A158 · Incorporating differential geometric features into deep learning models for lung cancer screening

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Lung cancer remains the leading cause of cancer-related deaths worldwide, and its survivability depends strongly on early diagnosis, which is difficult due to the lack of obvious symptoms. Although low-dose computerized tomography (CT) screening can detect lung cancer, its implementation is limited by time-intensive image interpretation and high false positive rates. Using image data from CT scans, segmented lung nodules were converted into three-dimensional simplicial meshes using the marching cubes algorithm. From these, nodule morphology was distilled into differential geometric, curvature-based features such as spiculation and lobulation, which are associated with malignancy. These mathematically derived descriptors were compiled into a feature vector and used diagnostically via a generalized metric learning vector quantization (GMLVQ) model.

Recent advances in artificial intelligence, particularly convolutional neural networks (CNNs), have produced accurate models for predicting lung nodule malignancy, but often lack interpretability. By incorporating differential geometric features, this work aims to improve both performance and interpretability, augmenting models with domain knowledge.

This project demonstrates that an interpretable, geometry-based GMLVQ model can achieve performance comparable to black-box neural networks while providing transparent, quantitative malignancy scores. Combined with UNet-based segmentation, this framework could offer a more interpretable and mathematically grounded approach to lung cancer screening.

Incorporating differential geometric features into deep learning models for lung cancer screening

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Abstract:
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