# Out-of-Distribution Detection via Uncertainty Learning for Robust Glaucoma Prediction

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## Introduction

- Glaucoma is one of the leading causes of irreversible blindness globally.
- Deep learning (DL) has emerged as a promising approach for the automated diagnosis of glaucoma.
- Challenges persist in translating these advancements to clinical settings. Conventional DL classification methods often exhibit overconfidence and lack robustness when faced with a shift in training data distribution, posing challenges in out-of-distribution (OOD) scenarios.
- These issues raise concerns about the suitability of current glaucoma DL diagnostic algorithms for real-world clinical deployment, potentially impacting patient safety.

## Hypothesis

When an image is far away from training samples, conventional deep learning models may:

- Fail to provide reliable predictions
- Experience a loss of performance

## Objective

Our proposed approach aims to improve the reliability of glaucoma predictions by:

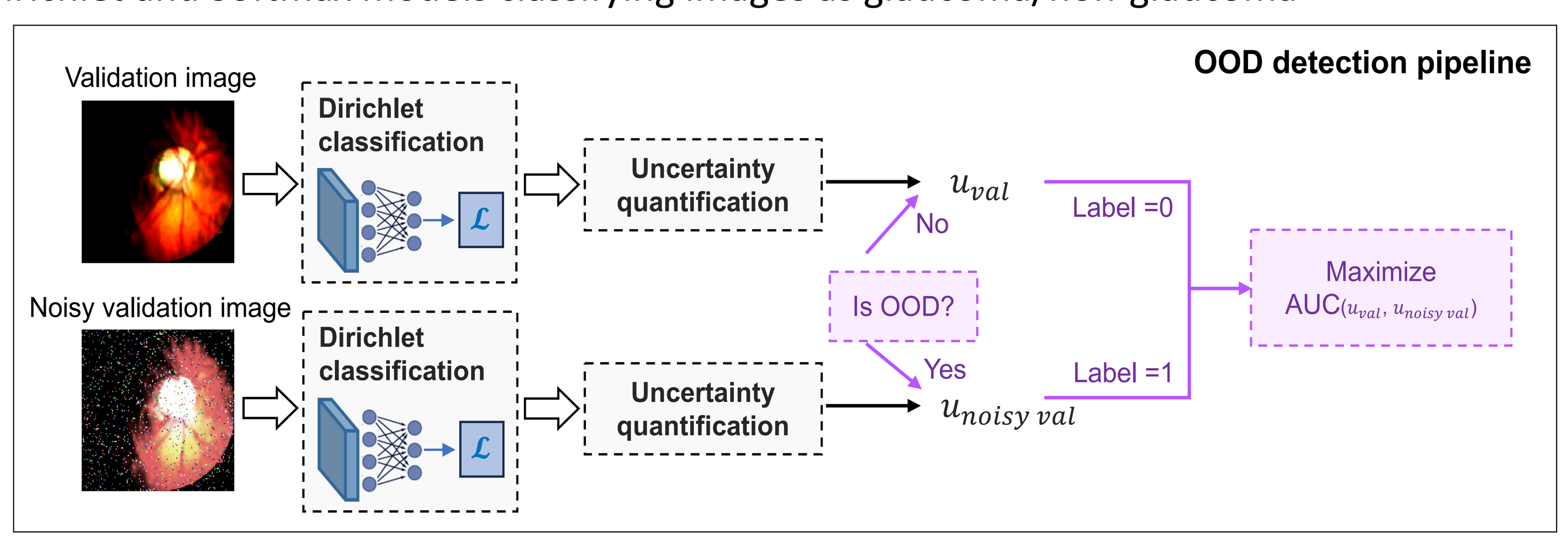
- Effectively identifying OOD samples
- Mitigating the overconfidence of conventional deep learning models on OOD data

## Data

- We trained our deep learning models on 712 fundus images from the Illinois Eye and Ear Infirmary
- We evaluated the models on 2 public fundus datasets: REFUGE and LAG, and 2 non-medical image datasets: CIFAR-10 and Fashion-MNIST

## Method

- We propose an Out-of-Distribution (OOD) detection method, which we will call the Dirichlet model
- Our baseline is a Convolutional Neural Network model, which we will refer to as the Softmax model
- Both Dirichlet and Softmax models classifying images as glaucoma/non-glaucoma



