Advanced Indoor Pathloss Prediction Using Deep Learning

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Introduction

- **Indoor pathloss prediction** is a critical task in wireless communication, especially for designing and optimizing indoor networks.
- **Challenges:** Complex indoor environments with obstacles like walls and furniture.
- **Limitations of Traditional Methods**
  - Empirical models struggle to capture real-world complexities.
  - Limited generalization across diverse indoor scenarios.
- **Deep Learning as a Solution**
  - Utilizes large datasets to learn intricate patterns.
  - Improves prediction accuracy and generalization to new environments.
- **Objective of the Work**
  - Leverage deep learning to enhance indoor pathloss prediction.
  - Evaluate performance on unseen indoor geometries.

3 Tasks

- **<u>Task-1</u>**

- **Simulation Parameters:** Isotropic antenna pattern **(Ant1)** at 868 MHz **(f1).**
- **Buildings:** Data for buildings **B1 to B25.**
- **Sample Generation:**
  - **50** radio maps generated for each building.
  - Valid sample names: **'B(1-25)_Ant1_f1_S(0-49)'.**
- **Objective:**
  - Assess model generalization to new geometries.
  - Test the model with samples from **5 new geometries** not included in the dataset.

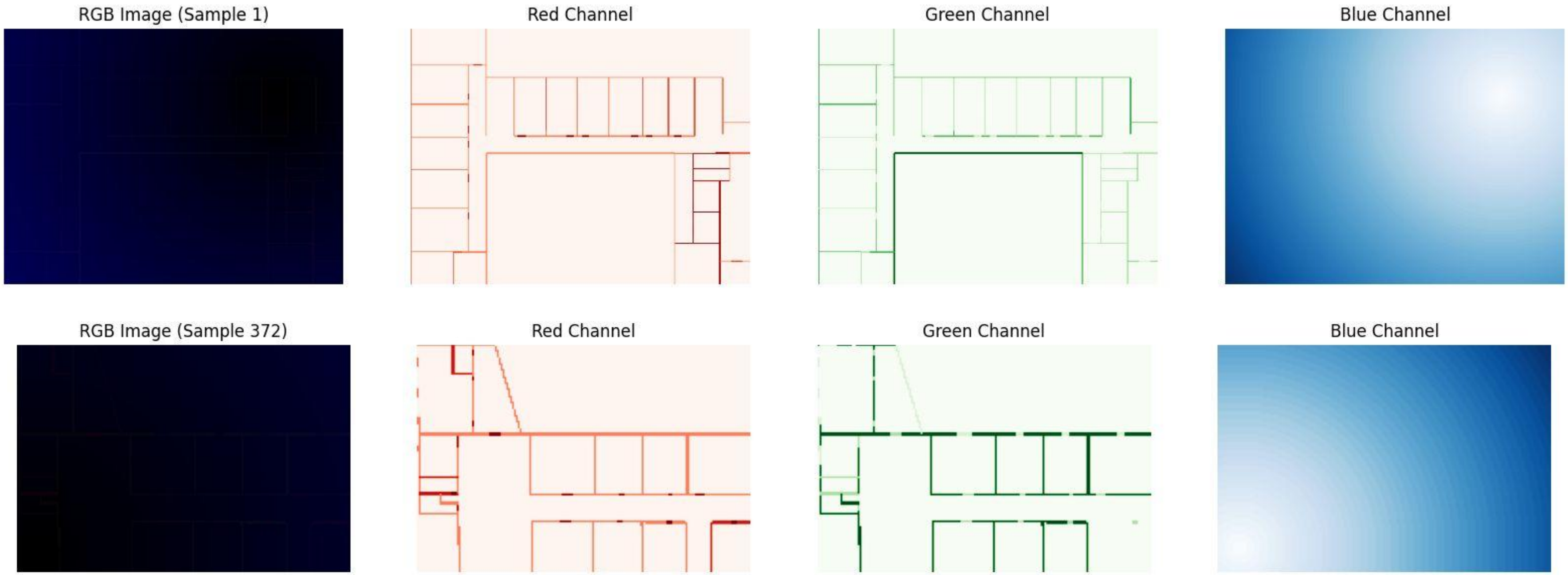
- **<u>Task-2</u>**

- **Simulation Parameters:** Isotropic antenna pattern **(Ant1)** at frequencies 0.868, 2, and 3.5 GHz **(f1, f2, f3).**
- **Buildings:** Data for buildings **B1 to B25** (includes data from Task 1).
- **Sample Generation:**
  - **50** radio maps generated for each building and frequency.
  - Valid sample names: **'B(1-25)_Ant1_f(1-3)_S(0-49)'.**
- **Objective:**
  - Assess model generalization to new geometries and frequencies.
  - Test the model with samples from **5 new geometries and a frequency** band not included in the dataset.

- **<u>Task-3</u>**

- **Simulation Parameters:** 5 different antenna radiation patterns **(Ant1 to Ant5)** at frequencies 0.868, 2, and 3.5 GHz **(f1, f2, f3).**
- **Buildings:** Data for buildings **B1 to B25** (includes data from Task 2).
- **Sample Generation:**
  - **For Ant1: 50** radio maps for each building and frequency (valid names: **'B(1-25)_Ant1_f(1-3)_S(0-49)').**
