Report of Advanced Indoor Pathloss Prediction Using Deep Learning

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Team Members and Contributions

Our team collaborated effectively to develop and implement advanced deep learning solutions for indoor pathloss prediction. Each member brought specific expertise and handled distinct project components:

Sajid Javid (PHD24002) Led the technical implementation and code development. Responsible for architecting and implementing the U-Net ASPP model, including the enhancement for multi-frequency capabilities and antenna pattern integration. Developed the comprehensive Python codebase for data preprocessing, model training, and performance evaluation across all three tasks.

Nikhil Suri (2021268) Conducted extensive literature review and contributed to model training optimization. Researched state-of-the-art approaches in radio map estimation and semantic segmentation, providing crucial insights for architectural decisions. Collaborated on training methodology refinement and hyperparameter optimization, particularly for Tasks 2 and 3.

Siddhant Gautam (2021100) Managed technical documentation and supported training processes. Created detailed documentation of implementation methodologies, experimental results, and architectural specifications. Assisted in training oversight and validation, ensuring robust model performance across different configurations.

1. Problem Statement and Related Work

Indoor radio propagation modeling represents a critical challenge in modern wireless communications, particularly as networks become more complex and demand higher precision in signal strength prediction. Our research addresses this challenge through an innovative deep learning approach that combines sophisticated neural network architectures with fundamental electromagnetic principles.

The accurate prediction of radio signal propagation in indoor environments is complicated by multiple factors. Building materials exhibit varying electromagnetic properties, leading to complex reflection, refraction, and diffraction patterns. Signal strength varies significantly with distance and frequency, while architectural features create intricate multipath effects. Traditional modeling approaches often struggle to capture these complex interactions, particularly when dealing with diverse building layouts and multiple frequency bands.

Our research utilizes the ICASSP 2025 Indoor Radio Map Dataset, which provides comprehensive coverage through buildings B1-B25. This dataset uniquely captures the complexity of indoor propagation through multiple input channels. The RGB channels represent critical propagation characteristics: transmittance (signal penetration capabilities), reflectance (material interaction properties), and precise transmitter location mapping. This multi-channel approach enables our models to learn the intricate relationships between building structure and signal propagation.

The advancement of deep learning in wireless communications has opened new possibilities for addressing these challenges. Recent work by Levie et al. (2021) with RadioUNet demonstrated the potential of convolutional neural networks in radio map estimation. Similarly, Bao et al.'s (2021) E-Unet++ showed promising results in semantic segmentation for complex environments. Our research builds upon these foundations while introducing several key innovations.

Our approach distinguishes itself through the comprehensive integration of physical electromagnetic principles with deep learning methodologies. We enhance traditional architectures by incorporating computed channels that capture Line-of-Sight effects and radiation patterns. This integration is particularly crucial for handling multiple frequency bands (0.868 GHz, 2 GHz, and 3.5 GHz) and varied antenna radiation patterns, aspects that significantly influence indoor signal propagation.

The practical implications of this research extend beyond theoretical advancement. Accurate indoor pathloss prediction directly impacts wireless network planning, optimization, and deployment. Our solution aims to provide reliable predictions across diverse indoor scenarios, supporting the development of more efficient and effective wireless networks.

Through systematic enhancement of base architectures and careful integration of physical principles, our research represents a significant step forward in indoor pathloss prediction. The progressive development from single-frequency modeling to comprehensive multi-frequency and multi-pattern prediction demonstrates the robustness and adaptability of our approach.

