SeeNN: Leveraging Multimodal Deep Learning for Long-Range Atmospheric Visibility Estimation in Aviation Safety Applications

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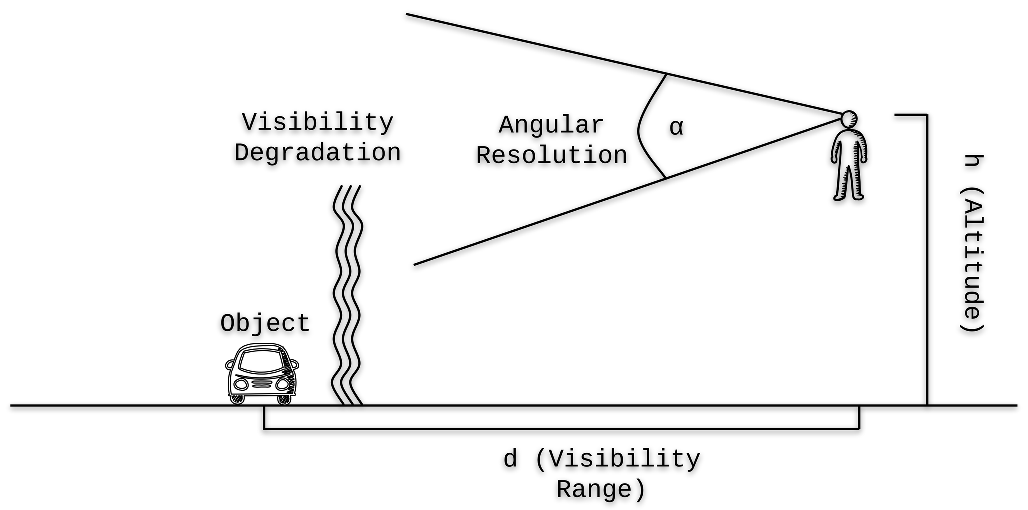
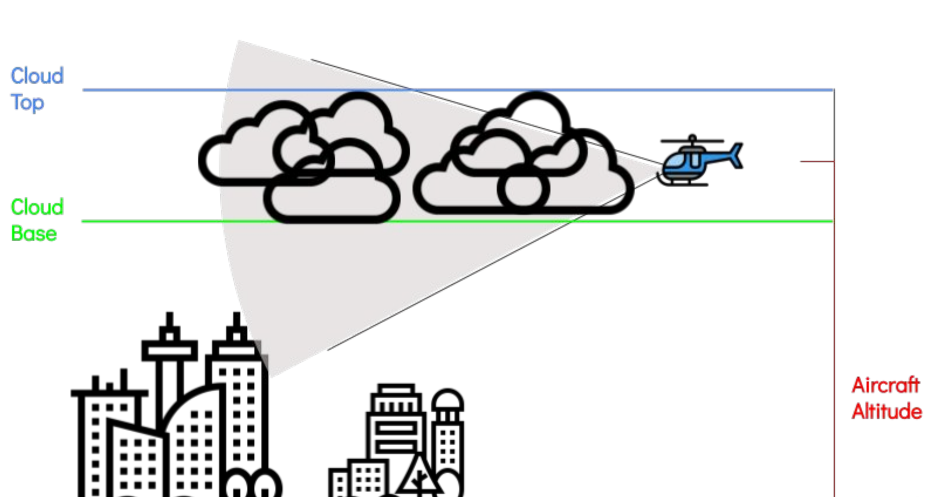
Abstract:



- SeeNN, a deep learning framework, tackles limitations in atmospheric visibility estimation.
- It leverages multimodal fusion (combining RGB images, depth maps, and more) to overcome challenges faced by traditional methods.
- A new benchmark dataset, SeeSet V1, is introduced for this task with more than 320 distinct sceneries.
- SeeNN achieves superior accuracy (97.31%) compared to single-modality models.
- This framework has potential for robust visibility estimation in various environments enhancing the aviation safety.

