Physics-Informed Machine Learning Models for Indoor Wi-Fi Access Point Placement

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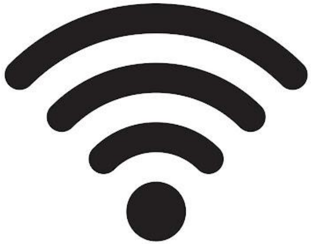
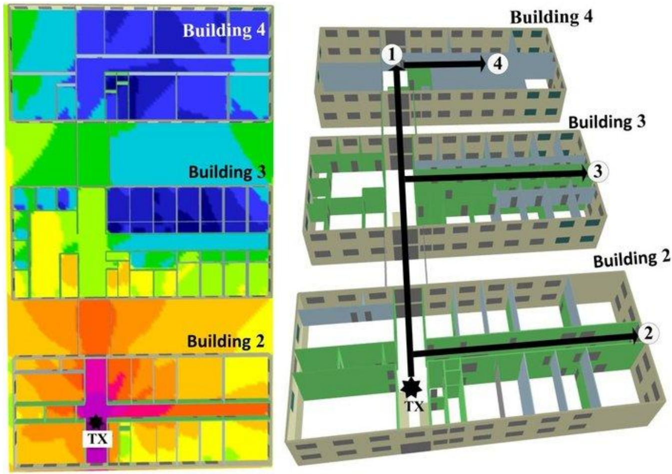
Background

- In 2019, there were 362 million public Wi-Fi hotspots available worldwide [1]
- Optimization of Wireless Access Point (WAP) placement improves:
  - Wi-Fi coverage
  - Quality of Internet service
- Wi-Fi Signal decays during the propagation.
- An optimizer needs estimation of the Received Signal Strength (RSS) given different WAP locations
- Ray-tracing simulation is required during the optimization process





An example of power map [2]

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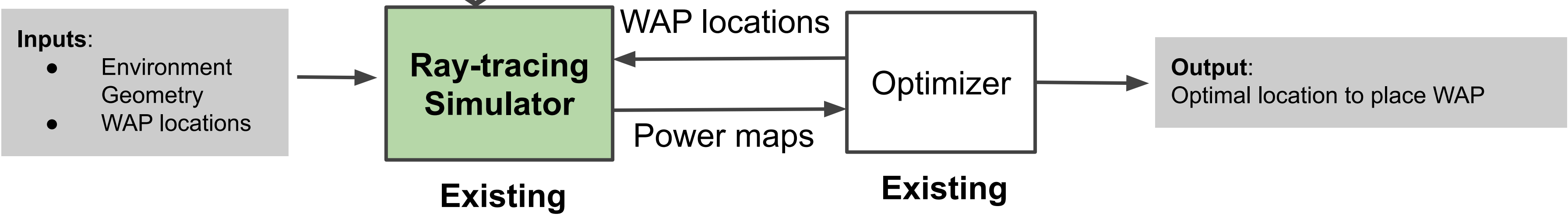
[1] L. S. Vailshery, “Global public wi-fi hotspots 2016-2022,” *Statista*, 22-Jan-2021. [Online]. Available: https://www.statista.com/statistics/677108/global-public-wi-fi-hotspots/. [Accessed: 01-Nov-2021].
[2] Fagiani, A. & Vogel, M. & Cerqueira S. Jr, Arismar. (2018). Material Characterization and Propagation Analysis of mm-Waves Indoor Networks. Journal of Microwaves, Optoelectronics and Electromagnetic Applications. 17. 628-637. 10.1590/2179-10742018v17i41548.

