人工智慧輔助肝脾CT分割，早期揪出脂肪肝

AI-Powered CT Liver & Spleen Segmentation for Early Fatty Liver Detection

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DeepRad.AI

Introduction

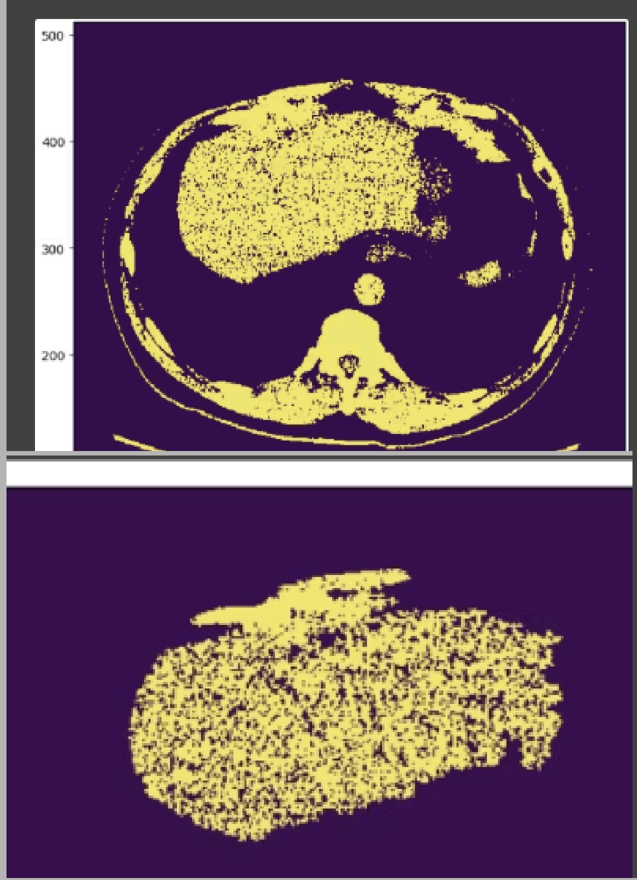
DeepRad.AI develops AI models for early disease detection from MRI and low-dose CT (LDCT), including dementia, coronary artery calcification (CAC), and lung nodule risk. In this project, I built a liver- and spleen-segmentation pipeline on LDCT to enable downstream assessment of fatty liver, cirrhosis, and liver-cancer risk.

Methods

Rule-Based (HU)

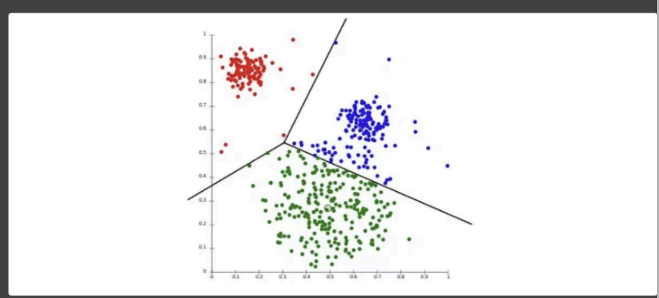
Thresholding followed by morphological operations.

Threshold: HU > 30



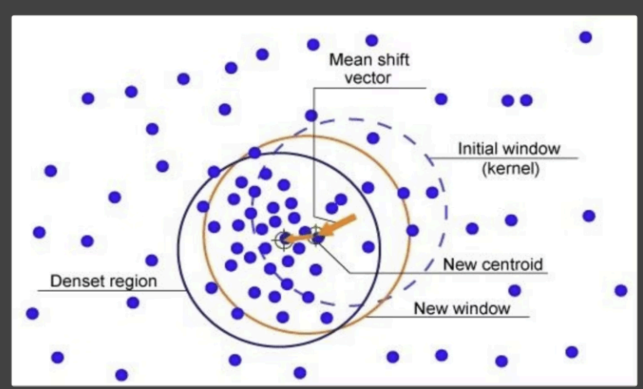
K-Means Clustering

Dimensions: Intensity-based clustering (± coordinates/texture).