  - **For Ant2 to Ant5: 80** radio maps for each building and frequency, with random steering angles (valid names: '**B(1-25)_Ant(1-5)_f(1-3)_S(0-79)').**
- **Objective:**
  - Assess model generalization to new **geometries, frequencies, and antenna radiation patterns.**

Dataset



Red, Green & Blue channels representing Transmittance, Reflectance and Tx Location

Overview: Our Progressive Approach

- Our comprehensive project has delivered several key outcomes across all three tasks:

- **Model Development:** UNET, WNET, and DeepLab architectures have demonstrated high accuracy in pathloss prediction, successfully handling multiple building maps, multiple frequencies, and antenna pattern variations.

- **Novel Feature Integration:** We have incorporated **ASSP** and several channels including Line of Sight **(LOS)**, wavelength-dependent characteristics **(lambda scaling)**, and a**ntenna radiation patterns**, significantly enhancing prediction accuracy.

Work Overview: A Progressive Approach

Our project demonstrates progressive advancement in indoor pathloss prediction through three distinct phases:

Task 1 established foundational models operating at **f1 868 MHz**, and **1 antenna radiation pattern** successfully implementing UNet, WNet, and DeepLabV3 architectures with **Line-of-Sight** considerations. There are **25 buildings** with this. **Generalize for different Building Maps.**

Task 2 extends our capabilities to **multiple frequencies (0.868 GHz, 2 GHz, 3.5 GHz)** incorporating **wavelength-dependent** characteristics (lambda scaling of LoS)**.** Our results were better with lambda scaling. **Generalize for different Building Maps and Frequencies.**

Task 3 advances the implementation by integrating **multiple antenna radiation patterns** (**5** ant1-ant 5). Results were better with extra channel.So 3 different frequencies,25 different buildings & 5 different antennas. **Generalize for different Building Maps, Frequencies and Antenna Radiation Patterns.**

LOS Channel and Antenna Radiation Pattern

Fourth LoS Channel = (R+G)/(B+ε)λ = (R+G)/(B+ε)c/f

where:

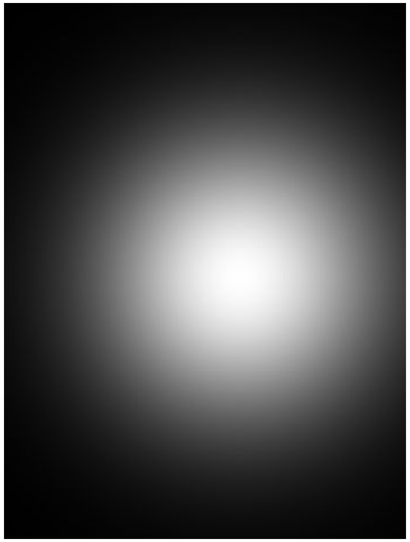
- R represents the reflectance values from input
- G captures transmittance characteristics
- B indicates distance from transmitter
- ε is a small constant preventing division by zero
- c speed of light
- f frequency

