The Core Metrics of CT Radiomics: Characterising Hepatocellular Carcinoma (HCC) Intensity and Texture - A pilot study

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Abstract – Computed tomography (CT) numbers, measured in Hounsfield Units (HU), reflect the average tissue density within a region of interest (ROI) and relate directly to tissue composition. However, tumours can share the same average density as normal tissue while having different internal structures. Radiomics features offer quantitative information that is not visible to the naked eye. This study aims to extract first-order radiomics features from CT images to better characterise the intensity and texture of HCC. Human ethical approval was obtained from the institutional ethical review board (Approval Code: USM/JEPeM/PP/24090793) prior to data collection. This retrospective study included a total of 60 images of radiologically confirmed HCC patients (n = 45) and normal patients (n = 15) undergone contrast-enhanced CT scan images between January 2020 and December 2024. Handcrafted tumour segmentation and radiomic feature extraction were performed by an expert radiologist using 3D Slicer software (Version 5.8.0). The core metrics of first-order features (related to HCC intensity and texture) were further analysed and compared between HCC and normal. The findings show that the mean HU for HCC was -542.24 ± 67.84 HU, and the normal liver tissue is -511.23 ± 45.15. However, the difference in mean HU is not statistically significant (p-value = 0.1017). The mean intensity is 80.25 ± 67.84 and 58.93 ± 67.84 for HCC and normal tissues respectively (p-value < 0.0001). The mean of mean absolute deviation (MAD) for HCC and normal is 22.97 ± 5.17 and 15.56 ± 2.01 (p-value < 0.0001). While the mean HU provides the centre of the intensity distribution, MAD quantifies the spread of pixel values around that centre. A higher MAD of HCC indicates that pixel values are widely scattered, suggesting a more heterogeneous texture of HCC compared to normal tissue (lower MAD indicates a more uniform texture). The limitation of using CT HU is that it relies solely on a single average value, which fails to capture the internal complexity and variability of the tissue. In conclusion, the first-order radiomics features of mean intensity and MAD successfully and quantitatively capture the tumors' distinct hyperenhancement and internal heterogeneity, making them superior diagnostic biomarkers.

Keywords – Radiomics, Hepatocellular carcinoma, LI-RADS, Feature extraction

1 INTRODUCTION

Hepatocellular carcinoma (HCC) is the primary malignancy of the liver and constitutes a major global health burden. Based on recent epidemiological data, it ranks as the third leading cause of cancer-related death worldwide, highlighting the urgent need for enhanced diagnostic and therapeutic strategies [1,2].

HCC is typically recognised on dynamic contrast-enhanced computed tomography (CT) scans because its large blood supply from the hepatic artery via neoangiogenesis causes it to appear much brighter (hyper enhanced) than the rest of the liver. While this feature often enables confident diagnosis, consistent and appropriate CT imaging protocols are absolutely requisite for

the optimal detection and characterisation of liver lesions, particularly in high-risk patient populations [3]. Conventional CT analysis fundamentally relies on a single metric which is Hounsfield Units (HU). CT HU represents the average X-ray attenuation, or tissue density, within a defined region of interest (ROI) [4]. However, this approach is inherently limited. The HU value reflects only a single, average attenuation value for the ROI, thereby failing to adequately capture the internal complexity and cellular heterogeneity of the tissue microenvironment.

Clinically, this limitation is manifested when a subset of HCC lesions exhibits imaging characteristics similar to the surrounding normal liver parenchyma, a phenomenon termed isodensity. Despite the differences in underlying pathological structures, these lesions frequently share an equivalent mean HU value with the adjacent healthy tissue. This prevents accurate visual and objective differentiation, leading to indeterminate diagnoses (e.g., LI-RADS LR-3 or LR-4) and subsequent delays in patient management [5]. The limitation of CT HU is that it provides only a single spatial average for the ROI, which is insufficient to distinguish the internal variability inherent to malignancy.

