Uncertainty for Disease Detection

Maksym Petyak, Mohamad Ali Baydoun, Ruofeng Yuan

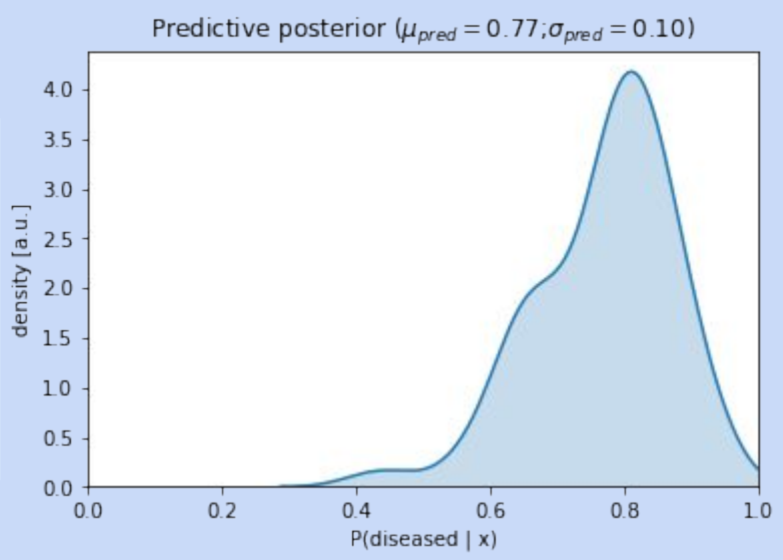
aml-project-group-6/project

Introduction

Deep neural networks (DNNs) have been shown to achieve expert level performance on a number of medical imaging tasks. However, the predictions of the network often come without any measure of certainty, leaving the model practically guessing the answer on unfamiliar images.

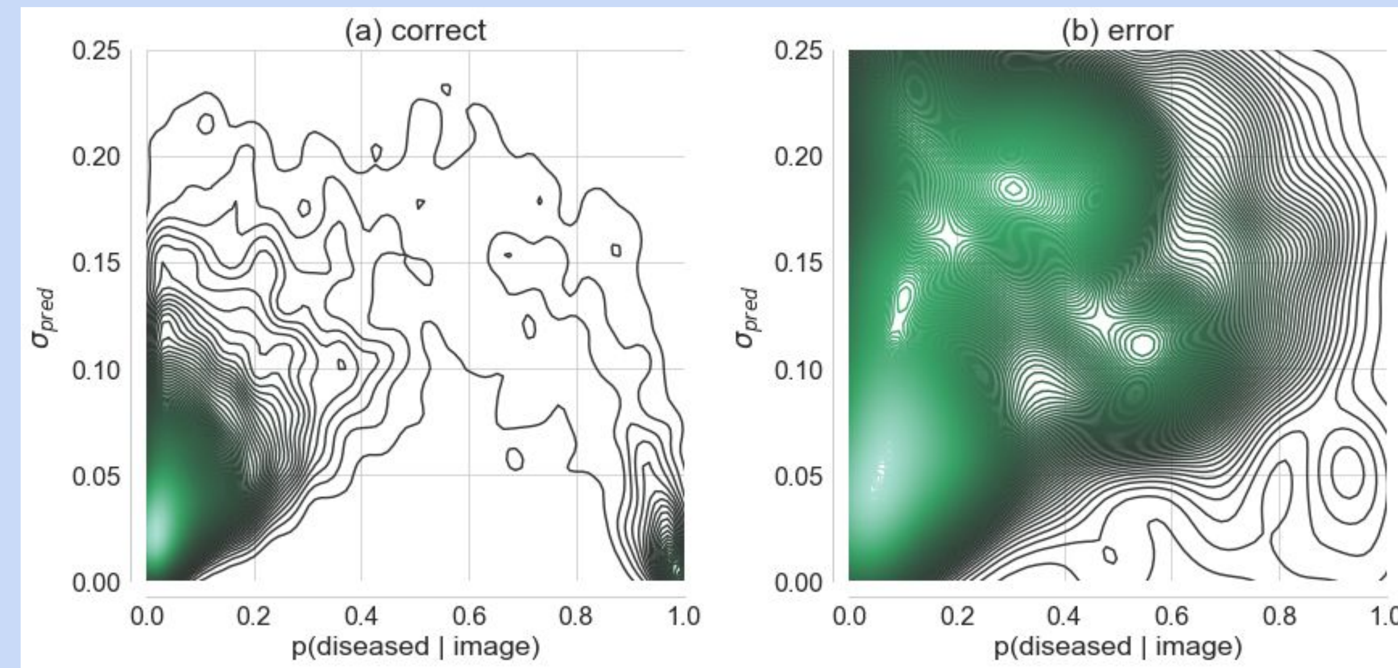
By applying drop-out based Bayesian uncertainty measures to detect diabetic retinopathy (DR) from fundus images, we show that uncertainty informed decision referral can improve diagnostic performance and help detect outliers.