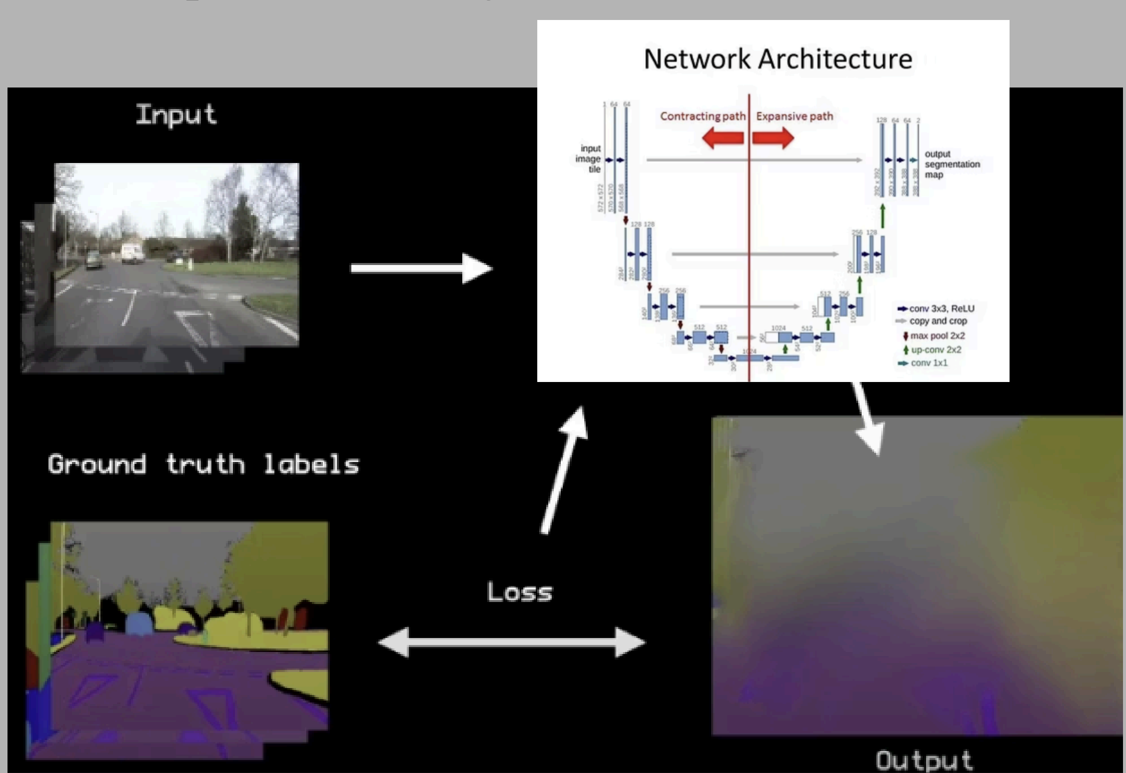
Mean-Shift Clustering

Mode-seeking algorithm.



U-Net Architecture

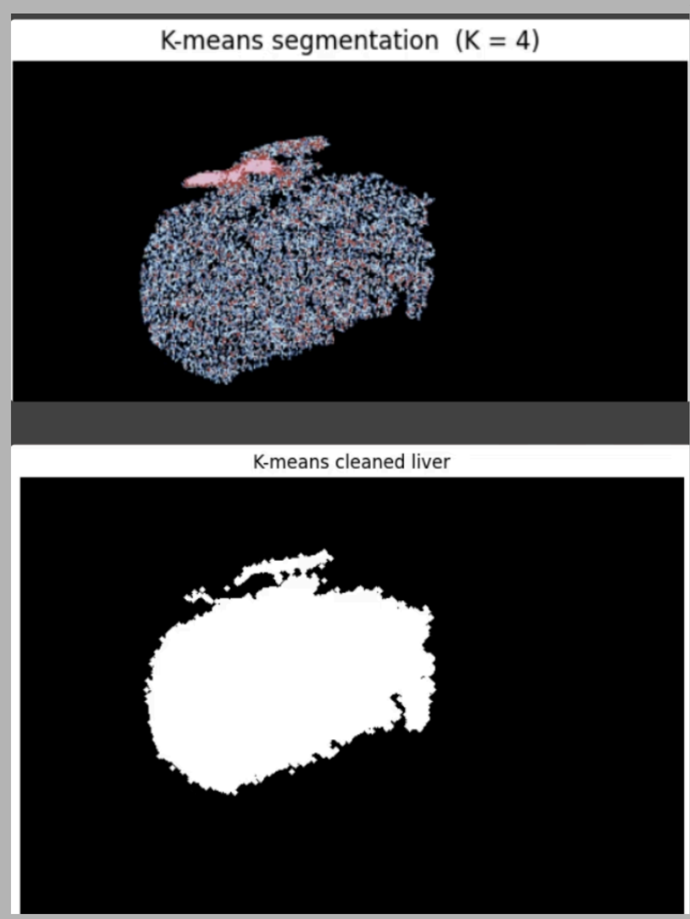
I used a 2D U-Net: an encoder–decoder with four downsampling blocks (3×3 conv → InstanceNorm → ReLU → MaxPool) that double the channels, a bottleneck, and four upsampling blocks (transpose-conv → skip-connection concat with the matching encoder feature → two 3×3 convs) to recover resolution and sharpen boundaries. A final 1×1 conv maps to 1 channel for binary (sigmoid) or 2 channels for liver/spleen (softmax), trained on windowed-to-HU inputs with Dice+BCE (or Focal-Tversky for imbalance) to emphasize overlap and clean edges.