Problem & Motivation

How does it work:
- Uses time-consuming ray-tracing Algorithm
- Tracks each ray along its propagation

Features:
- Requires **extensive computational resources**
- **Extensive delay**, inefficient during optimization process



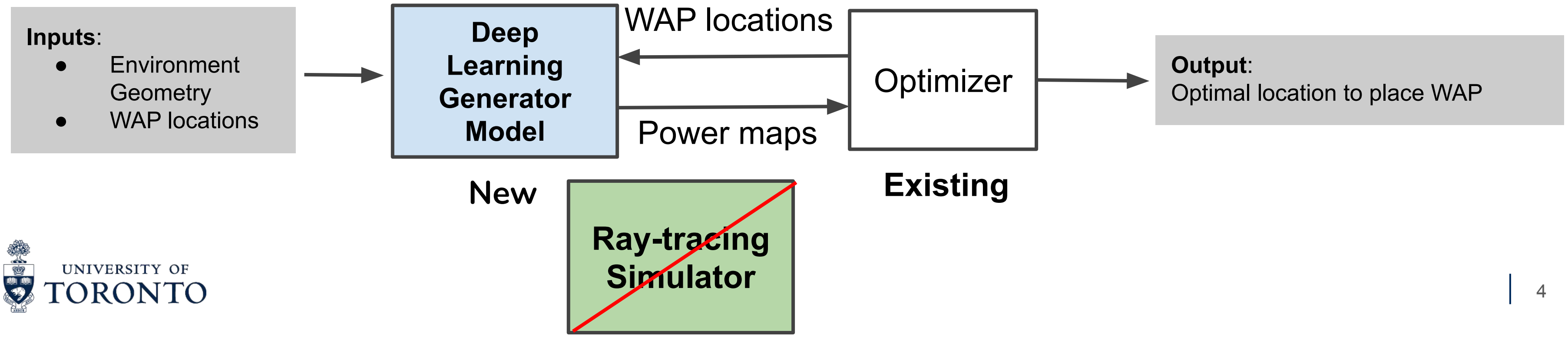
Goal

How does it work:

- Uses deep neural network (machine learning)

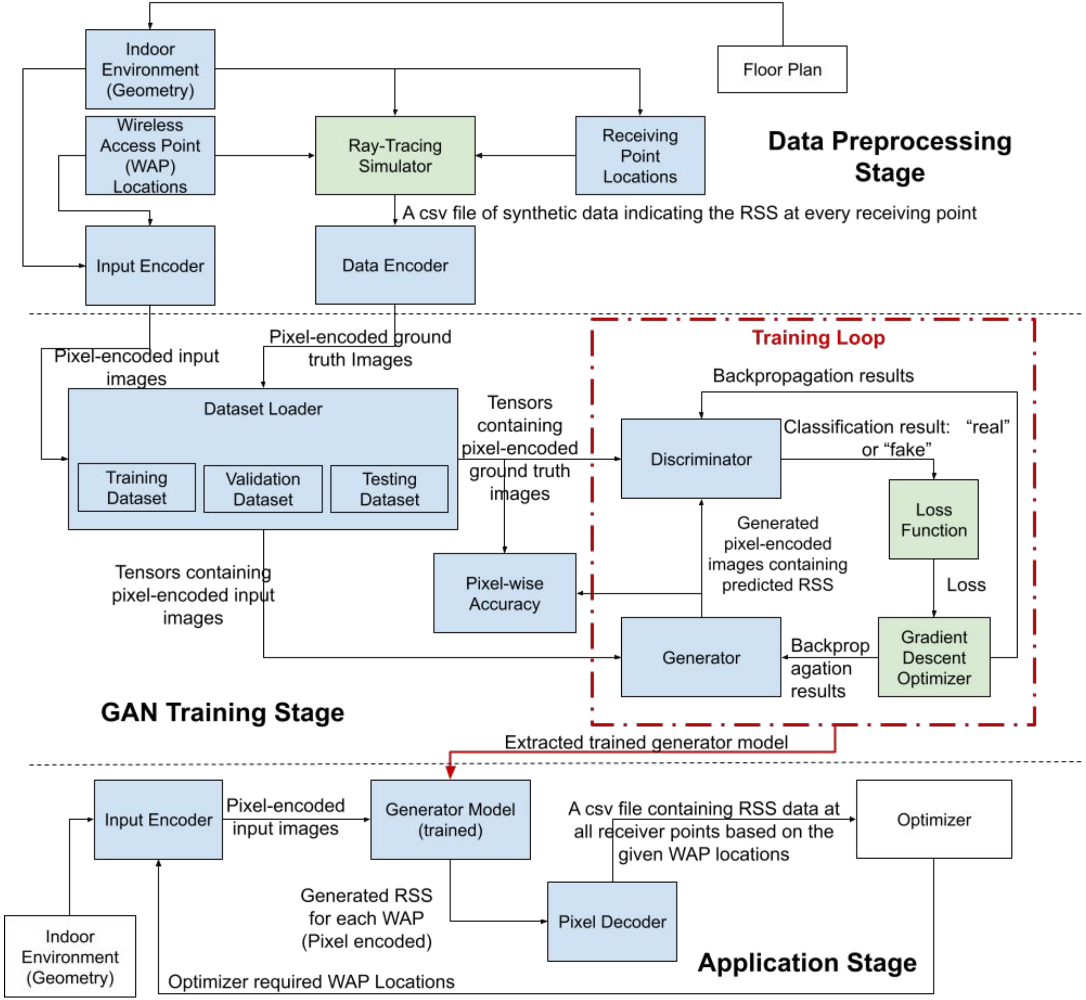
Features:

