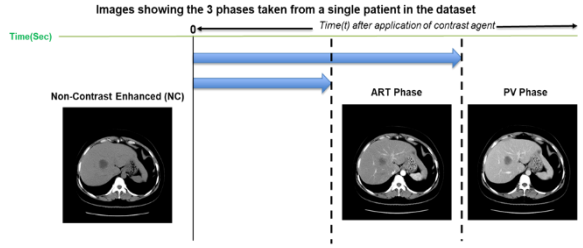

Figure 2.2 Illustration depicting the three CT image phases

The datasets were divided into training (80%) and testing (20%) subsets to ensure robust model development and independent validation for generalizability. For HCC early recurrence prediction, an in-house labeled dataset of 765 2D CT images was used, with 612 images for training and 153 for testing, maintaining the same 80:20 split. This structured approach upholds the statistical rigor required for machine learning in medical applications [7].

2.2 Feature Extraction

Radiomic features [1] were extracted using Pyradiomics [5], an advanced library for radiomic analysis. Features included shape descriptors (e.g., tumor volume, surface area), intensity-based metrics (e.g., mean voxel intensity, skewness), and texture-based features (e.g., Gray Level Co-occurrence Matrix [GLCM] metrics). Wavelet-transformed features further enhanced the analysis by capturing spatial-frequency information. Multi-phase CT imaging—including non-contrast (NC), arterial (ART), and portal venous (PV) phases—allowed for the extraction of complementary data across different imaging conditions. Early fusion techniques combined features from these phases into a unified representation, enhancing the model's ability to distinguish between tumor types. The early fusion process is illustrated in Figure 2.3

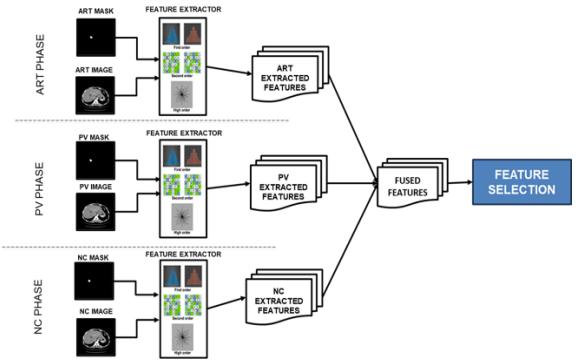

Figure 2.3 Illustration of early feature fusion for phases.

Feature extraction methodologies like these have proven effective in similar applications, as seen in studies focusing on radiomic biomarkers for cancer prognosis [8].

Table 2.1 Feature Extraction Summary for the experiments

Phase	Extracted Features
NC	474
PV	
ART	
Early Feature Fusion	1422

For HCC Early Recurrence prediction, Radiomic features were calculated and saved based on the feature classes for the 2D images. There were 473 radiomic features extracted from the images for each of the patients in the dataset as shown in table 2.2 below.

2.3 Feature Selection

The high-dimensional nature of radiomic data necessitated feature selection to improve computational efficiency and model interpretability. Two methods were employed: Least Absolute Shrinkage and Selection Operator (LASSO) regression given by,

$$\min_{\omega} \frac{1}{2}||\omega||^2 + C\sum_{i=1}^{N} max(0,1 - y_i(w \cdot x_i + b)) + \lambda||\omega||_1$$

where y_i are the target values, x_i are the feature vectors, and λ is the regularization parameter that controls the amount of shrinkage and Support Vector Machines (SVMs) with L1 regularization. The optimization problem for L1-SVMs can be formulated as:

$$\min_{\omega} \frac{1}{2N}\sum_{i=1}^{N}(y_i - x_i \cdot \omega)^2 + \lambda||\omega||_1$$

where C is the regularization parameter, y are the labels, x are the feature vectors, and λ controls the sparsity of the solution. LASSO regression is particularly effective in high-dimensional settings, as it penalizes less informative features by shrinking their coefficients to zero. This process ensured that only the most clinically relevant features contributed to the classification and prediction models. Feature selection not only reduces overfitting but also simplifies model interpretability, which is critical in clinical applications [9].