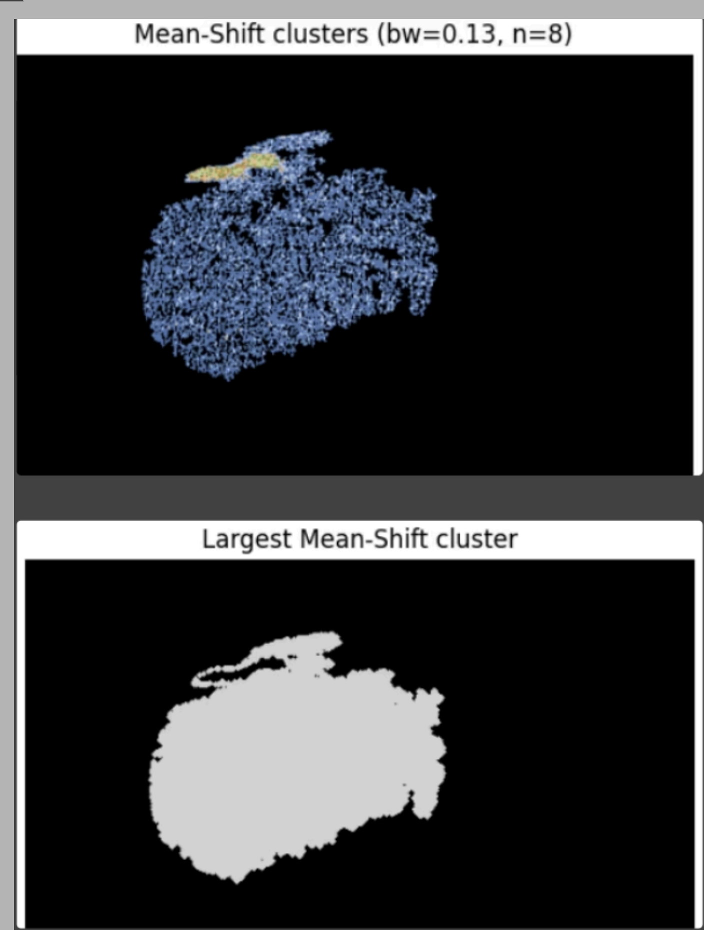


Conclusion

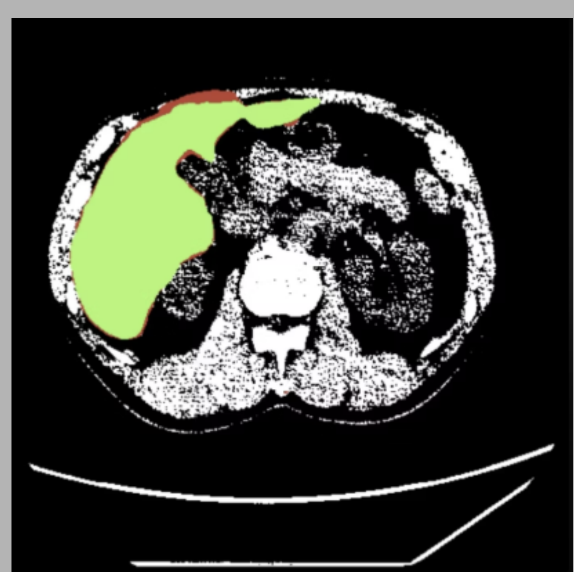
Classical methods—HU-thresholding with morphology or unsupervised clustering (k-means/mean-shift)—proved brittle and limited: intensity rules failed under contrast variability and overlapping HU ranges, while clustering lacked anatomical priors and defaulted to assumptions (e.g., spherical clusters), yielding unstable splits. By contrast, a 2D U-Net leveraged local-to-global context to deliver robust liver masks, consistent with its landmark role in biomedical segmentation and nnU-Net's later state-of-the-art generalization. The spleen was harder: smaller size and fewer slices worsen class imbalance, making Dice harsher and false negatives costlier; imbalance-aware losses and richer context (2.5D/3D) are natural next steps.