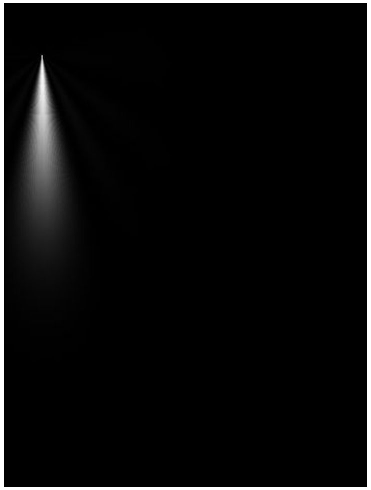
Antenna Radiation Pattern:

The fifth channel computation follows a systematic sequence of geometric and electromagnetic transformations:

- We calculate the distance between transmitter and prediction points using:
- **distance = $\sqrt{(xv-txx)^2 + (yv-txy)^2}$**
- **base_angle = (degrees(arctan2(yv-txy,xv-txx)) + 360) mod 360**
- **adjusted_angle = (base_angle + azimuth + 360) mod 360**
- **gain_linear = 10^(gain_pattern[adjusted_angle]/10)**
- **intensity = $\exp(-distance^2/(2 \cdot std\_dev^2)) \cdot gain\_linear$**

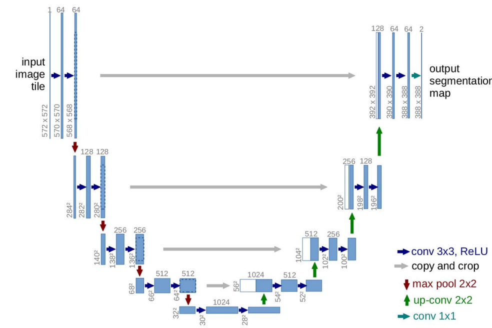
Antenna Radiation Pattern



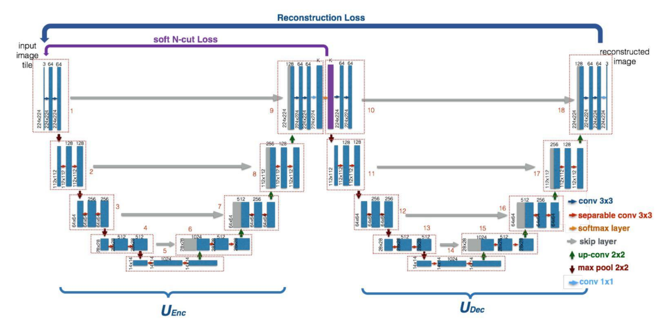


Methodology: Model Architectures

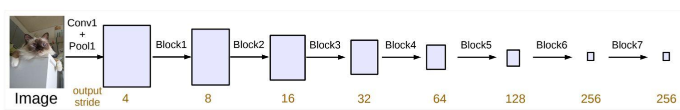
Baseline UNet : The UNet is a convolutional neural network specifically designed for image-to-image translation tasks. It features an encoder (downsampling path) to capture context and a decoder (upsampling path) for precise localization, connected by skip connections. This architecture effectively balances spatial and semantic information for accurate predictions.



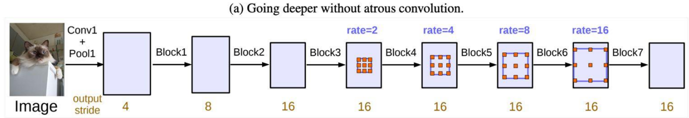
WNet : WNet builds on the UNet by incorporating dual encoder paths, allowing it to process different aspects of the input data simultaneously. By combining two units of data during processing, it captures more complex features and structural nuances, making it highly effective for tasks requiring detailed feature extraction.



DeepLabV3 with Group Normalization : DeepLabV3 leverages atrous convolutions to capture multi-scale contextual information, making it ideal for semantic segmentation. It replaces Batch Normalization with Group Normalization, which enhances performance with smaller batch sizes, ensuring robustness in diverse training conditions. This advanced architecture is well-suited for complex segmentation tasks.



(a) Going deeper without atrous convolution.



(b) Going deeper with atrous convolution. Atrous convolution with $rate > 1$ is applied after block3 when $output\_stride = 16$.

