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Reliable MD Prediction from OCT

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ABSTRACT

Purpose: MD values quantify visual loss. Through OCT images, physicians can obtain MD values to assess patients' visual status. This task is crucial for early patient screening. However, current AI-based MD prediction methods lack interpretability—a common limitation of deterministic neural networks. In medically sensitive scenarios, this hinders practical deployment of such models. This study proposes an evidence-based learning approach for MD prediction. The method actively models uncertainty, with the network simultaneously modeling both the outcome and its uncertainty. This provides partial interpretability while delivering strong performance. Method: We design an evidential learning–based model for MD prediction that outputs a predictive distribution rather than a single point estimate, thereby improving interpretability and reliability in clinical settings. Since MD is a continuous regression target, we assume its observations follow a Gaussian likelihood and impose conjugate priors on the unknown parameters , resulting in a Normal–Inverse-Gamma (NIG) evidential distribution. For each input image, the network simultaneously predicts the four NIG hyperparameters , where represents the predicted MD mean, captures aleatoric (data) uncertainty, and characterizes epistemic uncertainty. During training, we maximize the marginal likelihood (equivalently, the negative log-likelihood of a Student-t evidence distribution) and introduce an error-aware evidence regularization term to suppress incorrect yet overconfident predictions. As a result, the proposed model achieves strong MD regression performance while explicitly providing uncertainty estimates to support early screening and risk-aware clinical decision making.

INTRODUCTION

Mean Deviation (MD) is a clinically important indicator for quantifying visual field loss in glaucoma. It reflects the overall degree of functional impairment and is widely used to assess disease severity, monitor progression, and support early screening. Although MD is traditionally obtained from standard visual field testing, optical coherence tomography (OCT) provides high-resolution structural information of the retina and optic nerve head, making it possible to estimate visual function from anatomical changes. Recent studies have explored deep learning models for automatically predicting MD values from OCT images. These methods usually formulate MD estimation as a regression task and train neural networks to directly output a single predicted value. While such deterministic models can achieve promising predictive performance, they provide limited information about the reliability of each prediction. This limitation is particularly important in medical applications, where datasets are often small and noisy. To address this issue, we introduce an evidential learning-based framework for OCT-based MD prediction. Instead of generating only a point estimate, our method predicts a full evidential distribution over MD by modeling the uncertainty of both the predicted mean and variance.

METHODS AND MATERIALS

We propose an evidential learning-based framework for predicting MD from OCT imaging. Unlike conventional deterministic regression models that output a single MD value, our method predicts a full predictive distribution, allowing the model to explicitly estimate prediction uncertainty.Since MD is a continuous regression target, we assume that the observed MD value follows a Gaussian likelihood with unknown mean and variance. To model uncertainty over these unknown parameters, we place a conjugate Normal–Inverse-Gamma (NIG) prior over the Gaussian mean and variance.

Given an OCT input, the neural network directly predicts four NIG hyperparameters (γ, μ, α, β), where (γ) represents the predicted MD value. The aleatoric uncertainty, which reflects data noise, is estimated as $U_{\text{alea}} = \frac{\beta}{\alpha-1}$ and the epistemic uncertainty, which reflects model uncertainty, is estimated as $U_{\text{epis}} = \frac{\beta}{\nu(\alpha-1)}$. Training is performed by minimizing the negative log-likelihood of the marginal predictive distribution, which has a closed-form Student-t form. To prevent highly confident but incorrect predictions, we further introduce an error-aware evidence regularization term. This term penalizes large prediction errors when the predicted evidence is high, encouraging the model to express higher uncertainty for ambiguous or difficult cases. For OCT representation, volumetric OCT scans are converted into multi-slice inputs by stacking B-scans along the channel dimension. An EfficientNet backbone is used to extract high-level image features, followed by an evidential regression head that outputs the NIG parameters. The model is trained using the Adam optimizer with an initial learning rate of 1×10^{-4} and a cosine annealing learning rate schedule. All experiments are conducted on an NVIDIA RTX 4060 GPU with a batch size of 4.

RESULTS

The proposed method reduced MAE from 1.62 to 1.47 compared with the deterministic baseline. The GM metric changed from 1.15 to 1.20. Beyond prediction accuracy, our framework also generated uncertainty estimates for each case, supporting reliability-aware MD prediction.

Table 1. Performance comparison on the baseline method.

Method	MAE	GM
Baseline	1.62	1.15
Ours	1.47	1.20

DISCUSSION

The proposed evidential learning framework improves OCT-based MD prediction by jointly estimating the predicted value and its uncertainty. Our method provides uncertainty-aware predictions, which can help identify unreliable cases in small and ambiguous medical imaging datasets. By using a Normal–Inverse-Gamma evidential distribution, the model estimates both aleatoric uncertainty from data noise and epistemic uncertainty from model uncertainty. Experimentally, the proposed method reduces MAE from 1.62 to 1.47 compared with the deterministic baseline, indicating improved regression performance and reliability. The error-aware evidence regularization further reduces the risk of overconfident incorrect predictions.
This study is limited by the relatively small dataset size, and further validation on larger multi-center cohorts is needed. Future work may combine uncertainty estimation with visual explanation methods to provide more spatially interpretable MD prediction.

CONCLUSIONS

We propose an evidential learning-based framework for OCT-based MD prediction. Compared with regression models, the proposeddeterministic method predicts a full evidential distribution and explicitly estimates both aleatoric and epistemic uncertainty. Experimental results show that our method improves MD prediction performance, reducing MAE from 1.62 to 1.47, while providing uncertainty-aware predictions. This framework may support more reliable and risk-aware clinical decision-making for early glaucoma screening.

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