Motivation:

Accurate atmospheric visibility estimation is critical for aviation safety, traffic flow optimization, and environmental monitoring. However, traditional methods using only RGB images struggle in challenging weather conditions like fog, haze, or dust storms [1, 2]. While deep learning offers a promising solution, limitations like overfitting and difficulties with unseen data hinder its real-world application, especially in safety-critical tasks. Existing DL methods relying solely on RGB data are particularly prone to overfitting [1, 2], prioritizing irrelevant cues like vegetation over actual visibility cues, leading to inaccurate estimates. To overcome these limitations and develop more robust models, we propose utilizing multimodal deep learning techniques [3,4]. This approach integrates information from diverse data sources, beyond just RGB images. By leveraging this broader information, we aim to develop more accurate and reliable visibility estimation models for real-world scenario.



Our Solution: Artificial Intelligence Based SeeNN Framework

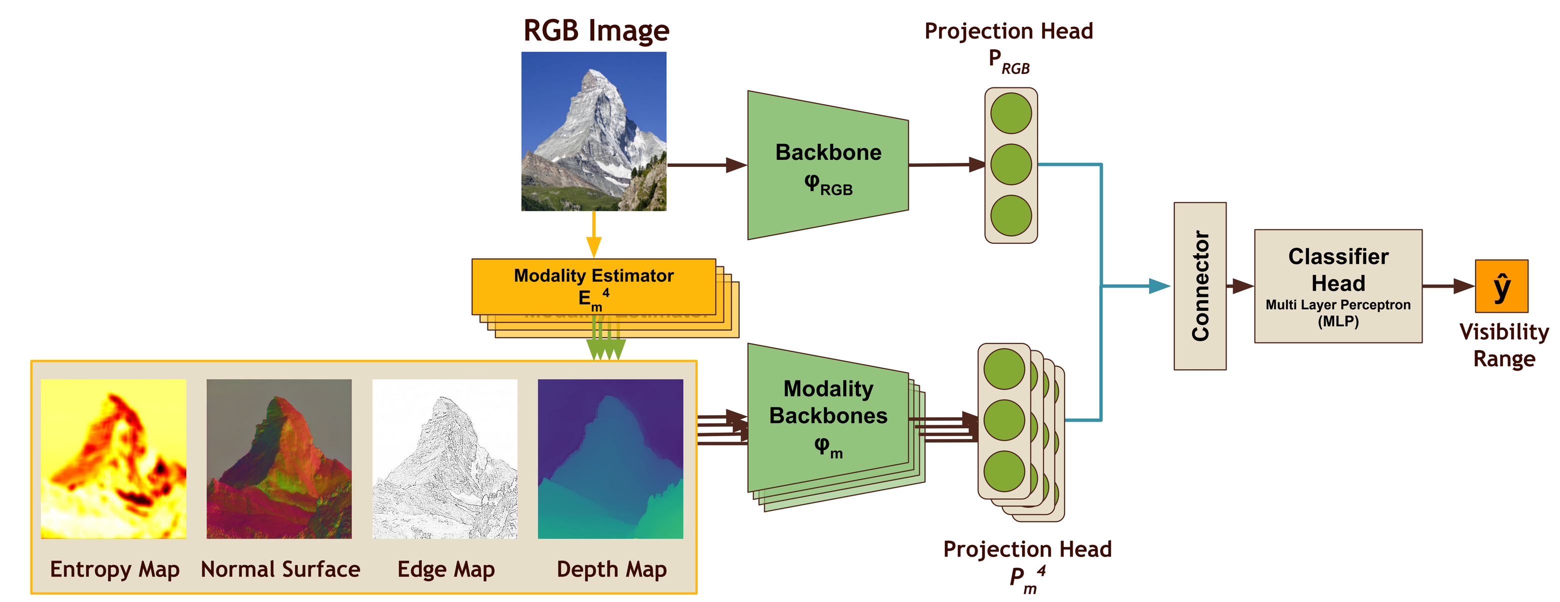


Figure 1: SeeNN Framework

Our Dataset: SeeSET V1.0

Table 1: Dataset Image Count

Count	Visibility Range	Bin/Categories
4,938	0 to 0.5	0
4,938	0.5 to 1	1
19,648	1 to 3	2
19,584	3 to 5	3
67,002	5 to 100	4