Figure 3. Cascaded modules without and with atrous convolution.

Data Preprocessing and Augmentation

Preprocessing Steps

- **Resizing:** Standardized all images to 256x256 pixels for consistent input dimensions.
- **Normalization:** Scaled pixel values to the range [0, 1] for both input and output images to facilitate stable training.

Data Augmentation Techniques

- **Flipping:** Applied vertical and horizontal flipping (Left-to-Right and Top-to-Bottom) to simulate varied orientations.
- **Rotations:** Introduced random rotations (0°, 90°, 180°, 270°) to enhance model robustness.
- **Synchronized Transformations:** Ensured identical transformations for input and output images to preserve spatial correspondence.
- **Building-wise Randomization (BR):** Randomized building selections for training, validation, and testing to evaluate model generalizability across different indoor environments.

Training Configuration

- **Loss Function:** Used Mean Squared Error (MSE) Loss to minimize the difference between predicted and actual path loss values.
- **Optimizer:** Adopted the Adam optimizer with learning rates fine-tuned for each model (e.g., 0.0001 or 0.001).
- **Number of Epochs:** Trained models for 200 epochs with early stopping (patience) to ensure convergence.
- **Batch Size:** Set to 16 samples per batch for optimal computational efficiency and accurate gradient estimation.

Experiments and Results

RB = Random Building

DA = Data Augmentation

RHF = Right Horizontal Flip

ROT = Rotation

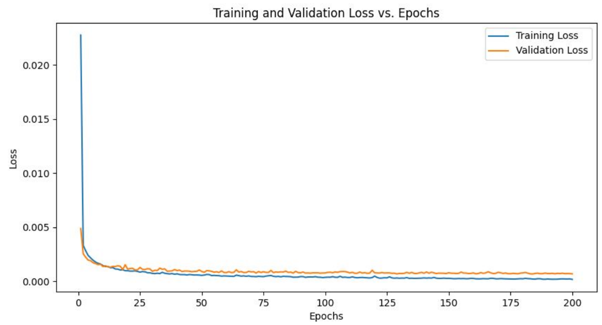
CWF = Complete Width Flip*

LOS = Line of Sight

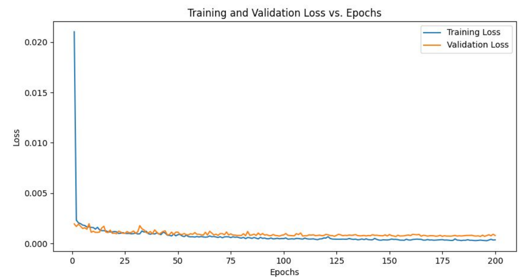
*flip in all directions

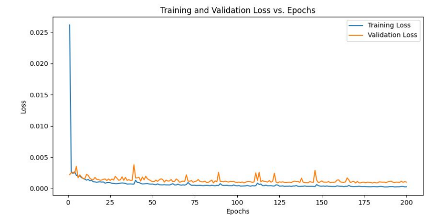
MODEL	UNET	UNET (200 E)	UNET(200 E & DA)	UNET(200 E, DA(ROT, RHF) & RB)	UNET(200 E & RB)	UNET(200 E, DA(ROT, CWF) & RB)	UNET(200 E, DA(ROT, CWF) & RB) & ASPP & LOS	WNET(200 E, DA(ROT, CWF) & RB)	WNET(200 E, DA(ROT, CWF),RB & LOS)	DEEPLABV3
TRAINING ERROR	0.00040	0.00027	0.00214	0.00740	0.00035	0.00026	0.00008	0.00022	0.00016	0.00018
VALIDATION ERROR	0.00060	0.00046	0.00242	0.00602	0.00078	0.00075	0.00056	0.00077	0.00068	0.00067
TEST ERROR	0.00060	0.00058	0.00218	0.00689	0.00104	0.00098	0.000095	0.00093	0.00091	0.00080
EARLY STOPPING	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
TOTAL NO OF PARAMETERS	31,043,521	31,043,521	31,043,521	31,043,521	31,043,521	31,043,521	56,216,65	43,584,769	43,584,769	58.2 M
TRAINABLE PARAMETERS	31,043,521	31,043,521	31,043,521	31,043,521	31,043,521	31,043,521	56,216,65	43,584,769	43,584,769	58.2 M
NON TRAINABLE PARAMETERS	0	0	0	0	0	0	0	0	0	0
NO OF ENCODER	4	4	4	4	4	4	4	8	8	7
NO OF DECODERS	4	4	4	4	4	4	4	8	8	BLIP
BOTTLENECK	1	1	1	1	1	1	1 AND ASPP	2	2	ASPP
EPOCHS	100	200	200	200	200	200	200	200	200	200
(TRAIN, VAL, TEST) SET SIZE	(0-875,876-1062,1063-1250)	(0-875,876-1062,1063-1250)	(0-875,876-1062,1063-1250)	(0-850,851-1050,1050-1250)	(0-850,851-1050,1050-1250)	(0-850,851-1050,1050-1250)	(0-850,851-1050,1050-1250)	(0-850,851-1050,1050-1250)	(0-850,851-1050,1050-1250)	(0-850,851-1050,1050-1250)
PATIENCE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
LEARNING RATE	0.001	0.001	0.001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
OPTIMIZER	ADAM	ADAM	ADAM	ADAM	ADAM	ADAM	ADAM	ADAM	ADAM	ADAM
BATCH SIZE	16	16	16	16	16	16	16	16	16	16