2. Methodology

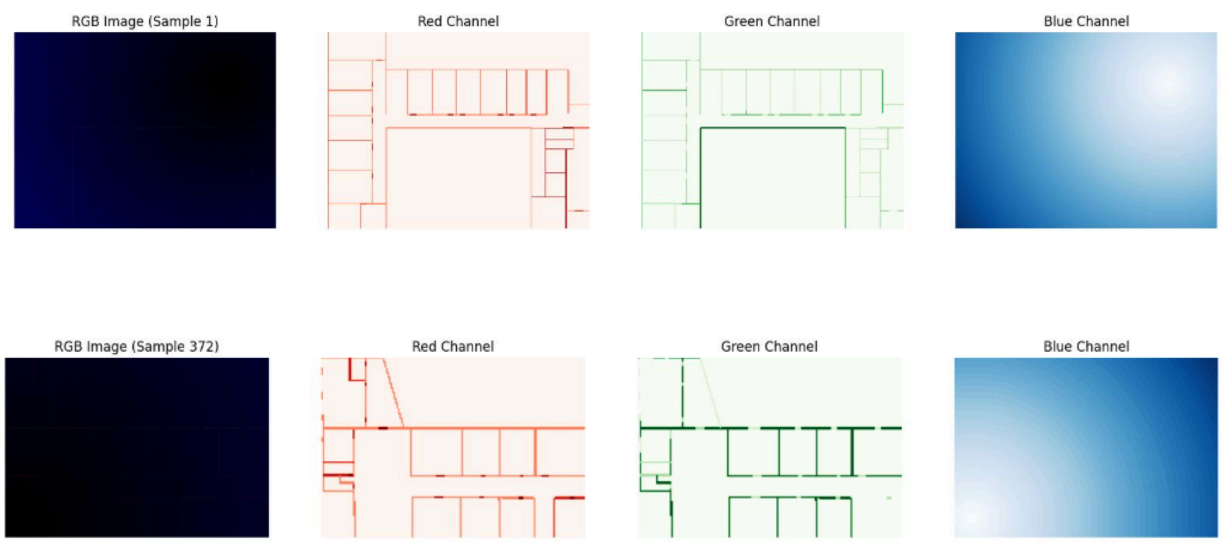
Our implementation establishes a comprehensive framework that integrates advanced deep learning architectures with physics-informed feature engineering for accurate indoor pathloss prediction. The methodology systematically incorporates electromagnetic principles while maintaining computational efficiency.

Dataset Architecture and Processing

The RadioMapDataset implementation forms the foundation of our approach, processing multi-channel input data that captures crucial propagation characteristics. The base input structure comprises RGB channels representing transmittance, reflectance, and transmitter location information. We enhance this with computed channels that incorporate physics-based features.

For Tasks 1 and 2, we implement a fourth channel that integrates Line-of-Sight information through the formula $[(R+G)/(B+\varepsilon)]\lambda$. This enhancement significantly improves the model's ability to capture direct signal paths and material interactions. Task 3 extends the feature set with a fifth channel dedicated to radiation pattern modeling, computed through a sequence of geometric and electromagnetic transformations:

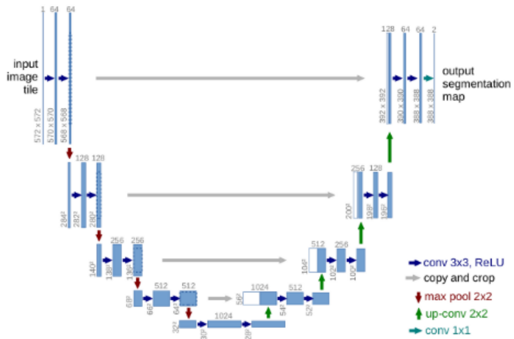
- Distance calculation: $\sqrt{(xv-txx)^2 + (yv-txy)^2}$
- Angle computation: (degrees(arctan2(yv-txy,xv-txx)) + 360) mod 360
- Azimuth adjustment: (angle + azimuth + 360) mod 360
- Gain transformation: 10^(gain_pattern[adjusted_angle]/10)
- Intensity mapping: $\exp(-\text{distance}^2/(2\cdot \text{std\_dev}^2))\cdot \text{gain\_linear}$



The above Figure shows Red, Green & Blue channels representing Transmittance, Reflectance and Tx Location