To overcome the inherent limitations of conventional HU analysis, advanced quantitative methods are required. Radiomics features address this limitation by transforming medical images into mineable, high-dimensional quantitative data. This approach allows for the extraction of numerous features that quantify the intensity, shape, and texture of the ROI, providing detailed information often invisible to the naked eye [6,7,8]. These features are hypothesised to serve as non-invasive biomarkers reflecting underlying tumor biology and genetic expression [9].

The initial step in the radiomics workflow involves the analysis of first-order features, which statistically characterise the intensity distribution within the ROI. By quantifying metrics like central tendency (mean, median) and dispersion (standard deviation, Mean Absolute Deviation (MAD)), these features provide a quantitative basis for diagnosis, revealing the intratumoral heterogeneity obscured by the single HU average [10]. This pilot study aims to extract and evaluate key first-order radiomics features from CT images to better characterise the intensity distribution and internal texture of HCC lesions, thereby providing a robust and quantitative basis for accurate tissue differentiation.

2 MATERIALS & METHODS

2.1 Study population

This study employed a retrospective analysis of imaging data. A total of 60 patients undergone multiphasic contrast-enhanced CT scans between January 2020 and December 2024 at the Radiology Department, Hospital Pakar Universiti Sains Malaysia (HPUSM) were included. The cohort consisted of 45 patients with radiologically confirmed HCC and a control group of 15 individuals with normal liver parenchyma. Ethical approval was secured from the Institutional Review Board (approval code: USM/JEPeM/PP/ 24090793). Inclusion criteria included adult patients (aged ≥ 18 years) diagnosed with HCC classified as LI-RADS category 4 or 5 (probably HCC or definite HCC), with adequate image quality and complete arterial and portal venous phase datasets. The normal control group comprised individuals confirmed by imaging reports to have no evidence of liver pathology.

2.2 Image Acquisition and Processing

All CT examinations were performed using a standard multiphasic liver protocol on a Siemens SOMATOM Definition AS+ CT scanner at the Radiology Department, HPUSM, Kelantan, Malaysia. The standard protocol included non-contrast, arterial, portal venous, and delayed phases. CT image sequences were retrieved from the Picture Archiving and Communication System (PACS). The corresponding 3D Digital Imaging and Communications in Medicine (DICOM) volumes were imported into the open-source platform 3D Slicer (Version 5.8.0) software for further analysis including volumetric segmentation and radiomics feature extraction.

2.3 Segmentation and Feature Extraction

Regions of interest (ROIs) corresponding to the HCC tumours were manually delineated (segmented) by an experienced radiologist using the level-tracing tool within the 3D Slicer, as shown in Figure 1. Segmentation was performed on the delayed-phase CT volumes to maximise conspicuity and fully capture the tumor boundaries. For the control group, corresponding ROIs of normal liver parenchyma (matched for size, away from major vessels or ducts) were concurrently segmented for comparative analysis.

Radiomics feature extraction was performed using the PyRadiomics extension in 3D Slicer. Standardised pre-processing steps were strictly followed to ensure feature reproducibility.

