Probabilistic Radiomics: Ambiguous Diagnosis with Controllable Shape Analysis

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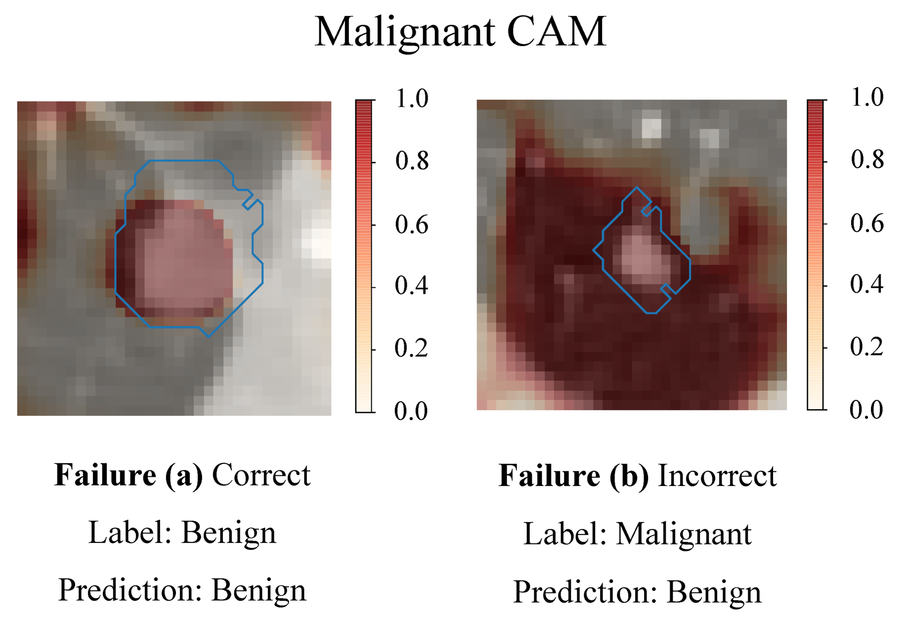
Analysis of CNN Failures



Saliency maps visualized by CAM technique, using a 3D DenseNet on LIDC Lung Nodule dataset.

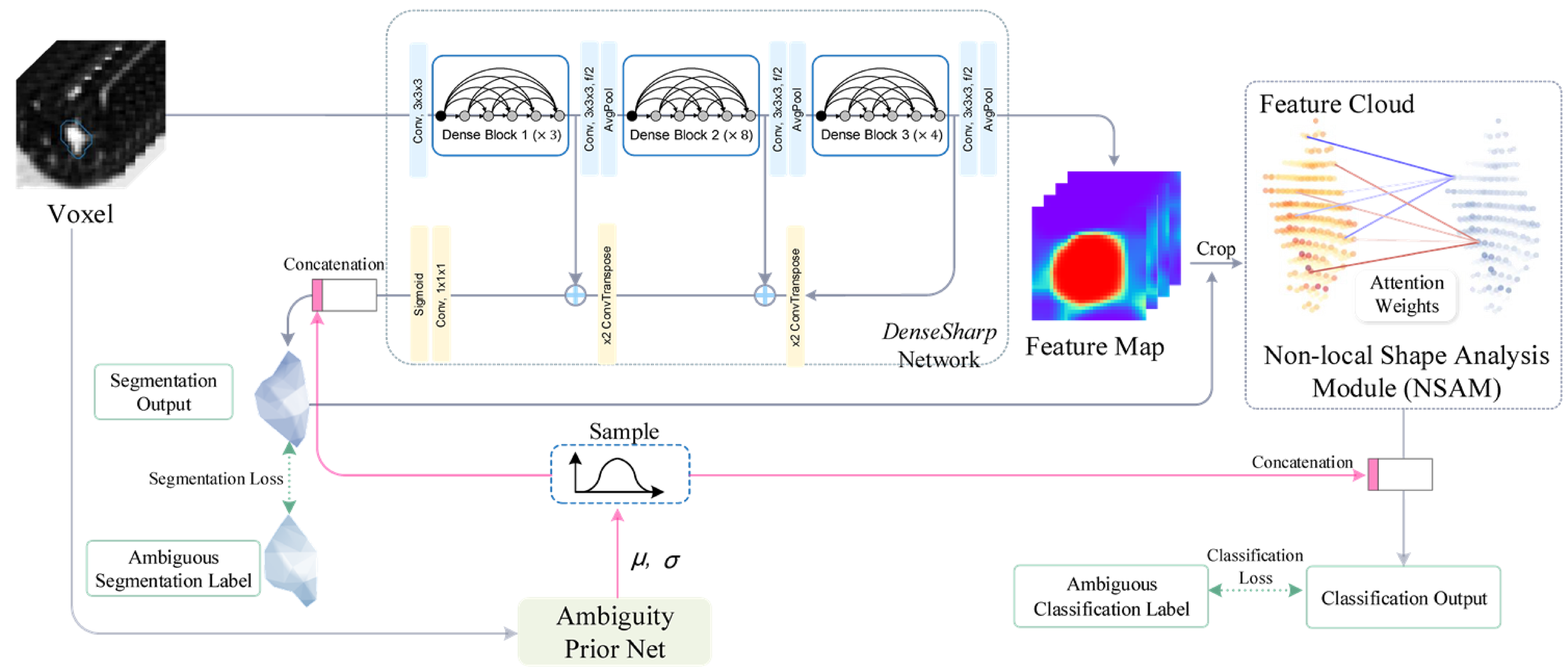
CNNs are classifying **voxels**, rather than **lesions**.