Neural Network Architecture

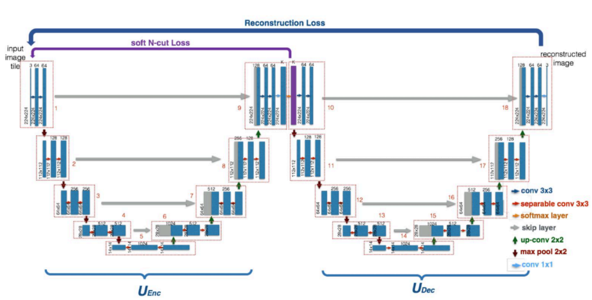
Our solution employs a U-Net architecture enhanced with Atrous Spatial Pyramid Pooling (ASPP), combining the strengths of both approaches for robust feature extraction. The network processes inputs through carefully designed layers:



The encoder pathway implements 3x3 convolutional layers with ReLU activation, followed by 2x2 max pooling operations for downsampling. Each downsampling step doubles the feature channels, enabling the network to capture increasingly complex propagation patterns. The decoder pathway utilizes 2x2 up-convolutions for upsampling, with skip connections from corresponding encoder layers preserving crucial spatial information.

The ASPP module enhances feature extraction through dilated convolutions at rates 6, 12, and 18. This multi-scale approach enables the model to capture features at varying spatial scales without increasing computational complexity. Global context integration through average pooling further improves the model's understanding of overall signal distribution patterns.

The WNet architecture extends these capabilities through dual encoder paths, enabling parallel processing of input features. This dual-path approach allows simultaneous extraction of different aspects of the propagation environment. The architecture processes data by combining two units of information, effectively capturing structural nuances that might be missed by single-path approaches. The unified decoder then integrates these parallel features, producing comprehensive pathloss predictions that benefit from this multi-perspective analysis.



Training Framework and Optimization

Our training methodology employs a comprehensive approach to ensure robust model performance:

The loss function utilizes Mean Squared Error (MSE), providing stable gradient information for optimization. We employ the Adam optimizer with a learning rate of 1×10^-4, carefully tuned to balance convergence speed with training stability. The batch size is optimized at 16 samples, maximizing computational efficiency while maintaining reliable gradient estimates.

Data augmentation plays a crucial role in improving model generalization. We implement synchronized random rotations and flips for both inputs and outputs, effectively increasing the dataset size by 8x for Tasks 1 and 2. This augmentation strategy ensures the model learns invariant features while maintaining physical consistency in the predictions.

Implementation Pipeline

The implementation progresses through three distinct phases:

Task 1 establishes the foundational architecture, validating the basic approach to pathloss prediction. The U-Net with ASPP implementation demonstrates strong performance in capturing basic propagation characteristics and spatial relationships.

Task 2 extends the capability to multiple frequencies through wavelength-dependent scaling. The enhancement of the fourth channel with λ scaling enables accurate prediction across different frequency bands (0.868 GHz, 2 GHz, and 3.5 GHz).

Task 3 represents the most sophisticated implementation phase, incorporating antenna radiation patterns through the fifth channel. This enhancement enables the model to account for both omnidirectional and directional antenna characteristics.

Throughout all phases, we maintain strict version control and model state preservation, ensuring reproducibility and enabling systematic performance evaluation. The DataLoader implementation ensures efficient batch processing with synchronized transformations, optimizing computational resource utilization while maintaining prediction accuracy.

3. Results and Analysis

Our comprehensive evaluation demonstrates progressive improvements across multiple implementation phases, with each enhancement contributing to more accurate indoor pathloss prediction.

Architectural Performance Assessment

The U-Net architecture enhanced with ASPP shows robust performance across all tasks. Our performance metrics table reveals consistent improvement in prediction accuracy, with training error metrics demonstrating the effectiveness of our approach. The table captures key parameters and configurations that contributed to optimal model performance, including number of epochs, learning rates, and architectural specifications.