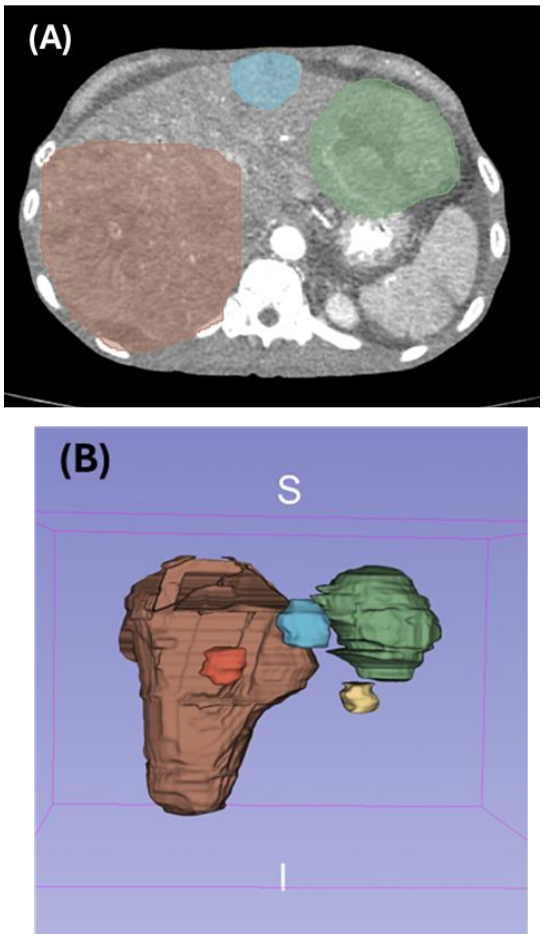

Figure 1: 3D Slicer interface demonstrating handcrafted segmentation and extraction of the HCC lesions

The pre-processing steps included voxel resampling and intensity normalisation. A total of 18 first-order statistical features were extracted from each ROI characterise the voxel intensity distribution. Three key features including mean HU, mean intensity, and mean absolute deviation (MAD) were selected for evaluation and analysis. These features represent the distribution of voxel (3D pixel) intensity values within a defined ROI of HCC and normal liver tissue.

2.4 Statistical Analysis

Statistical analysis was conducted using Python-based libraries, specifically utilizing NumPy for numerical computations and the SciPy statistical package for hypothesis testing. Comparison of the quantitative radiomics features between HCC and normal liver tissues were performed. Welch's *t*-test was employed for normal data distribution to compare the mean feature values between the two groups. In all analyses, a two-sided *p*-value of ≤0.05 was defined as the threshold for statistical significance.

3 RESULTS & DISCUSSION

From a total of 18 first-order radiomics features extracted from the segmented CT volumes, three core radiomics metrics were chosen due to their established relevance to tumour heterogeneity and their strong discriminatory capability between malignant and normal tissues. Mean intensity and MAD were included due to their sensitivity to subtle pathological alterations and their demonstrated utility as quantitative biomarkers for distinguishing malignant HCC tissue from normal parenchyma.

Figure 2 illustrates the distributional differences of selected first-order radiomics features including (A) mean CT HU, (B) mean intensity, and (C) mean absolute deviation (MAD) between HCC and normal groups. From the findings, the mean HU for HCC was -542.24 ± 67.84 HU, compared to the normal tissue, it was -511.23 ± 45.15 HU. However, the observed difference in mean HU was not statistically significant ($p = 0.1017$). The normal liver tissue on a clinical CT scan typically ranges between +30 to +70 HU (within the soft tissue range). But in this study, the unusually large negative HU values were observed are certainly due to preprocessing steps applied during the volumetric ROI segmentation and radiomics analysis by the PyRadiomics extension in 3D Slicer [11,12,13]. The analysed HU values are not raw clinical HU values but are normalised or transformed into intensity values.

However, the mean intensity was 80.25 ± 67.84 for HCC and 58.93 ± 67.84 for normal tissue, showing a highly significant difference ($p < 0.0001$). A significantly higher mean intensity in HCC compared to normal liver tissue, especially on the arterial phase CT, provides a robust quantitative signature of Arterial Phase Hyperenhancement (APHE). This captures the defining physiological characteristic of HCC, which has higher blood supply from the hepatic artery, important for diagnosis.

The mean absolute deviation (MAD) was also higher in HCC (22.97 ± 5.17) than in normal tissue (15.56 ± 2.01), with a significant difference ($p < 0.0001$). While mean HU reflects the central intensity, MAD shows the spread of intensity values around the mean. A higher MAD in HCC indicates more scattered voxel values, reflecting non-uniform internal architecture and more heterogeneous tumour texture. The lower MAD in normal tissue suggests a more uniform texture.