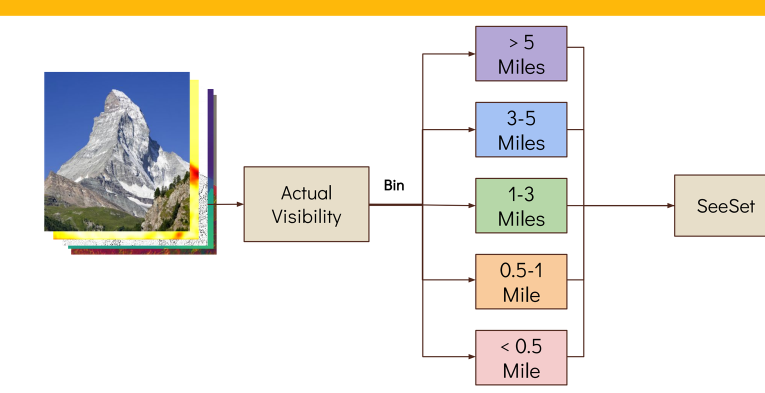


Figure 2: Labeling Process

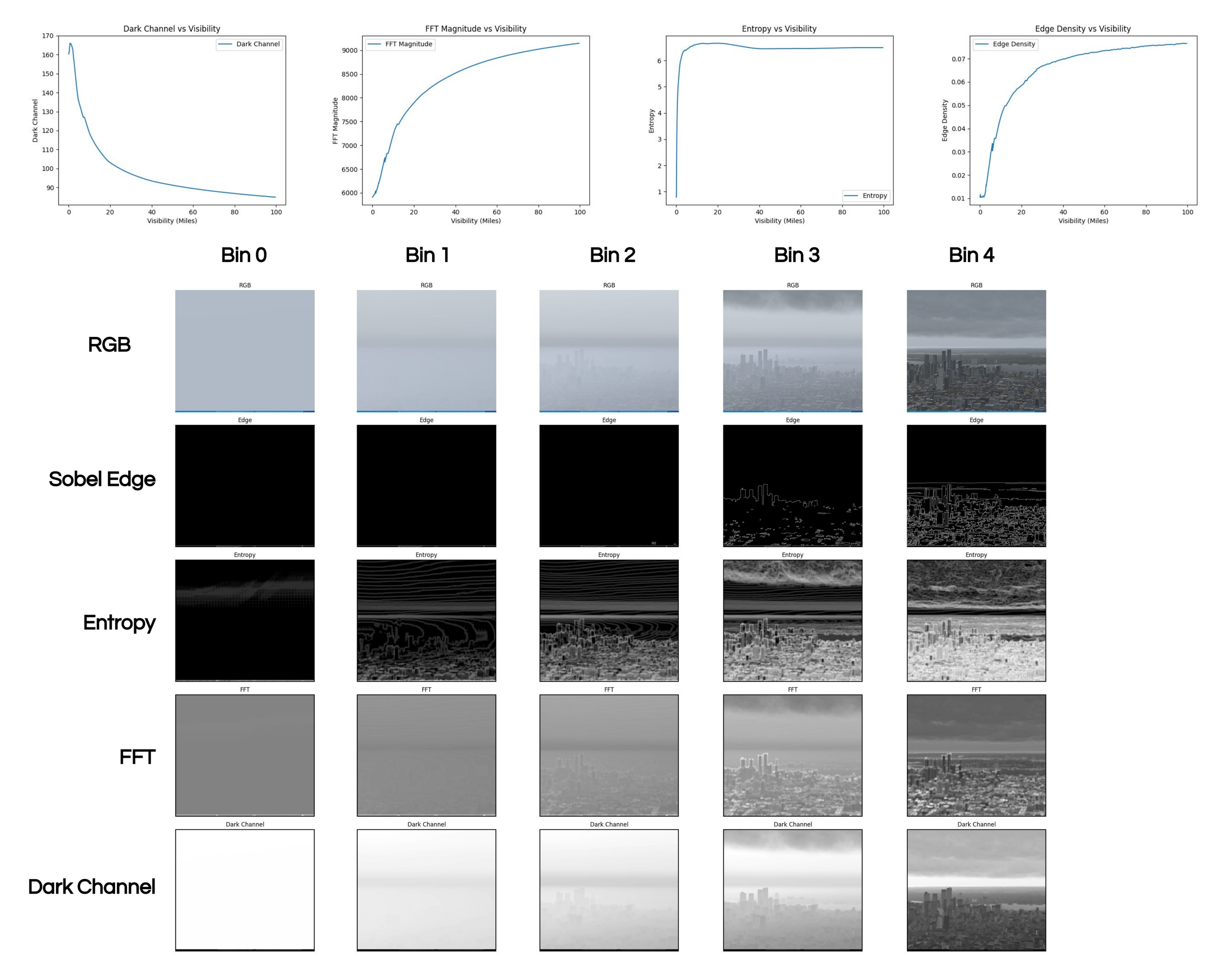


Figure 3: Impact of Visibility Degradation on Different Feature Extractors

Experimental Setup:

