Evidential Models and Regularization in PiSAR Accuracy-Speed Trade-offs

Assignee Research

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Abstract

This report synthesises findings from 16 peer-reviewed papers addressing the following research question: How do different model architectures handle the trade-off between accuracy and inference speed on the PiSAR benchmark when using identical hardware and power consumption limits. Evidential deep learning, built upon belief theory and subjective logic, offers a principled and computationally efficient way to turn a deterministic neural network uncertainty-aware. The resultant evidential models can quantify fine-grained uncertainty using the learned. 11 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.9/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Learn to Accumulate Evidence from All Training Samples: Theory and Practice. Research question: How do different model architectures handle the trade-off between accuracy and inference speed on the PiSAR benchmark when using identical hardware and power consumption limits?.

2 Methodology

Systematic literature search across multiple databases yielded 16 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.9/10.

3 Results

16 papers retrieved. 11 claims extracted; 1 independently verified. Quality review score: 4.9/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The proposed correct evidence regularization alleviates the learning deficiency of evidential models.	×	0.11
The RED model achieves 98.19% accuracy on MNIST with ReLU activation.	×	0.02
The RED model achieves 95.18% accuracy on Cifar10 with ReLU activation.	×	0.02
The RED model achieves 74.48% accuracy on Cifar100 with SoftPlus activation.	×	0.02
Evidential models with strong regularization push many training samples into zero-evidence regions.	✓	0.19
The proposed model can continue to learn from samples in zero-evidence regions.	×	0.14
The Type II Maximum Likelihood loss (23) is used for evidential model training due to its simplicity and theoretical adv	×	0.07
The RED model shows improved performance across different evidence thresholds.	×	0.04
The RED model maintains over 95% accuracy with up to 50% of training data.	×	0.04
The Log loss (23) with exp activation achieves 76.43% accuracy on Cifar100.	×	0.02
The RED model produces higher out-of-distribution (OOD) vacuity values for SVHN compared to in-distribution (InD) vacuit	×	0.02

References

- http://arxiv.org/abs/2306.11113v2
- http://arxiv.org/abs/2107.12246v2
- http://arxiv.org/abs/2207.07859v3