Below is an example of a fundus with a disease and our model prediction:

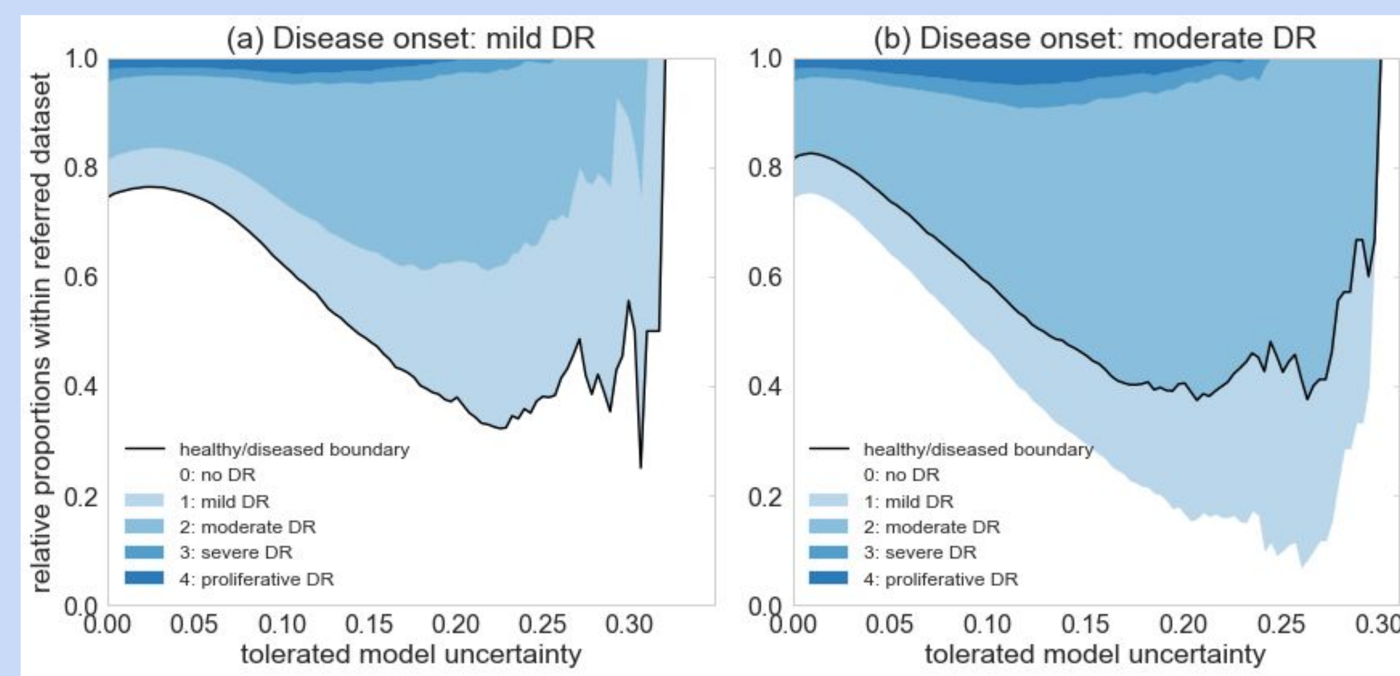


Are we certain in our uncertainty?

Model uncertainty is generally significantly higher for erroneous predictions. This is exactly what we want in practice!