Experiments and Results

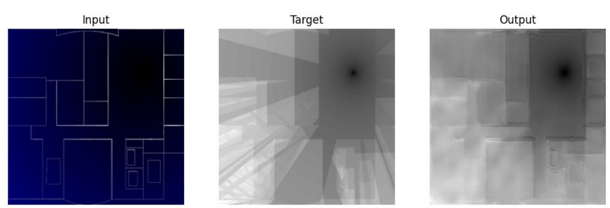


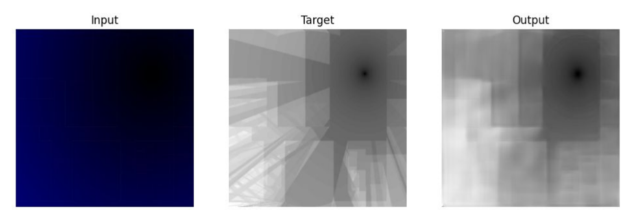
Loss Curve for WNet Model with Data Augmentation.





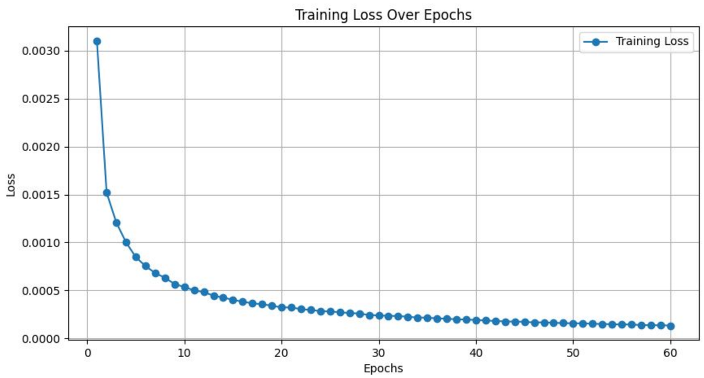
Loss Curves for UNet Model with and without Data Augmentation, respectively.



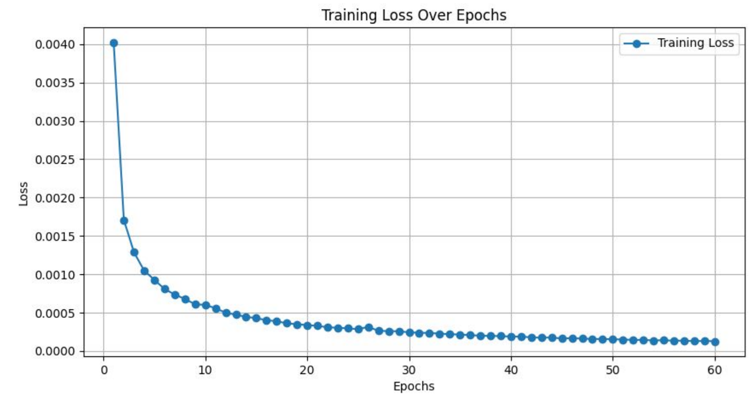


Prediction v/s Ground Truth with and without LOS, respectively for the UNet Model.