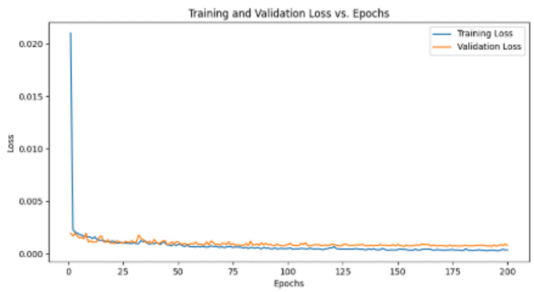
MODEL	UNET	UNET (200 E)	UNET(200 E & DA)	UNET(200 E, DA(ROT, RHF) & RB)	UNET(200 E & RB)	UNET(200 E, DA(ROT, CWF) & RB)	UNET(200 E, DA(ROT, CWF) & RB) & ASPP & LOS	WNET(200 E, DA(ROT, CWF) & RB)	WNET(200 E, DA(ROT, CWF),RB & LOS)	DEEPLABV3
TRAINING ERROR	0.00040	0.00027	0.00214	0.00740	0.00035	0.00026	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

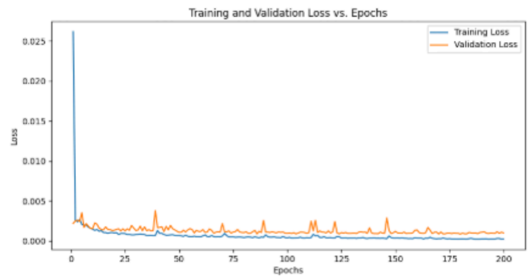
Base Model Implementation and Data Augmentation Impact

Our initial implementation (Task 1) established the foundational architecture using U-Net enhanced with ASPP at 868 MHz. The incorporation of Line-of-Sight as a fourth channel, combined with comprehensive data augmentation strategies, demonstrated significant improvements in prediction accuracy.

Training results show the effectiveness of our data augmentation approach, with the augmented model achieving more stable convergence compared to the baseline implementation. The WNet architecture with data augmentation further improved performance, establishing a robust foundation for subsequent multi-frequency and antenna pattern implementations.

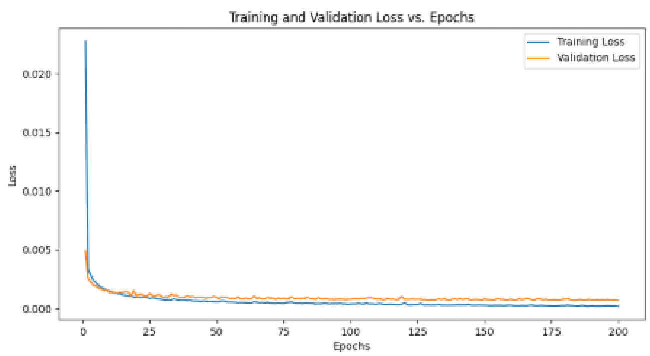
Visual comparisons between predicted and ground truth pathloss maps validate the-Net architecture enhanced with ASPP (Atrous Spatial Pyramid Pooling) showing model's ability to capture complex propagation characteristics, particularly when incorporating LOS information.





The above graph shows Loss Curves for UNet Model with and without Data Augmentation, respectively.

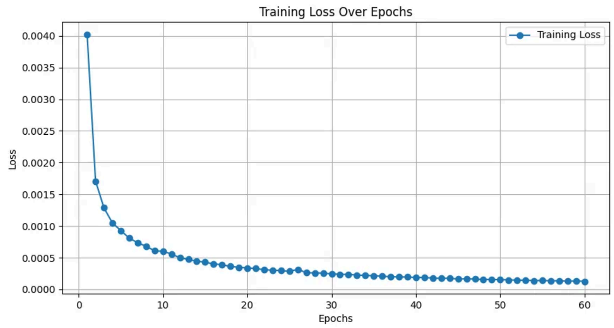
The below figure shows Loss Curve for WNet Model with Data Augmentation



