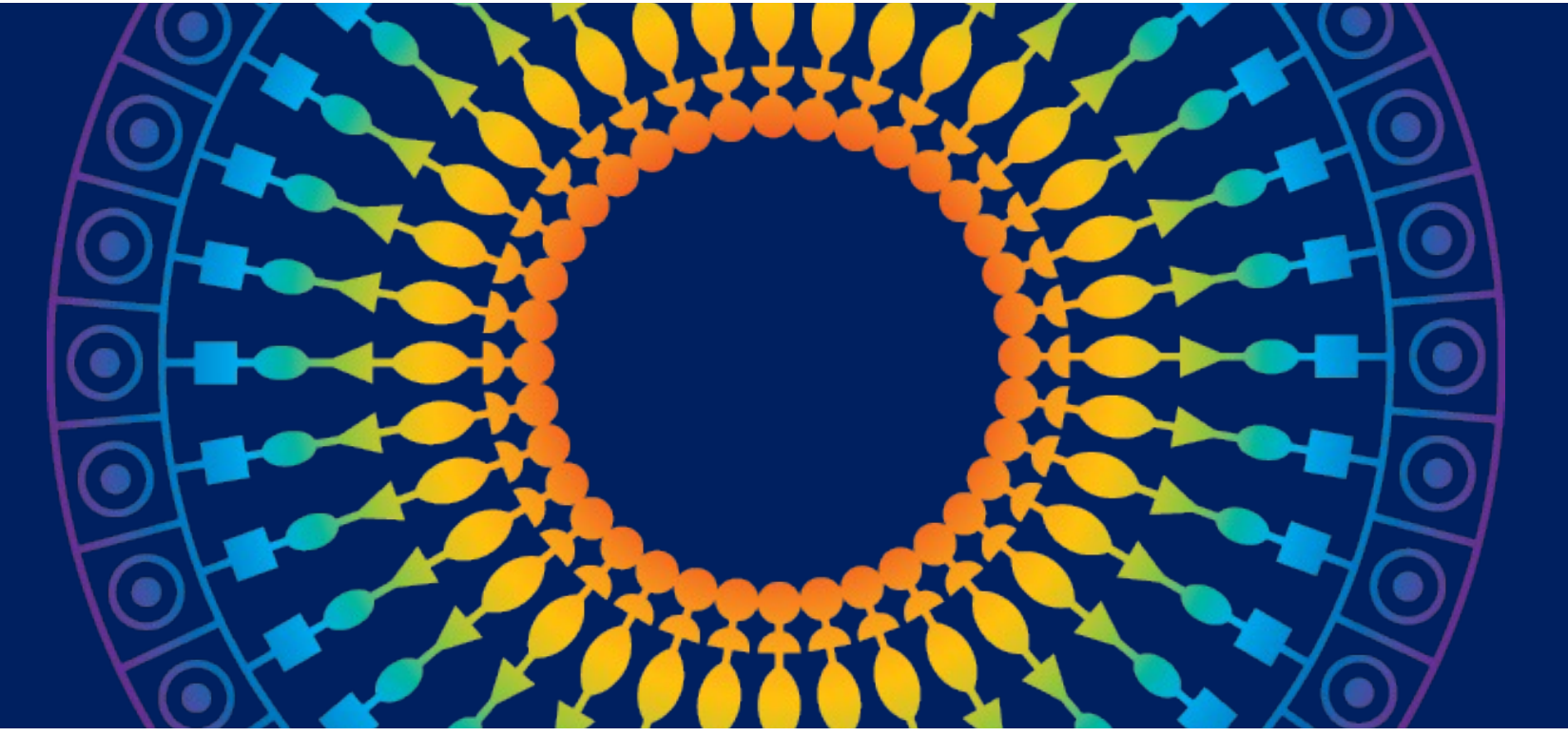


Out-of-Distribution Detection via Uncertainty Learning for Robust Glaucoma Prediction

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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.