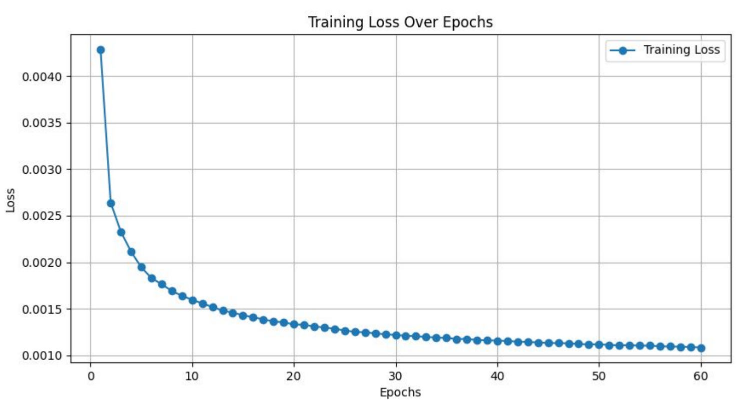
Task 2 without lambda scaler



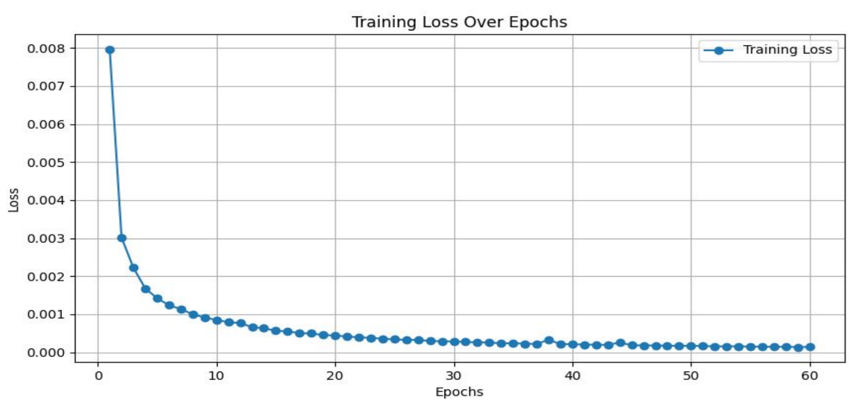
Task 2 with lambda scaler



Task 3 without radiation pattern



Task 3 with radiation pattern



Conclusions

- Our **Project** demonstrates significant advancements in indoor pathloss prediction through **innovative deep learning approaches.**
- Robust integration of **antenna radiation patterns** and **multi-frequency propagation characteristics** has improved prediction **accuracy and model stability.**
- Novel features, such as the **custom fourth channel (LOS)** and **fifth channel (Radiation Patterns)**, have enhanced **input representations**, enabling **precise handling** of **omnidirectional and directional antenna configurations**.
- Advanced techniques like **ASPP (Atrous Spatial Pyramid Pooling)** have optimized **multi-scale feature extraction,** while **efficient training strategies** with **dynamic resizing and batching** have ensured scalability.
- These **developments highlight** the **potential of deep learning in designing reliable models** for **indoor wireless network planning and optimization**, paving the way for future advancements in this field.

References

1. **Ronneberger, O., Fischer, P., & Brox, T. (2015).** "U-Net: Convolutional Networks for Biomedical Image Segmentation." *arXiv preprint arXiv:1505.04597.*

   Introduced the UNet architecture for image-to-image translation tasks.

2. **Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2017).** "DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs." *IEEE Transactions on Pattern Analysis and Machine Intelligence.*

   Detailed the use of atrous convolutions and multi-scale context in segmentation tasks.

3. **Task Dataset and Challenge Documentation (ICASSP 2024).**

   Provides detailed information on the dataset, tasks, and evaluation metrics for indoor pathloss prediction.