Me-NDT: Neural-backed Decision Tree for visual Explainability of deep Medical models

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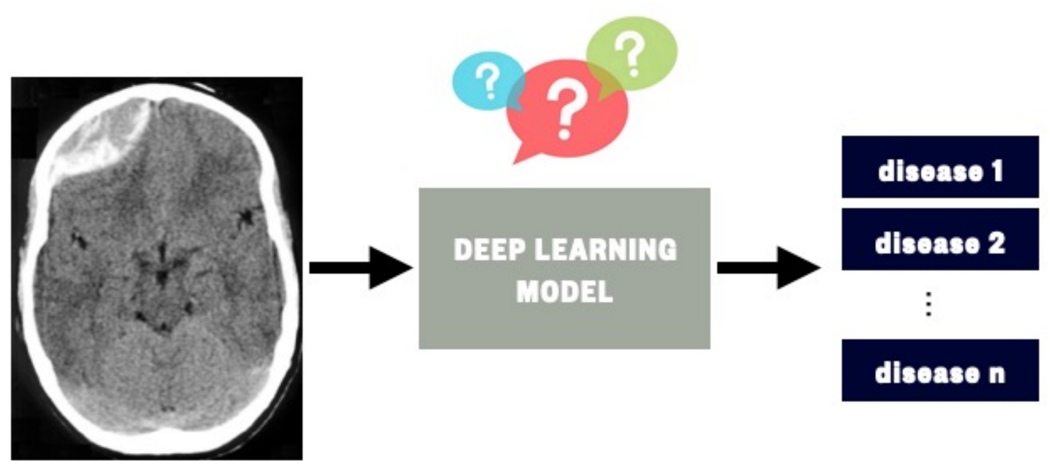
Guanghui Fu[1], Ruiqian Wang[1], Jianqiang Li[1], Maria Vakalopoulou[2,3], Vicky Kalogeiton[4]

MIDL Lübeck 2021

Introduction

Goal: Good performance and explainable medical CV model.

