Quantifying uncertainty of deep neural networks in skin lesion classification

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Background

Deep learning → SOTA in image classification

Can we augment the **dermatologist** workflow?

Skin lesion classification

- ISIC Archive
- At MICCAI: ISIC Challenge

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‼ Limitations of neural networks

- only a point estimate
- typically overconfident for a single class

Correctly capturing uncertainty is indispensable

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Bayesian modelling → introduces uncertainty in deep learning

e.g. MC dropout

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Contribution

Uncertainty metric that leverages MC dropout

- based on the overlap between output distributions
  ➡ models doubt
- bounded between 0 and 1
  ➡ interpretable by a dermatologist

Quantifying uncertainty

$$BC(h_1, h_2) = \frac{1}{T} \sum_{i=1}^{n} \sqrt{h_{1i} h_{2i}}$$

$$T := \text{number of forward passes}$$

$$n := \text{number of histogram bins}$$

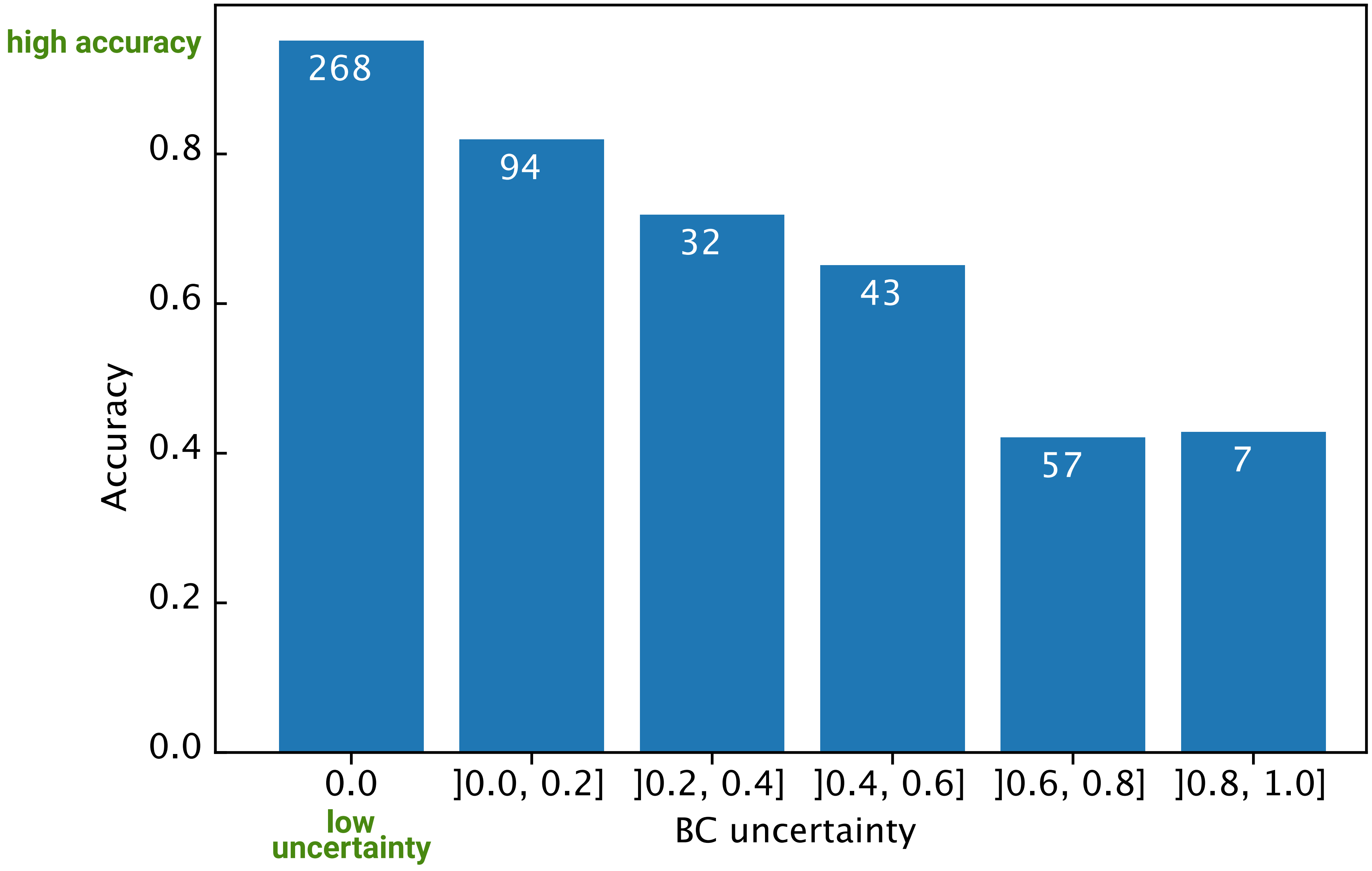
$$h_{1i} := \text{number of members in bin } i \text{ for histogram } h_1$$

$$h_{2i} := \text{number of members in bin } i \text{ for histogram } h_2$$

Results

Expectation

When the model is confident, it should perform better



Thank you for your attention

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