Tools: Jax/Keras/Tensorflow/WandB
Batch Size: 128
Optimizer: Adam
Learning Rate: 0.003
Loss: Categorical Cross-Entropy
Backbone: DenseNet121 (7m)
Validation Split: Holdout of images collected from 5 views to insure that our data split is independent and identically distributed (IID)

Ablation Study:

Investigate the impact of different components of our system:

- Single Modality AI Model:
  - RGB
  - Edge
  - Depth
  - Normal Surface

Results:

- The Unimodal RGB model failed to fit the problem and shows signs of overfitting the dataset with above 98.7% training accuracy and about 87.9% Validation Accuracy
- The multimodal (SeeNN) approach proved to have the best performance across all the 5 classes with an accuracy of 97.37%

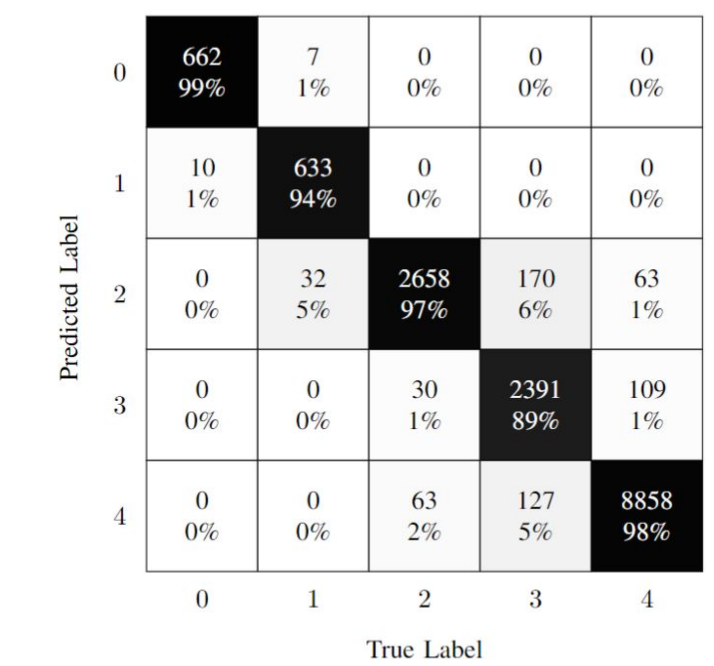


Figure 4: SeeNN Confusion Matrix

Table 2: Results Comparison of different experiments

	RGB	Entropy Map	Edge Map	Depth	Normal Surface	image size	#param	val acc.
	✓					224^2	7M	87.92
		✓				224^2	7M	95.6
			✓			224^2	7M	97.23
				✓		224^2	7M	81.49
					✓	224^2	7M	85,68
SeeNN	✓	✓	✓	✓	✓	$5 * 224^2$	38M	**97.31**

Conclusion and Future Perspective:

Current methods struggle with visibility, especially in bad weather. Our solution: multimodal deep learning! This approach uses more than just images, creating robust models for real-world applications like safe aviation and efficient traffic flow.

Future Work: Expanding datasets and exploring representation learning for pre-training the SeeNN model will further enhance accuracy and solidify this technology's role in critical tasks.

References:

[1] T. Bouhsine et al. "Atmospheric Visibility Image-Based System for Instrument Meteorological Conditions Estimation: A Deep Learning Approach". In: Proc. 2022 9th International Conference on Wireless Networks and Mobile Communications (WINCOM).
[2] K. Ait Ouadil, S. Idbraim, T. Bouhsine, et al. "Atmospheric visibility estimation: a review of deep learning approach". In: Multimedia Tools and Applications (2023).
[3] K. Liu et al. Learn to Combine Modalities in Multimodal Deep Learning.
[4] E. Blasch et al. "Machine Learning/Artificial Intelligence for Sensor Data Fusion-Opportunities and Challenges". In: IEEE Aerospace and Electronic Systems Magazine 36.7 (July 2021)