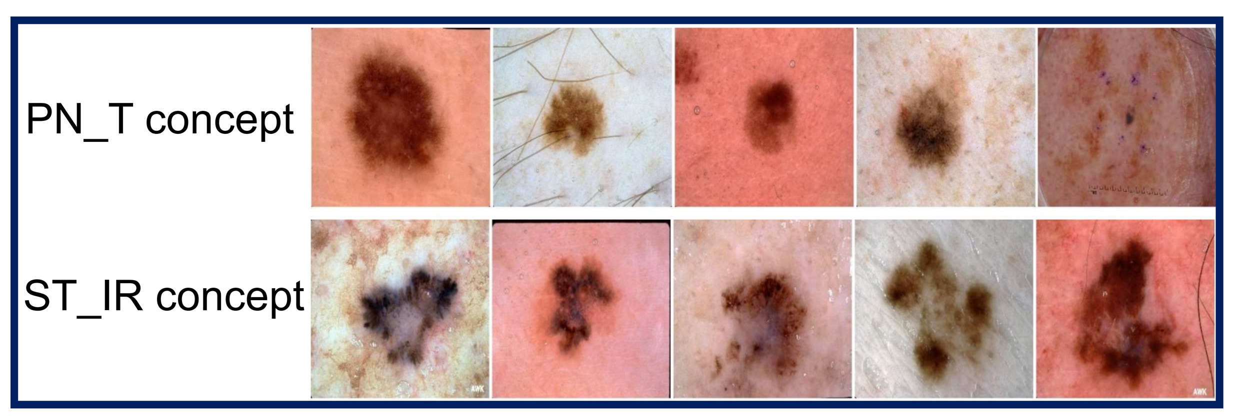


Explainable CV model: (1) saliency maps (2) sequential Decision processes

Related Work

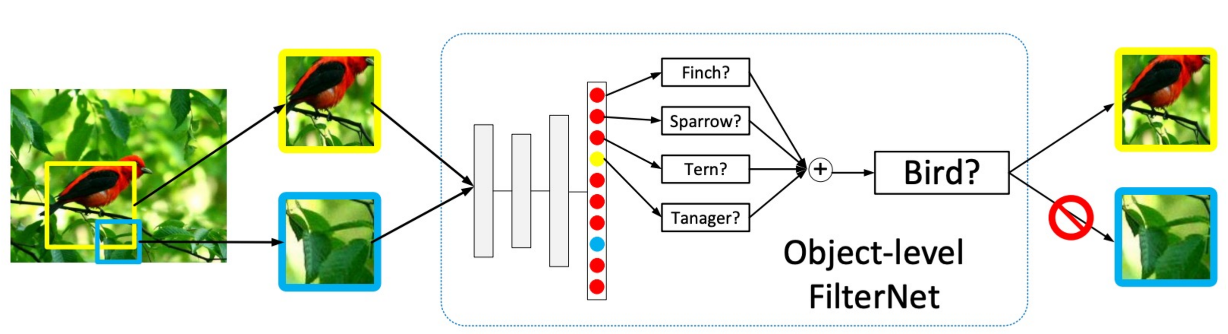
Not true understanding of (i) what is leant and (ii) how decisions are made.

[Lucieri et al. 2020]: prediction + most similar concept.



!!! Without knowing the decision basis.

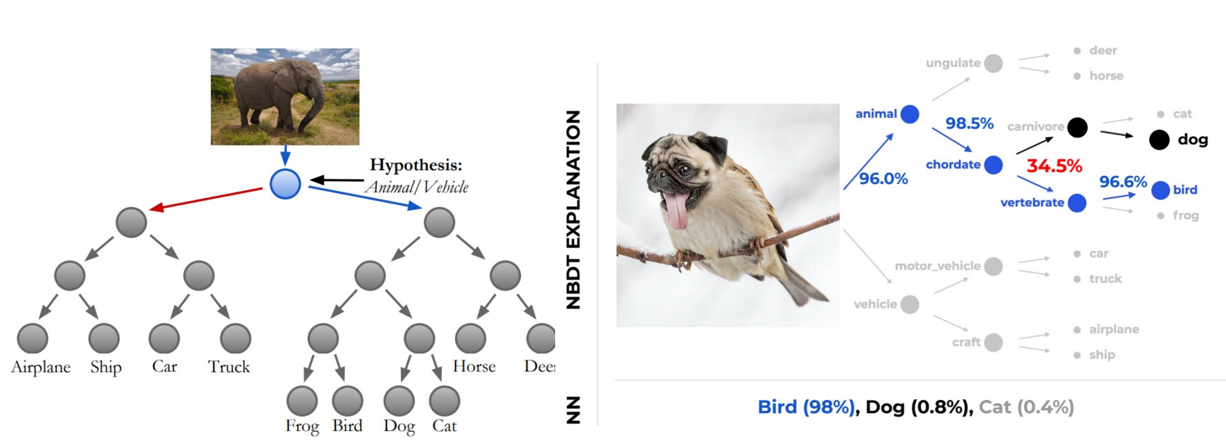
[Xiao et al. 2015]: DL model with visual attention.



!!! Without knowing the decision process.

[Balestriero et al. 2017], [Yang et al. 2018], [Wan et al. 2020]: deep learning model + decision trees.

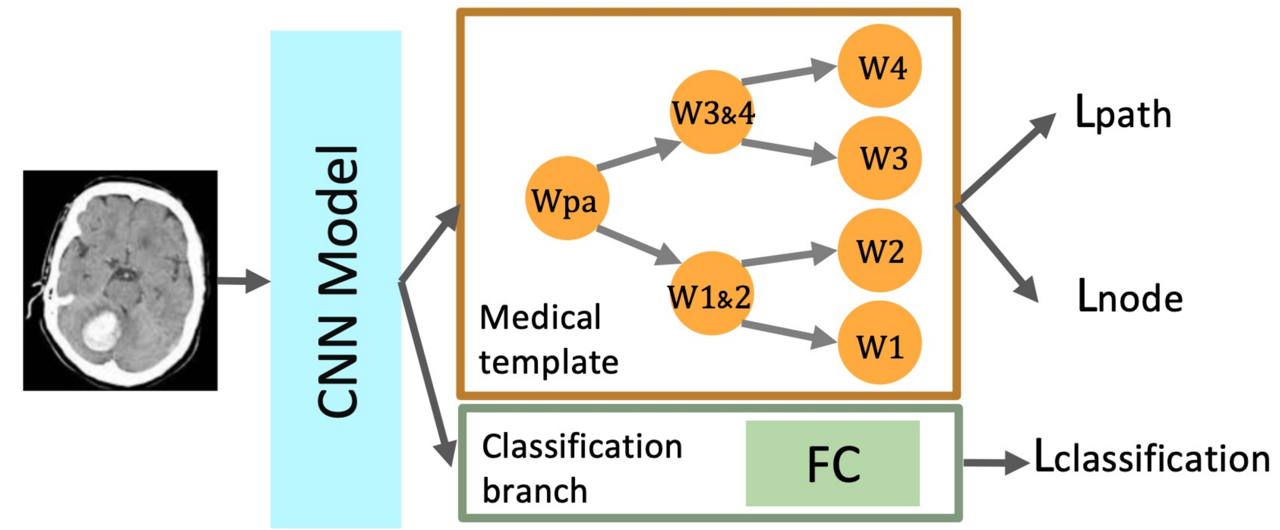
NBDT: backbone+hierarchies→accuracy↑+interpretability↑