Table 2.1 Hepatic Tumor Feature extraction and selection distribution summary

CT PHASE	RADIOMIC FEATURES SUMMARY			
	EXTRACTED	SELECTED		
		LASSO	SVMs	COMBINED (LASSO+SVMS)
NC	474	95	2	95
PV		97	1	97
ART		97	3	99

Table 2.2 HCC Early Recurrence Feature extraction and selection distribution summary

HCC RADIOMIC FEATURE SUMMARY			
EXTRACTED	SELECTED		
	LASSO	SVMs	COMBINED (LASSO+SVMS)
473	84	8	92

2.4 Classification Models

The study implemented two machine learning classifiers: Artificial Neural Networks (ANNs) and SVMs. The decision function for an SVM can be expressed as:

$$f(x) = \text{sign}\left(\sum_{i=0}^{N} \alpha_i y_i K(x_i, x) + b\right)$$

where $\boldsymbol{\alpha_i}$ are the Lagrange multipliers, $\boldsymbol{y_i}$ are the labels, $\boldsymbol{x_i}$ are the support vectors, $\boldsymbol{K(x_i, x)}$ is the kernel function, and b is the bias term ANNs, due to their ability to model non-linear relationships, were optimized using hyperparameter tuning, including learning rate, batch size, and dropout rates. The models used categorical cross-entropy for tumor classification and binary cross-entropy for HCC recurrence prediction. SVMs, known for their robustness in high-dimensional data, complemented the ANNs, offering comparative insights into the model's performance across different feature spaces. These methods align with best practices in radiomic feature classification for oncology [10].

2.5 Practical Implementation

A significant contribution of this study is the development of MaLRaBDIA, a Flask-based web application integrating the trained ML models. The application allows clinicians to upload CT images, delineate Regions Of Interest (ROIs), and receive detailed classification and recurrence predictions. The user interface, designed with HTML, CSS, and JavaScript, ensures accessibility and usability for healthcare providers, bridging the gap between complex computational models and practical clinical application. Such web-based tools are increasingly recognized as essential for deploying AI solutions in clinical settings [11]. The code for the implementation is available via request on email.

3. Results and Key Contributions

3.1 Hepatic Tumor Classification

The ML framework demonstrated an impressive 80% accuracy in classifying the five hepatic tumor types. Early feature fusion from 2D CT slices was particularly effective, combining complementary information from NC, ART, and PV phases. The inclusion of ROI-focused preprocessing further improved model performance by isolating tumor-relevant regions and minimizing background noise. These results are consistent with prior findings where multi-phase imaging significantly enhanced tumor differentiation [12].

Table 3.2 Feature classification results

CT phase	Neural Network	SVMs
PV	0.60	0.68
ART	0.72	0.76
NC	0.48	0.52
Early Feature Fusion	0.80	0.76

3.2 HCC Early Recurrence Prediction

The ANN model achieved a 71% accuracy rate in predicting early recurrence of HCC. This capability is crucial for clinical decision-making, enabling early identification of high-risk patients. The combination of LASSO-selected features and ANN classification proved most effective, highlighting the importance of robust feature selection in achieving reliable predictions. Accurate recurrence prediction is vital for tailoring post-treatment strategies, as highlighted in recent oncology research [13].

ALGORITHM		ACCURACY
CLASSIFICATION	SELECTION	
SVMs	LASSO	0.65
	SVMs	0.62
	(LASSO+SVMS)	0.65
ANNs	LASSO	0.71
	SVMs	0.69
	(LASSO+SVMS)	0.73

3.3 User-Friendly Web Application

MaLRaBDIA exemplifies the practical integration of machine learning in clinical workflows. Its intuitive interface enables clinicians to perform complex analyses without requiring technical expertise. By automating feature extraction, selection, and classification, the application significantly reduces the time and effort required for hepatic tumor diagnosis and prognosis. The availability of user-centric tools like MaLRaBDIA can accelerate the adoption of AI in healthcare, particularly in resource-constrained environments [14].

4. Discussion and Conclusion

This study underscores the transformative potential of radiomics and machine learning in addressing longstanding challenges in hepatic tumor diagnosis and prognosis. By leveraging multi-phase imaging and advanced computational techniques, the research achieved robust diagnostic results: an 80% accuracy for hepatic tumor classification and a 71% accuracy for early HCC recurrence prediction. These results not only validate the efficacy of the proposed ML framework but also highlight its applicability in diverse clinical settings. The practical implementation of these models into MaLRaBDIA further emphasizes their clinical relevance. By providing a scalable, accessible solution for hepatic tumor diagnosis, the web application bridges the gap between cutting-edge AI technologies and everyday clinical practice. Its design ensures that even resource-limited settings can benefit from advanced diagnostic capabilities, addressing disparities in healthcare access.

Future work should focus on expanding datasets to include a broader range of tumor types, incorporating additional imaging modalities, and refining algorithms to further enhance accuracy and applicability. Integrating patient-specific clinical data, such as laboratory findings and treatment histories, may also improve model performance, paving the way for personalized medicine. The potential for integrating real-time imaging with predictive analytics also warrants further exploration [15].

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