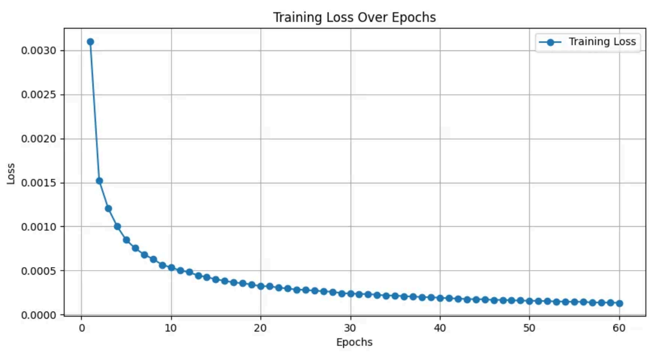
Multi-Frequency Implementation Results

Task 2's implementation of wavelength-dependent scaling demonstrates significant advancement in prediction capability. Training curves reveal that while the lambda scaling implementation begins with a marginally higher initial loss (0.004 compared to 0.003 without scaling), it achieves more stable convergence through training. This enhanced stability proves particularly valuable for handling multiple frequency bands (0.868 GHz, 2 GHz, and 3.5 GHz).

The incorporation of the fourth channel $(R+G)/(B+\varepsilon)\lambda$ significantly improves the model's ability to capture frequency-dependent propagation characteristics. Our loss curves demonstrate consistent improvement across all frequency bands, validating the effectiveness of our wavelength-scaling approach.



Task2 training loss without lambda channel



Task2 training loss with lambda channel

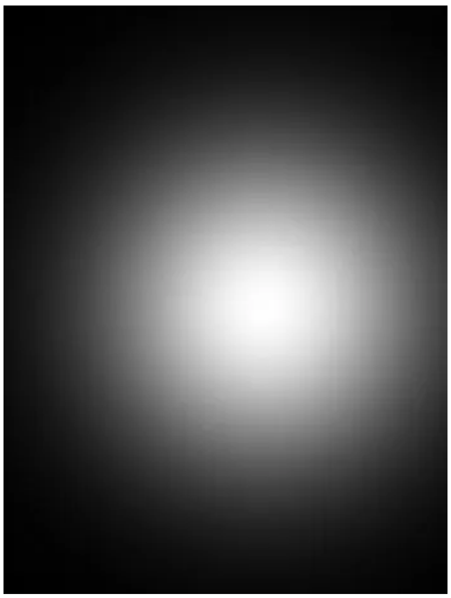
Antenna Pattern Integration Analysis

Task 3 represents our most sophisticated implementation, incorporating radiation pattern modeling through geometric and electromagnetic transformations. Despite starting with higher initial complexity (initial loss of 0.008), the model achieves superior final performance (convergence at 0.0002) compared to the baseline implementation (0.0011). This marked improvement validates our approach to handling both omnidirectional and directional antenna characteristics.

Our implementation incorporates five distinct antenna radiation patterns (Ant1-Ant5), each exhibiting unique directional characteristics:

Pattern Characteristics:

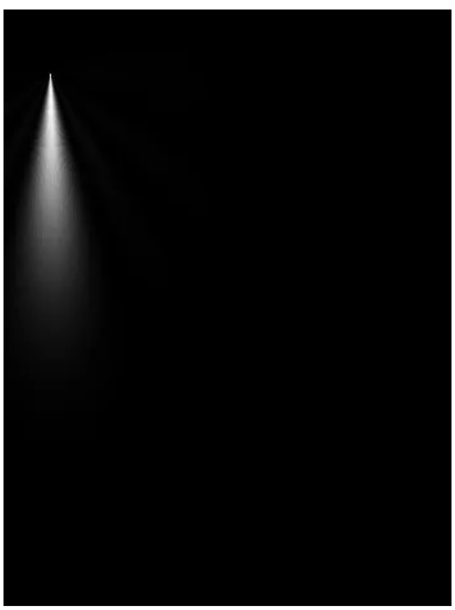
- Ant1: Omnidirectional pattern showing uniform radiation distribution