Balance between accuracy and interpretability.

Model Structure

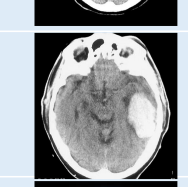
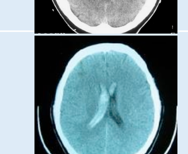
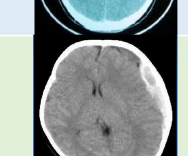
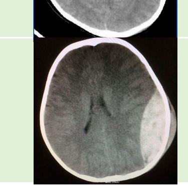
Me-NDT=backbone + two branches: classification branch & medical template



Step 1: Pre-training the CNN model;
Step 2: Load the weights of the adaptive max pooling layer of the pre-trained model;
Step 3: Define the medical template according to the anatomical positional relationships & dependencies among diseases;
Step 4: Combine two branches together and retrain (each node is trained as a FC layer);
Step 5: Visualize and generate reports.

Medical Template

Dataset: Provide by RSNA brain CT hemorrhage challenge [7] which contains six types of intracerebral hemorrhage.

Parent-level	Child-level	Abbreviation	Image
Brain Tissue	Subarachnoid	SAH	
	Intraparenchymal Hemorrhage	IPH	
	Intraventricular Hemorrhage	IVH	
Near the Skull	Subdural	SDH	
	Extradural	EDH	

Loss Functions

The overall loss=classification loss+ path loss+ node loss

$=w_c L_{cls} + w_p L_{path} + w_n L_{node}$

- Node loss supervises all nodes n, with a multi-label cross-entropy:

$$L_{node} = -\sum_{i=1}^{c} \left((y_i^n \cdot \log(\hat{y}_i^n) + (1 - y_i^n) \cdot \log(1 - \hat{y}_i^n) \right)$$

- Path loss supervises the tree path with multi-label cross-entropy:

$$L_{path} = -\sum_{i=1}^{c} \left((y_i^n \cdot \log\left(\hat{y}_i^{n^{pa}} \cdot \hat{y}_i^{n^{ch}}\right) + (1 - y_i^n) \cdot \log(1 - \hat{y}_i^{n^{pa}} \cdot \hat{y}_i^{n^{ch}}) \right)$$

[Note] The final prediction is made **solely** by L_{path} and L_{node}.

Experiments

- Backbone: VGG16 network.
- Do experiments on 5-fold cross-validation.
- Hyperparameters: $w_c, w_p, w_n = 1{,}1000{,}10$

Model	L_{cls}	#Parameters	F1-score	Precision	Recall
VGG	-	134,281,029	0.79686	0.80947	0.81915
Me-NDT	-	16,557,905	0.80349	0.81513	0.82556
Me-NDT	√	**16,560,470**	**0.80535**	**0.81679**	**0.82755**

Table 1: Comparison experiment and ablation experiments on a part of RSNA brain CT dataset.