- Requires much **less computational resources**
- **Less runtime**, **more efficient** during optimization process



System Overview

- Data Preprocessing Stage
- GAN Training Stage
- Application Stage

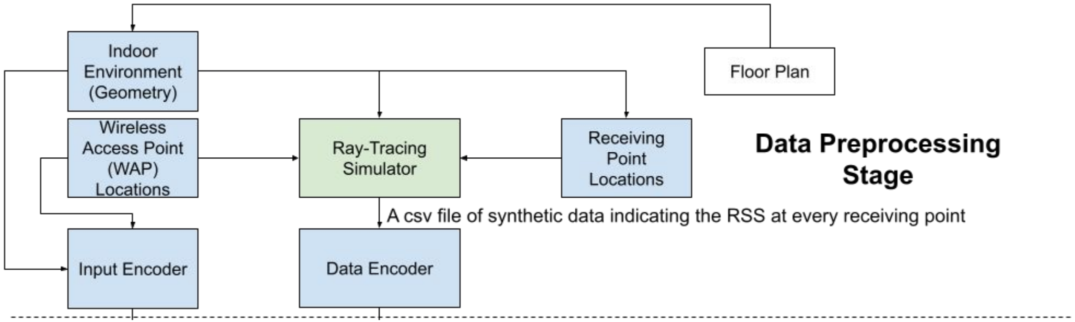


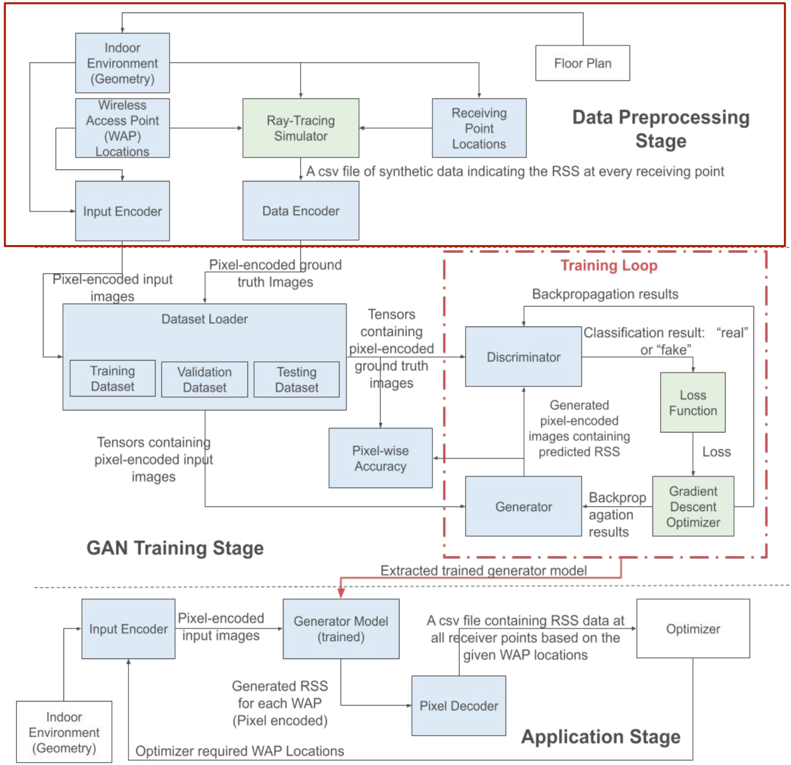
* White boxes: user inputs
* Green boxes: provided or external resources
* Blue boxes: implemented modules