Failure (a), the model predicts "benign" on a benign nodule **correctly**. However, the "correct" prediction comes from the voxels apart from lesions.

Failure (b), the model outputs "benign" on a malignant nodule **incorrectly**. However, it is indeed predicted as malignant within the lesion voxels.

A **Probabilistic Radiomics** framework is proposed for **controllable** and **explainable** Computer-Aided Diagnosis (**CADx**).

DenseSharp+: Instantiation of Probabilistic Radiomics Framework



Backbone: *DenseSharp* [1]

A 3D CNN based on DenseNet, which learns both nodule **classification** and **segmentation** results in a multi-task learning fashion. The auxiliary segmentation task enables a better learning of classification task.

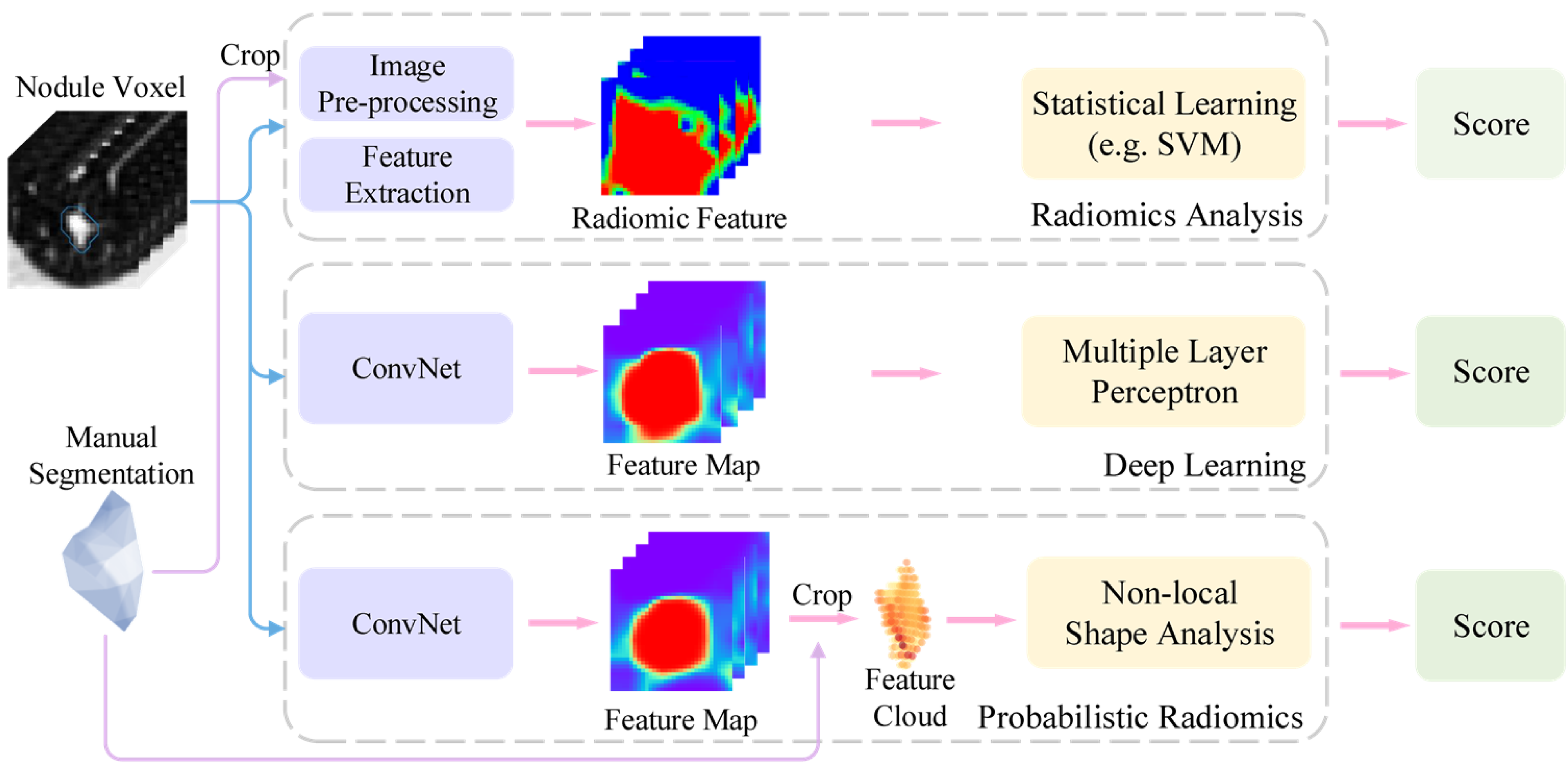
Non-local Shape Analysis

Features from the lesion region are cropped and regarded as **feature clouds**. The feature clouds are then processed by **Non-local Shape Analysis Module**, mimicking a light-weight variant of **Self-Attention** transformer [2].

Ambiguity PriorNet

To deal with the ambiguous labels from multiple experts, a probabilistic **Ambiguity PriorNet**, is developed to model the prior distribution of expert annotations, with reparameterization technique to enable back-prop [3].