METHODS

DATA

- We trained our deep learning models on 712 fundus images from the Illinois Eye and Ear Infirmary
- We evaluated the models on 8 public fundus datasets and 5 non-medical image datasets

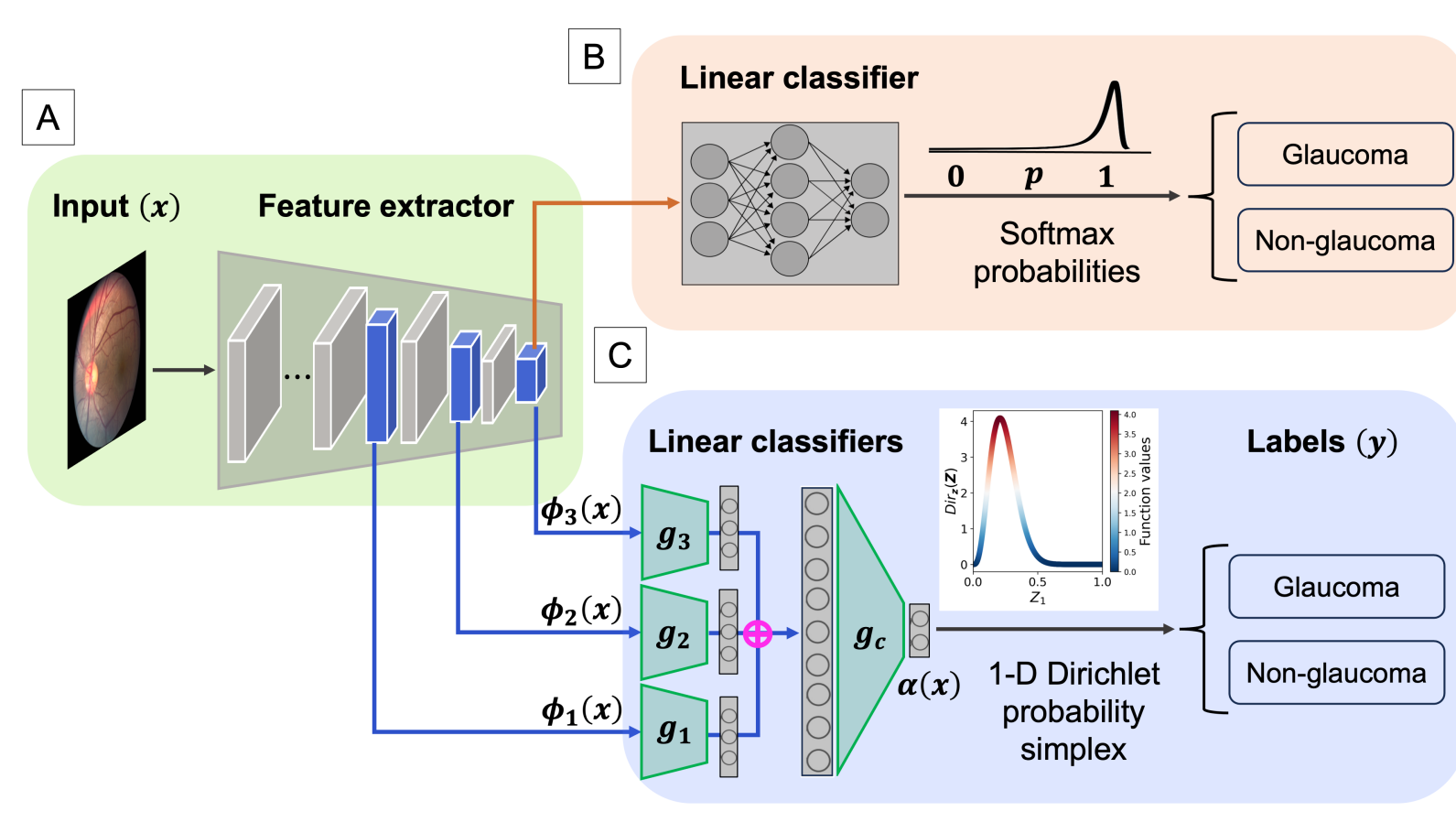


FIGURE 1 Glaucoma classification models. (A) Schematic illustration of base architecture, VGG-16 feature extractor. (B) Baseline softmax classifier. (C) Proposed Dirichlet classifier.