System Overview: Data Preprocessing Stage

Purpose: Collect and encode input and data (ground truth) for training network

- Main Modules:
  - Ray-Tracing Simulator
  - Data Encoder
  - Input Encoder

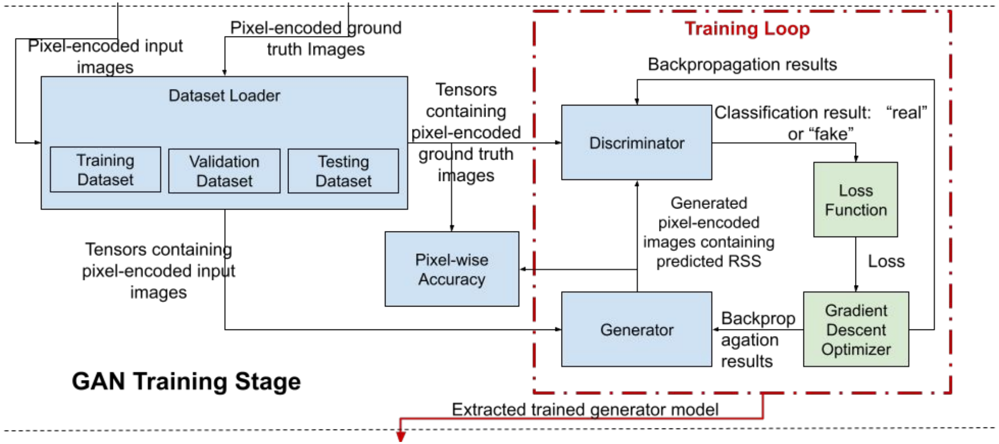


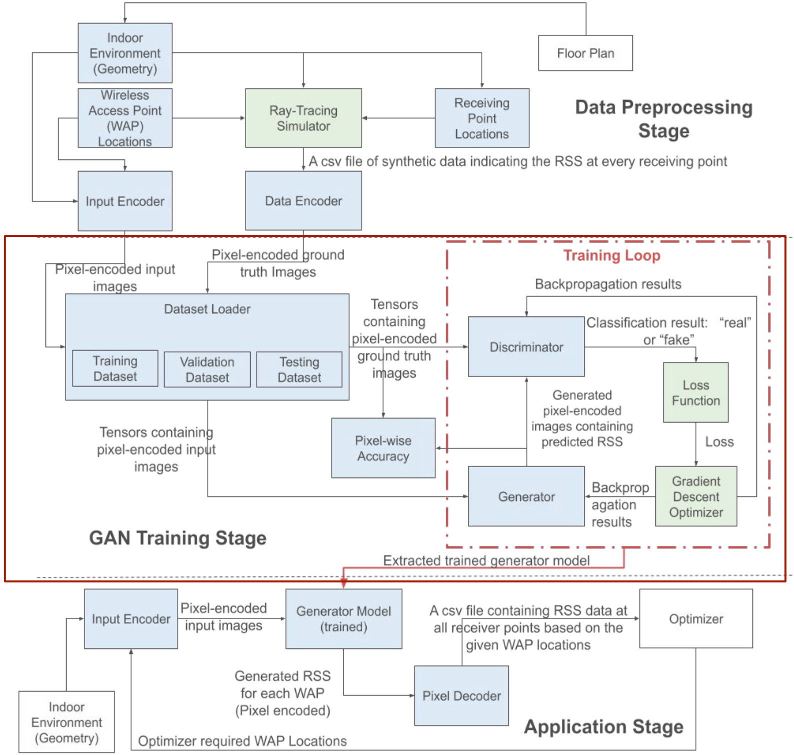


System Overview: GAN Training Stage