- **Better Performance**: Higher F1-score, Precision and Recall.
- **Lighter Model**: Less parameters

Visualizations

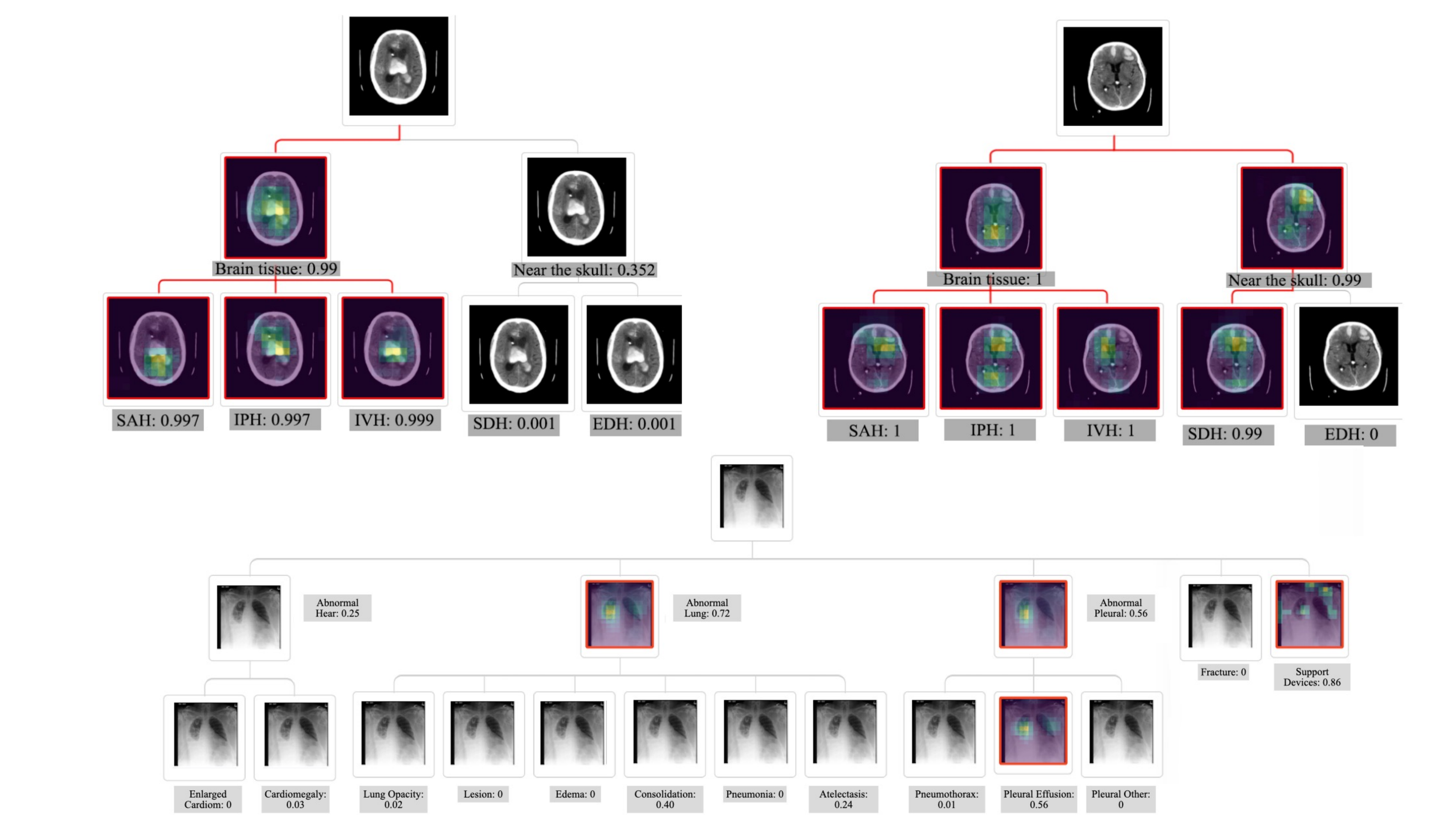


Figure 1: This is the result of our model prediction and the visualized decision processes and basis.

- **Explanatory increased!**: Correct Prediction + Highlighted Areas + Visualized Decision Process

Conclusions

1. Me-NDT: A multi-label multi-class classification model in the medical domain.
2. Explainable: able to classify diseases and visualize both decision basis & paths.
3. Good Performance: lighter, faster & more accurate.

In the future, our research should focus on Template-free and Sequence-level [8].

References

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