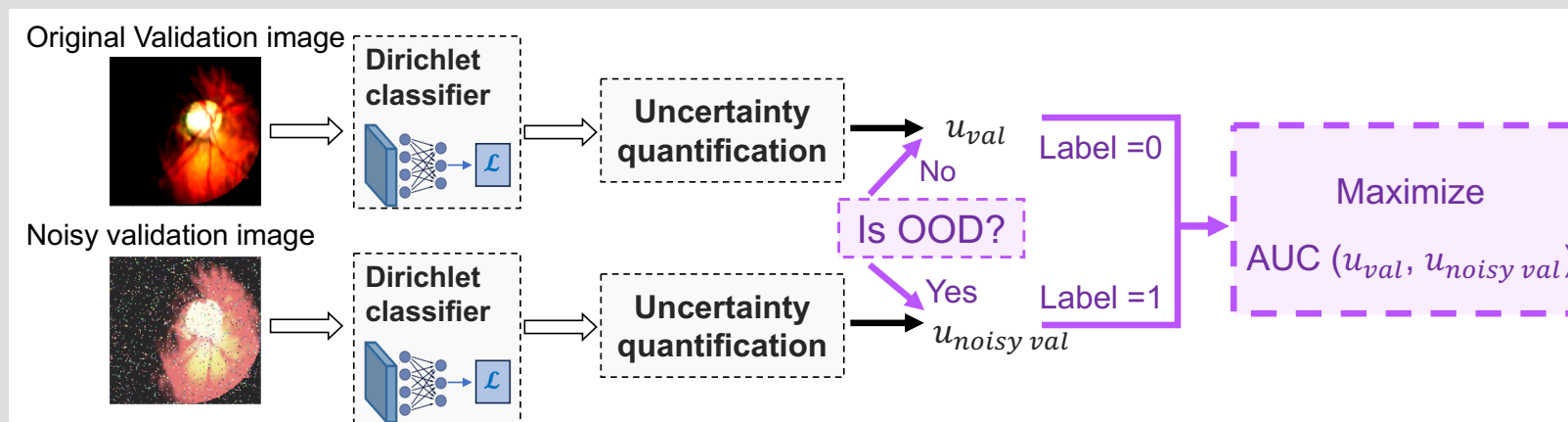


FIGURE 2 Proposed Out-of-Distribution (OOD) detection through uncertainty quantification pipeline.

RESULTS

OOD DETECTION RESULTS

OOD Datasets	Fundus?	Label?	Mean AUC [95% Confidence Interval]	
			Dirichlet	Softmax
RIMONE-DL	✓	✓	76.0 [75.4, 76.6]	54.7 [53.9, 55.5]
O-RIGA	✓	✓	75.1 [74.4, 76.0]	69.2 [68.6, 70.1]
REFUGE	✓	✓	64.4 [63.2, 65.6]	59.4 [58.4, 60.3]
LAG	✓	✓	60.0 [59.9, 60.3]	42.4 [41.9, 42.7]
GL-S	✓	X	82.6 [86.1, 86.2]	73.5 [73.3, 73.7]
Kaggle	✓	X	63.3 [63.0, 63.7]	58.4 [58.0, 58.7]
MESSIDOR-2	✓	X	80.4 [80.1, 81.0]	65.1 [64.8, 65.8]
IDRiD	✓	X	90.2 [89.8, 90.9]	84.4 [83.9, 85.3]
CIFAR-10			95.3 [95.3, 95.4]	92.9 [92.8, 92.9]
Omniglot			98.0 [97.8, 98.0]	95.2 [95.1, 95.2]
F-MNIST	X	X	98.0 [97.9, 98.0]	95.1 [95.0, 95.1]
SVHN			98.3 [98.3, 98.3]	95.1 [95.0, 95.1]
KMNIST			98.0 [98.0, 98.0]	95.6 [95.5, 95.6]

TABLE 1 OOD detection results for Dirichlet versus softmax model. Max performance in bold.

