Uncertainty-Aware Digital Diagnosis from Sounds

Tong Xia
University of Cambridge
tx229@cam.ac.uk

Lorena Qendro
University of Cambridge
lq223@cam.ac.uk

Cecilia Mascolo
University of Cambridge
cm542@cam.ac.uk

1. INTRODUCTION

The popularity of mobile sensors, particularly, microphones, with artificial intelligence is reshaping respiratory disease diagnosis and monitoring. Through deep learning, preferable performance can be achieved in-the-lab settings. However, deep learning generally lacks explainability and is sensitive to input data shifts. Most importantly, these models are over-confident leading to irrational decisions which have severe healthcare consequences. In this regard, to allow extensive deployment of automatic diagnosis, a proper understanding of the confidence of digital output is indispensable.

Uncertainty estimation in deep learning is a key solution to the aforementioned issue. Though softmax probability indicates the confidence of the prediction, to some extent, it only captures the relative probability that an instance is from a particular class, and it tends to overestimate confidence and thus requires further calibration. In brief, probabilistic approaches have been proposed to estimate uncertainty more accurately. However, they have not been well explored in sound-based disease detection models [1].

With uncertainty, the system is aware of the risk of automatic diagnosis and it is able to refer samples with low predictive confidence to doctors for reliable results. Consequently, the robustness of the system and the safety of patients can be improved simultaneously. Also, the estimated uncertainty itself, as a feedback signal, is helpful to boost the performance of deep learning. All these considerations pave the way for a more practical sound-based automatic diagnosis system.

2. PROBLEM STATEMENT

The study of exploring uncertainty in sound-based deep learning disease detection models can be divided into several aspects, ranging from estimation to understanding and utilization.

Effective uncertainty estimation. Bayesian Neural Networks are able to accurately estimate uncertainty through learning infinite models, but at a high computational cost. Monte Carlo Dropout is a more efficient paradigm, however, the reduced model capacity may lead to lower accuracy. For mobile health with limited training data and computation source, deep ensemble learning [2] is more promising as finite models are learned as Bayesian approximation.

Uncertainty understanding and referral. Uncertainty consists of epistemic (model) uncertainty and aleatoric (data) uncertainty. Disentangling those two aspects is important to interpret whether the uncertainty comes from limited model capacity or abnormal input. An informed decision can be made accordingly, deciding if the input should be corrected or a referral to doctors is necessary [3].

Uncertainty-enhanced model learning. Sounds collected from microphones are generally multi-modal, including speech, respiratory sounds or background noise. In addition, sounds can be combined with other features like symptoms and demographics reported by smartphone users. Regarding this, uncertainty-aware modality fusion can help to further improve the model performance by informing the robustness of each modality.

3. PRELIMINARY WORK & DISCUSSION

In this work, we plan on developing state-of-the-art approaches to estimate and understand uncertainty in audio-based deep learning models for respiratory disease diagnosis, in order to achieve the goals discussed in Section 2. Our core approach is deep ensemble learning including assembling models trained from various samples and combining different modalities. With uncertainty measured by the disagreement level of ensembles, we are able to empower smartphone-based respiratory disease automatic diagnosis with better risk management.

4. REFERENCES

[1] H. D. Kabir and et al. Neural network-based uncertainty quantification: A survey of methodologies and applications. *IEEE access*, 6:36218–36234, 2018.

[2] B. Lakshminarayanan, A. Pritzel, and C. Blundell. Simple and scalable predictive uncertainty estimation using deep ensembles. In *Proceedings of the 31st International Conference on Neural Information Processing Systems (NeurIPS)*, 2017.

[3] C. Leibig and et al. Leveraging uncertainty information from deep neural networks for disease detection. *Scientific Reports*, 7(1):1–14, 2017.