Stato dell’arte: paper 17, 18, 13, 14 (questione ACCURACY UC UI CC CI)

METTERE SICURAMENTE HERSHKOVITCH2018

Eventualmente 5 paper unread pasqua

Eventualmente leggere 2007.07584 per non-monotonicity

Eventualmente approfondire AG14: 3 19 20 21 22 23

Eventualmente approfondire AG15: 50

AG13: Skinet a deep learning framework for skin lesion diagnosis with uncertainty estimation and explainability

Abstract of abstract:

SkiNet is proposed to provide faster screening solution and asssistqance to newly trained physicians in the process of clinical diagnosis of skin cancer. Proposed SkiNet is a two-stage pipeline wherein the lesion segmentation is followed by the lesion classification. A novel segmentation model named Bayesian MultiResUNet is used to estimate the uncertainty on the predicted segmentation map. Saliency-based methods like XRAI, Grad-CAM and Guided Backpropagation are explored to provide post-hoc explanations of the deep learning models.

Notes:

Aleatoric uncertainty captures noise inherent in the data and cannot be abated by collecting more data. Epistemic uncertainty (model uncertainty) accounts for variability in the parameters of the model and analyzes what the model is not aware owing to the lack of training data.

Uncertainties are formulated as probability distributions over the model parameters (epistemic) or model inputs (aleatoric).

For epistemic uncertainty, the authors used Monte-Carlo dropout: given a test sample, they sample the network different times over its parameters and thereby giving and estimate of the predictive posterior distribution. The sampling is known as Monte Carlo sampling, and the mean over these iterations is considered as the final result on a given test sample.

For aleatoric uncertainty, the authors used test-time data augmentation: a test sample is augmented to form different versions of the image and is forwarded to the network; the *mean* of these iterations is considered the final result of a given test sample.

These two approaches are then combined to calculate the overall uncertainty where a test sample is augmented to form different versions of the image and is forwarded to the network with the dropout activated during test time: the mean over these iterations is considered as the final result on a given test sample.

In order to estimate the model uncertainty, they calculate the Shannon Entropy of the averaged probability vector across the N classes.

The authors employ the Bayesian MultiResUNet.

EVALUATION METRICS to validate classification, segmentation, uncertainty estimation and explainability.

For segmentation 🡪 Dice

Uncertainty 🡪 Shannon Entropy normalized with min-max scaling (the entropy would depend on the number of Monte Carlo samples). To split predictions into certain and uncertain, they set a threshold where a prediction is deemed to be certain if under, uncertain if over that threshold: 4 prediction could happen, being UI (uncertain-incorrect), UC (uncertain-correct), CI (certain-incorrect) and CC (certain-correct). The overall accuracy of the uncertainty estimation could be expressed as a ratio of all the desirable cases: A = (CC+UI)/(CC+UI+CI+UC).

The addition of segmentation as a pre-processing step for classification has greatly helped the efficiency of the classification model. The uncertainty score of the segmentation model’s output is used to pass only the most confident predictions to classification model.

Figures:

FIG6

In soldoni: fanno una cosa simile come approccio ma non è che ci facciano troppo. AG14 fa molto di più a riguardo, ma ci sta segnalarlo come “cosa in più”

AG14: Aleatoric uncertainty estimation with test-time augmentation for medical image segmentation with convolutional neural networks

Aleatoric and epistemic uncertainties: in this paper they analyze different types of uncertainties for CNN-based 2D and 3D medical image segmentation tasks at both pixel level and structure level.

They propose test-time augmentation-based aleatoric uncertainty to analyze the effect of different transformations of the input image on the segmentation output: they propose a theoretical formulation of test-time augmentation where a distribution of the prediction is estimated by Monte Carlo simulation with prior distribution of parameters in an image acquisition model that involves image transformation and noise. They compare and combine the proposed aleatoric uncertainty with model uncertainty.

To obtain the transformation-related uncertainty, they augment the input image at test time, and obtain an estimation of the distribution of the prediction based on test-time augmentation (TTA). They propose a mathematical formulation for TTA and analyze its performance for the general aleatoric uncertainty estimation in medical image segmentation tasks.

Both the variance and entropy of the distribution p(y|X) can be used to estimate uncertainty; however, variance is not sufficiently representative in the context of multimodal distributions. In this paper they yse Shannon Entropy for uncertainty estimation.

For segmentation tasks, pixel-wise uncertainty estimation is desirable.