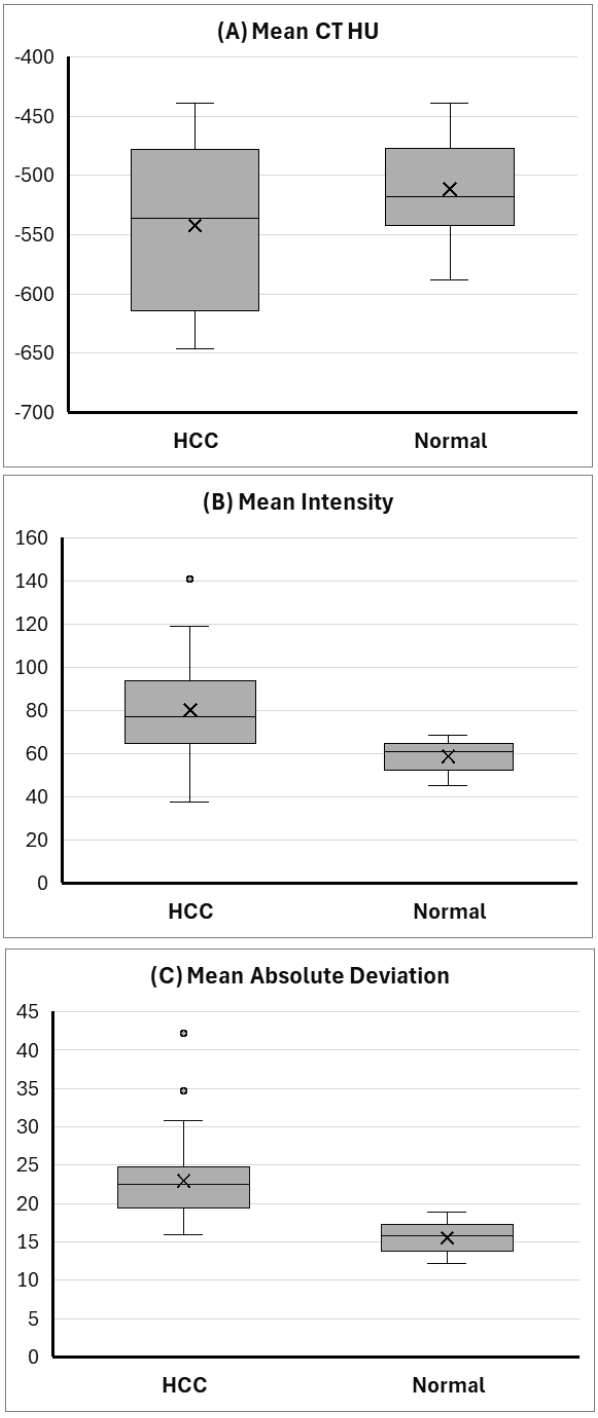

Figure 2: Plots of the comparison of selected first-order radiomics features including (A) mean CT HU, (B) mean intensity, and (C) mean absolute deviation (MAD) between HCC and normal groups.

These findings demonstrate that while the single-value CT HU average is unreliable for differentiation, the first-order radiomics features such as mean intensity and MAD successfully capture the crucial imaging phenotypes of HCC (APHE and internal heterogeneity). This highlights their potential as robust quantitative biomarkers for HCC diagnosis, especially for lesions that appear isodense in conventional visual assessment. This highlights the power of radiomics to quantify subtle differences in tissue texture and composition that are invisible to traditional metrics.

4 CONCLUSION

HCC is predominantly supplied by the hepatic artery, resulting in increased enhancement during the arterial phase. However, in certain cases, HCC lesions may exhibit imaging characteristics similar to normal liver tissue, rendering them less distinguishable on CT attenuation values (HU) or through visual assessment by radiologists. This study demonstrates that while conventional mean HUs are insufficient for differentiating HCC from normal liver tissue. In conclusion, the first-order radiomics features, specifically mean intensity and MAD have successfully quantified the distinct hyperenhancement and internal heterogeneity of the tumors, establishing their potential as superior quantitative biomarkers for accurate HCC diagnosis. By utilising these features, radiomics models can achieve more accurate tissue differentiation than visual assessment, making them essential tools for distinguishing HCC, particularly in indeterminate cases (LI-RADS LR-3 or LR-4).

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