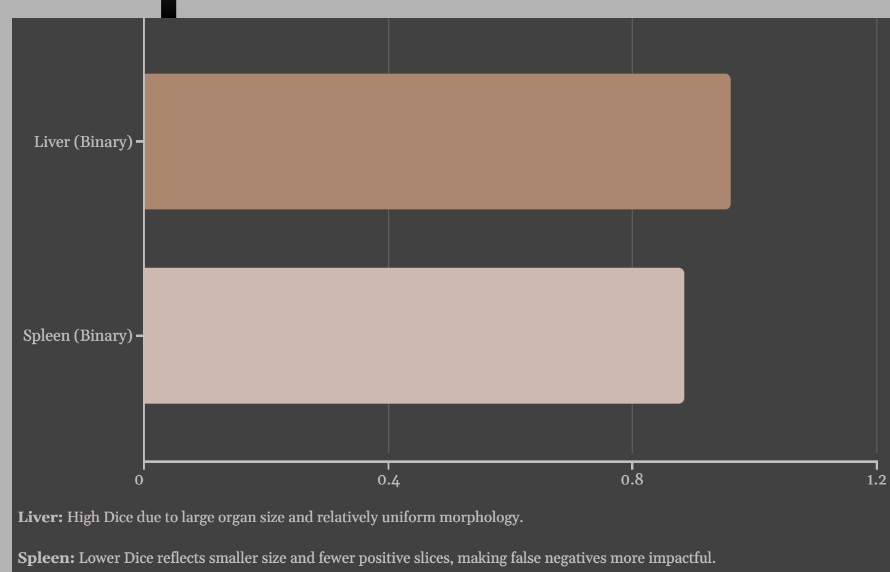
Results





For both k-means and mean-shift method, DICE = 0.94 for 1 liver slice of a selected patient.

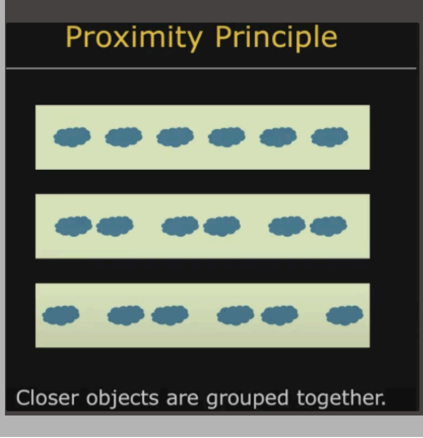




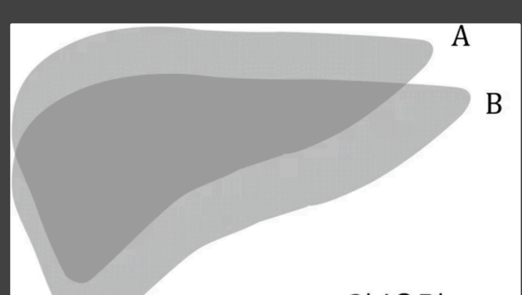
3D DICE = 0.96 for all liver slices, 0.884 for spleen slices

Background/Terminologies

How Humans do Segmentation



DICE calculations



$$DSC = \frac{2|A \cap B|}{|A| + |B|}$$

DSC: Dice similarity coefficient

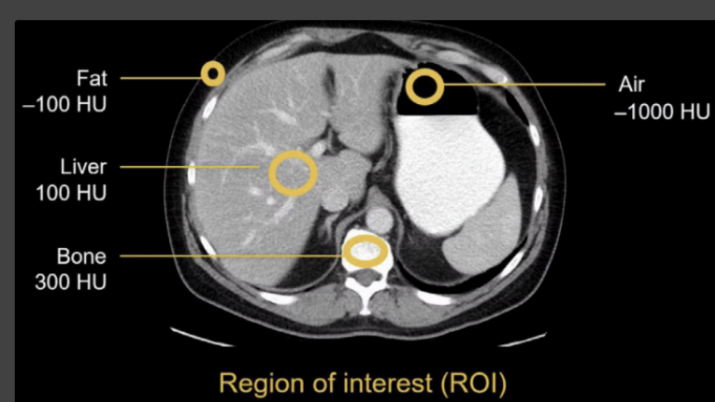
CT Basics

Understanding Hounsfield Units

Hounsfield Units (HU): Calibrated CT density scale.

- Air: -1000 HU
- Water: 0 HU
- Normal liver: ~50-65 HU (non-contrast)

$$HU(x, y) = 1000 \cdot \frac{\mu(x, y) - \mu_{\text{water}}}{\mu_{\text{water}} - \mu_{\text{air}}}$$



Ref: https://litfl.com/abdominal-ct-attenuation/