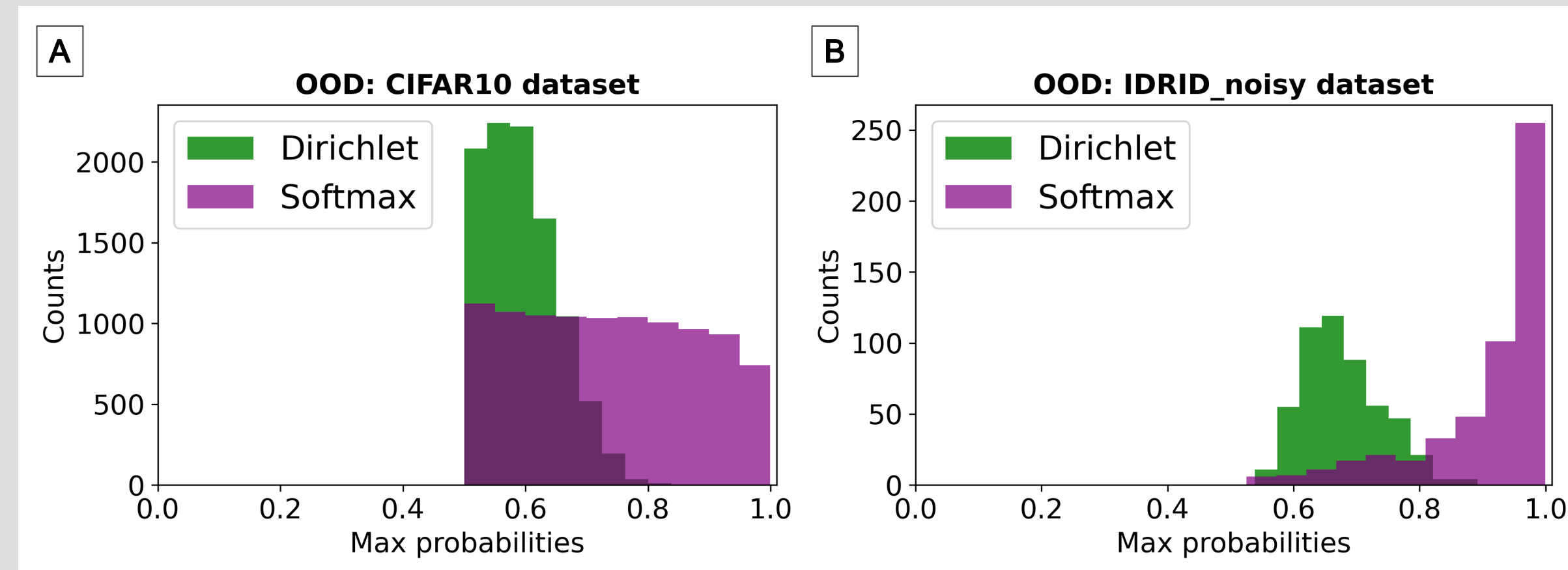


FIGURE 3 Histogram of maximum probabilities predicted by Dirichlet versus Softmax models. Evaluation on (A) CIFAR-10 OOD image dataset, and (B) IDRiD OOD fundus image dataset.

CONCLUSION

- We showed that when an image is far away from training samples, conventional deep learning models using the Softmax function:
 - Fail to provide reliable predictions
 - Experience a loss of performance
- Our proposed uncertainty-aware Dirichlet model effectively outperforms the Softmax model in the OOD detection task
- 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 the reliability of conventional models for glaucoma assessment
- Incorporation of uncertainty scores in our model could alert users to instances where the model lacks sufficient information for a confident decision

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FINANCIAL DISCLOSURES

Homa Rashidisabet, R.V. Paul Chan, Thasarat Vajaranant, and Darvin Yi report no financial disclosure.

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