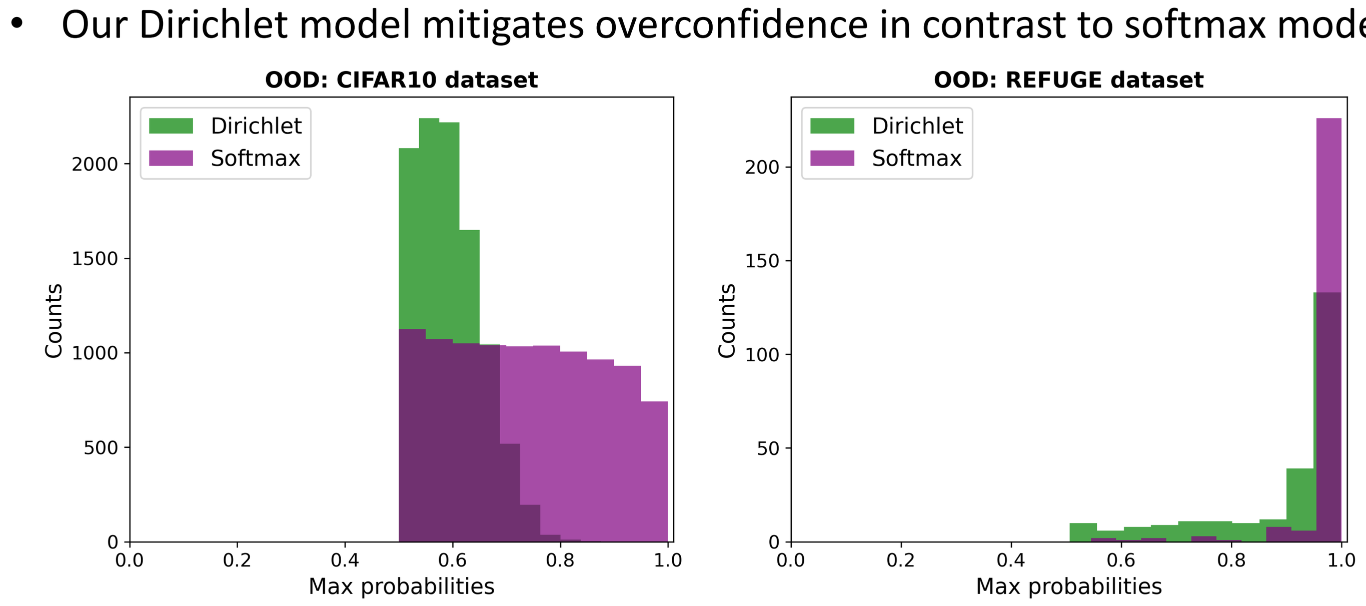

## Results

- Our proposed model consistently outperforms the softmax model in OOD detection
- Our proposed model maintains competitive glaucoma classification compared to softmax

**Mean AUC with [95% CI] on OOD data**

| Dataset | Is fundus? | Glaucoma labels? | OOD detection | | Glaucoma classification | |
|---|---|---|---|---|---|---|
| | | | Dirichlet | Softmax | Dirichlet | Softmax |
| REFUGE | ✓ | ✓ | **64.4 [63.2, 65.6]** | 59.4 [58.4, 60.3] | **91.2 [90.7, 91.9]** | 89.9 [89.4, 90.7] |
| LAG | ✓ | ✓ | **60.0 [59.5, 60.3]** | 42.4 [41.9, 42.7] | **86.7 [86.6, 86.7]** | 86.1 [86.0, 86.2] |
| CIFAR10 | X | X | **95.3 [95.3, 95.4]** | 92.9 [92.8, 92.9] | - | - |
| Fashion-MNIST | X | X | **98.0 [97.9, 98.0]** | 95.1 [95.0, 95.1] | - | - |

- Our Dirichlet model mitigates overconfidence in contrast to softmax model




## Conclusions

- We showed that our proposed uncertainty aware Dirichlet model effectively outperforms Softmax model in OOD detection
- Our proposed method achieves comparable glaucoma classification performance across diverse domains, extending its utility beyond the initial training dataset
- Our proposed method mitigates over-confident glaucoma diagnosis and improves reliability of conventional models
- Incorporation of uncertainty scores in our model alerts users to instances where the model lacks sufficient information for a confident decision

## Support

All work done for this project was supported by the Research to Prevent Blindness (RPB) Foundation.

Research to Prevent Blindness