Conventional Radiomics, CNNs & Proposed Probabilistic Radiomics



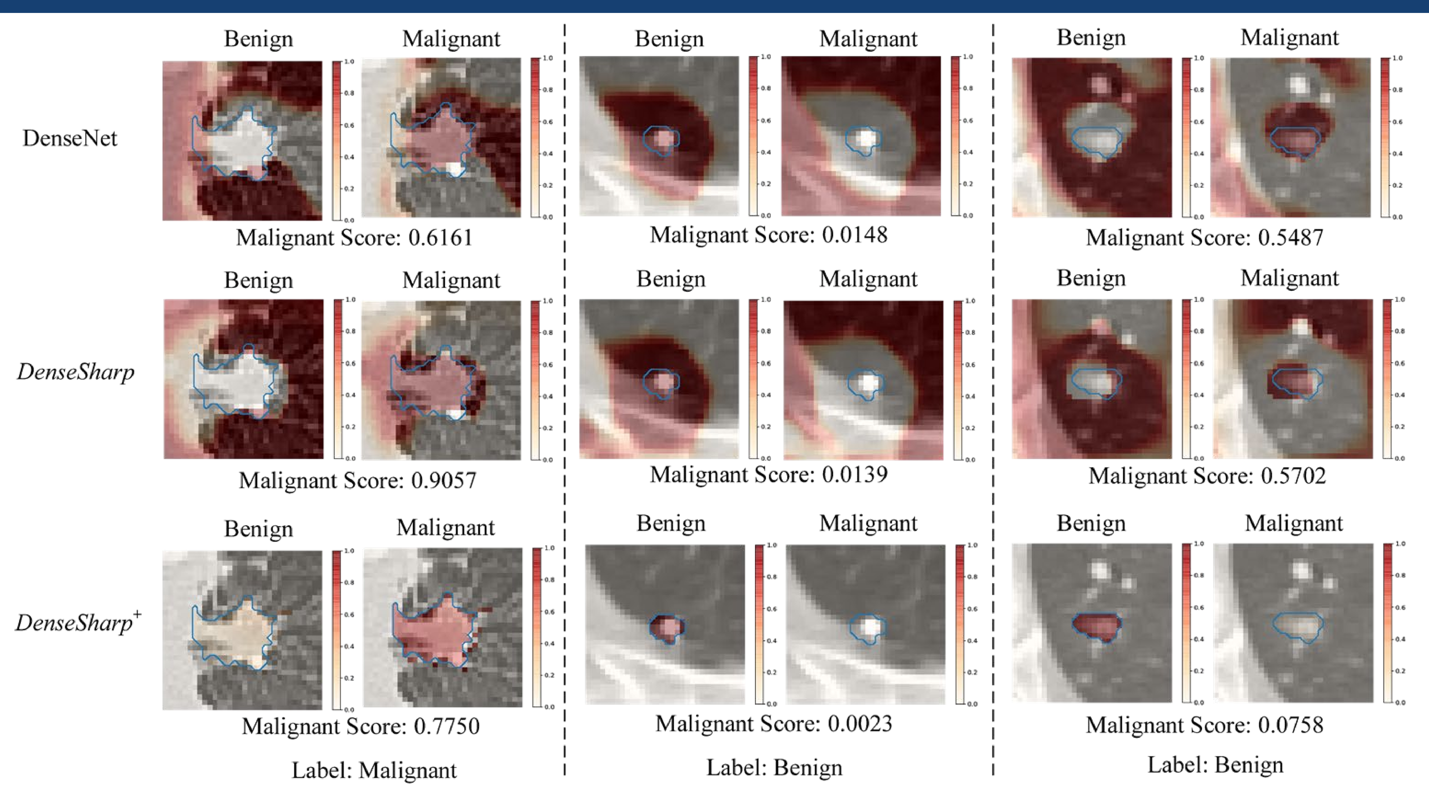
Comparison of conventional **Radiomics Analysis** (top), conventional CNN-based **Deep Learning** (middle), and the proposed **Probabilistic Radiomics** framework (bottom).

Method	Pros	Cons
Conventional Radiomics Analysis	Grey-box interpretability: Only corresponds to the **user-delineated VOIs.**	Insufficient expressiveness of hand-crafted features.
Conventional CNN-based Deep Learning	**End-to-end learnable** representation.	Black-box interpretability: Prone to the CNN failures (a) and (b).
Probabilistic Radiomics (Proposed)	**End-to-end learnable** representation. Only corresponds to the **user-delineated VOIs.** **Capability to model the label ambiguity.**	

Results

Method	AUC	Accuracy (%)
3D DPN [4]	-	88.28
3D DPN ensemble [4]	-	90.44
3D CNN w. MTL [5]	-	80.08
3D CNN w. sparse MTL [5]	-	91.26
3D DenseNet	0.9218	87.82
DenseSharp [1]	0.9393	89.26
DenseSharp+ (LowAmbig-trained)	0.9480	90.87
DenseSharp+ (HighAmbig-trained)	**0.9566**	**91.52**

Lung nodule classification on **LIDC-IDRI** dataset. With the ability to model label ambiguity, the *DenseSharp+* directly trains on the **5-mode** labels, rather than prior studies using binary labels. The metrics are 5-fold cross-validated in binary classification on LowAmbig dataset.
LowAmbig: 1,183 nodules with ≥3 radiologists' consistent diagnosis. **HighAmbig**: all 2,635 nodules.



Saliency map visualization of 3D DenseNet, *DenseSharp*, and *DenseSharp+*. Even though MTL fashion of *DenseSharp* does help the model to better locate the lesions than, both DenseNet and *DenseSharp* not only activate the features within lesions, but also activate that within the background, which not precisely utilizes the features of lesions themselves (the "**correct evidences**"). As a comparison, *DenseSharp+* only adapts the features upon lesions.

References

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CONTACT
& Related Study
DenseSharp
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