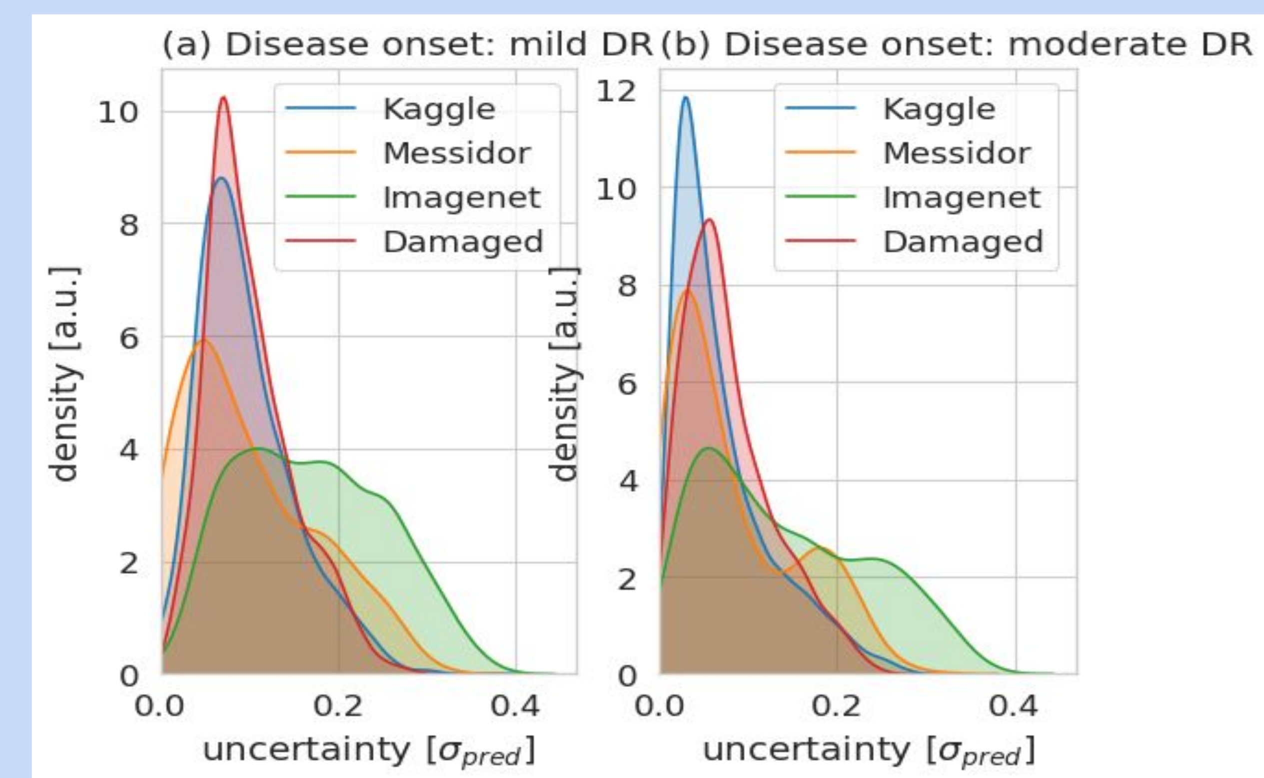


By inspecting which images are referred we further see that uncertainty is high around class decision boundary.



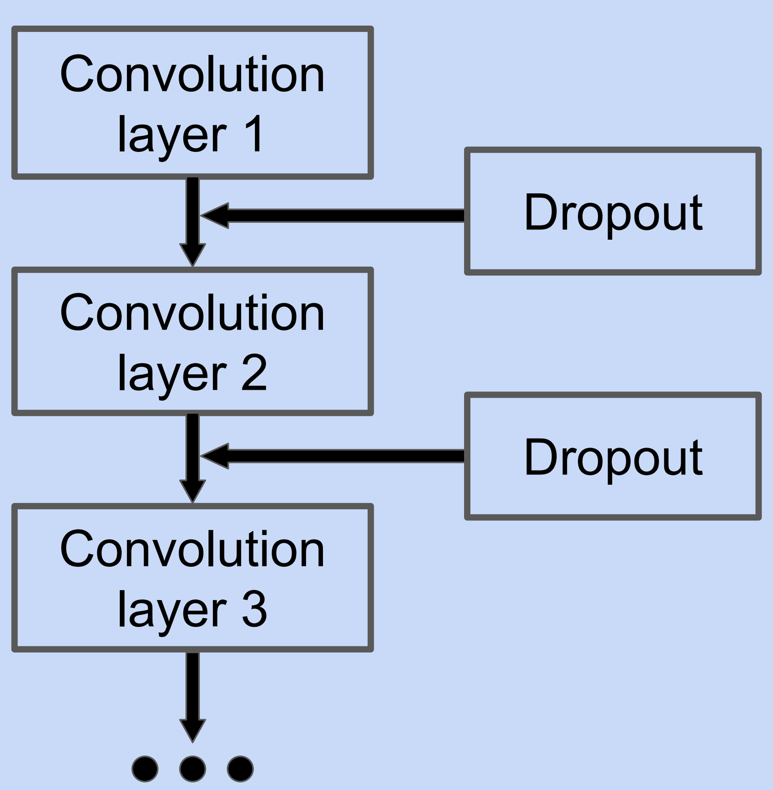
Uncertainty Distribution

It's easy to demonstrate that our DNN will be uncertain when given totally unfamiliar yet semantically meaningful data. We used Kaggle data, Messidor data, ImageNet and as an extension, a damaged dataset.