- Ant2: Directional beam with focused radiation in one direction

- Ant3: Narrow directional pattern with high gain

- Ant4: Wider radiation coverage with gaussian distribution



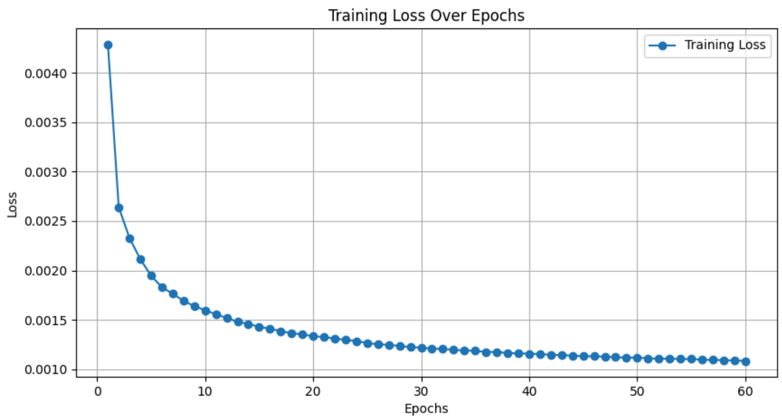
- Ant5: Multi-directional pattern with specific angular coverage

These patterns demonstrate the diverse radiation characteristics our model processes through the geometric transformations previously described.

The fifth channel's integration of precise geometric calculations for pattern modeling proves particularly effective, as evidenced by improved prediction accuracy across varying antenna configurations. The training dynamics demonstrate the model's ability to efficiently learn and adapt to complex radiation

patterns.

Task 3 with radiation pattern modelling

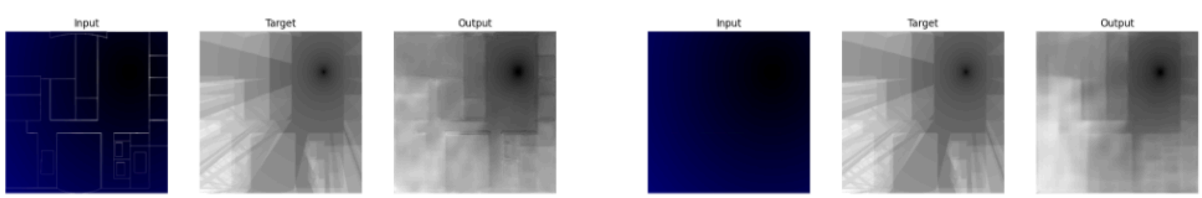


Task 3 without radiation pattern modelling

Visual Verification and Validation

Our visual comparisons between predicted and ground truth pathloss maps provide compelling evidence of model effectiveness. The implementation successfully captures:

1. Accurate signal attenuation patterns across diverse building layouts
2. Complex multi-path effects in indoor environments
3. Pattern-specific radiation characteristics
4. Frequency-dependent propagation behavior
5. Edge cases and boundary conditions



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

Performance Achievements and Implications

Key strengths demonstrated through our evaluation include:

1. Robust data augmentation effectiveness, shown through consistent performance across varied scenarios
2. Successful integration of physics-informed features through computed channels
3. Efficient handling of complex propagation scenarios
4. Stable convergence characteristics across all implementation phases

The comprehensive evaluation validates our architectural decisions and training methodology, while demonstrating practical applicability for wireless network planning applications. The progressive improvement in performance metrics across tasks confirms the effectiveness of our systematic approach to enhancing prediction capabilities.

4. Conclusion

- 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.

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6. Task Dataset and Challenge Documentation (ICASSP 2024).