Model Architecture

Simply add dropout layers (p=0.2) between each convolutional layer of a pretrained model. Our starting point was a model placed 5th in Kaggle competition.



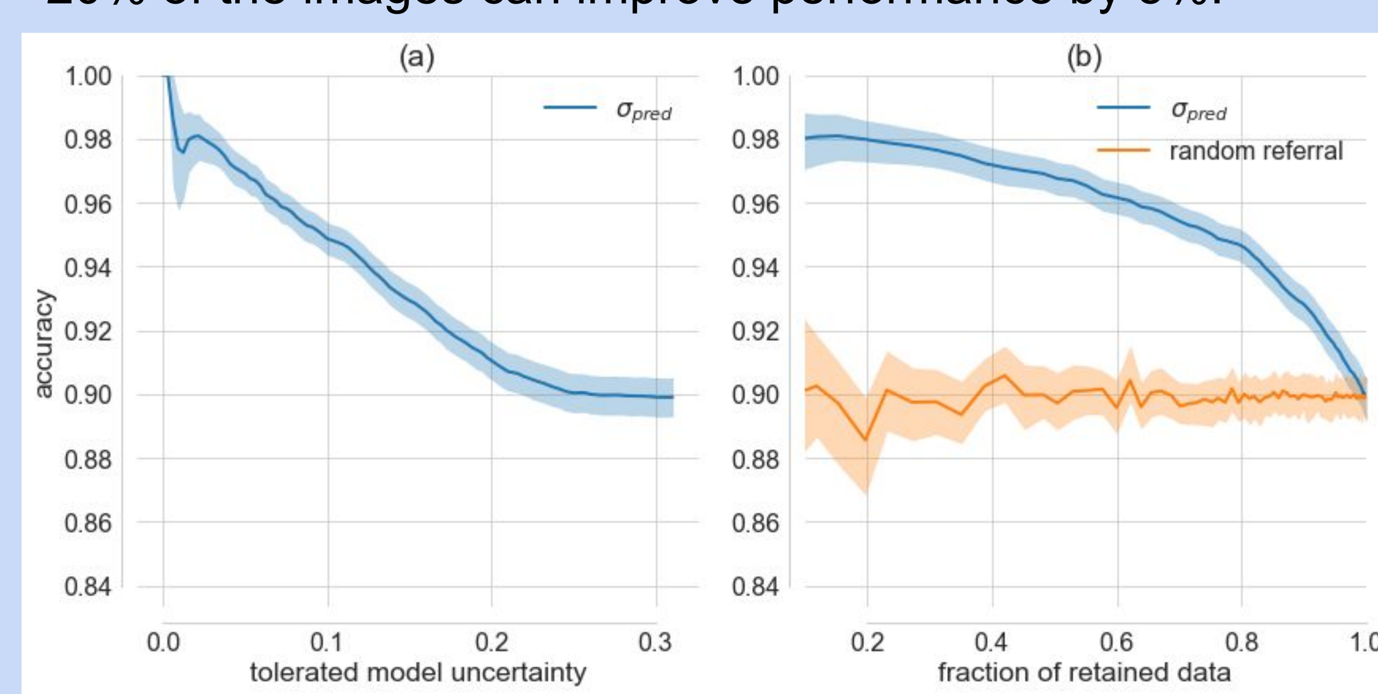
$$\hat{\mu}_{pred} = \frac{1}{T}\sum_{t=1}^{T} p(y^*|\mathbf{x}^*, \theta(\hat{\omega}_t))$$

$$\hat{\sigma}_{pred} = \frac{1}{T-1}\sqrt{\sum_{t=1}^{T}\left(p(y^*|\mathbf{x}^*, \theta(\hat{\omega}_t)) - \hat{\mu}_{pred}\right)^2}$$

By leaving the dropout layers on during prediction, we can draw T Monte Carlo samples and calculate the uncertainty - σ

Leveraging Uncertainty

By allowing a fraction of the dataset to be sent for further inspection when uncertainty is high we can significantly improve model performance. For example, leaving out 20% of the images can improve performance by 5%!



Conclusions

- Drop-out based Bayesian uncertainty is a reliable metric to rank the prediction performance
- It can be used to identify tricky cases and increase model performance, if data referral is allowed
- Unfamiliar data and data on class boundaries have high uncertainty