Purpose: Train the generator to generate high quality pixel encoded images

- Main Modules:
  - Dataset Loader
  - Training Loop

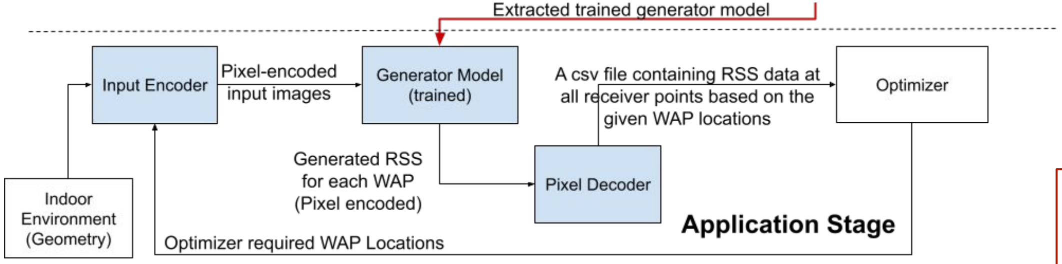


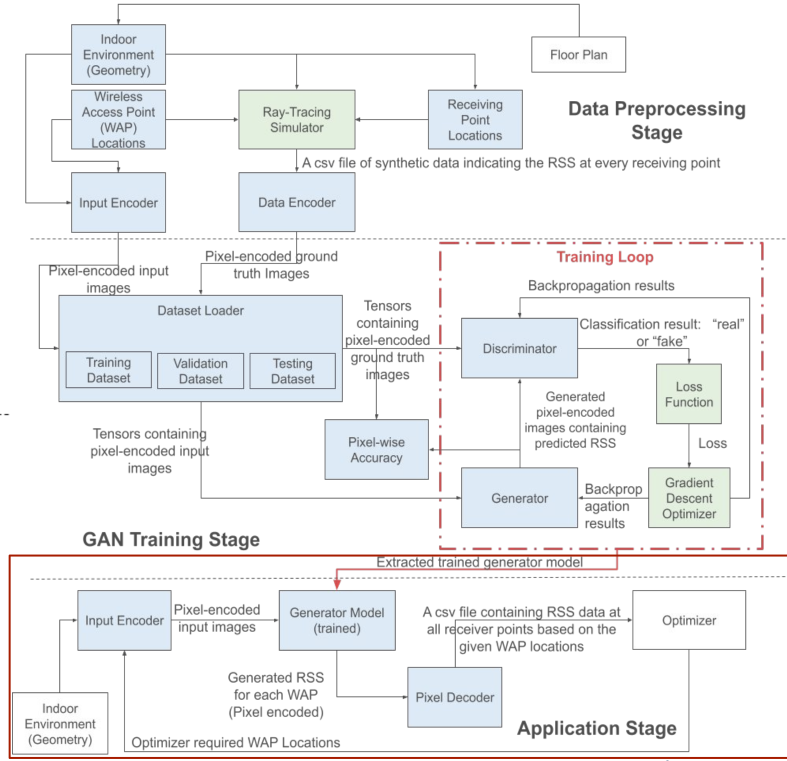


System Overview: Application Stage

Purpose: Enable our trained generator model to generate RSS data with given inputs

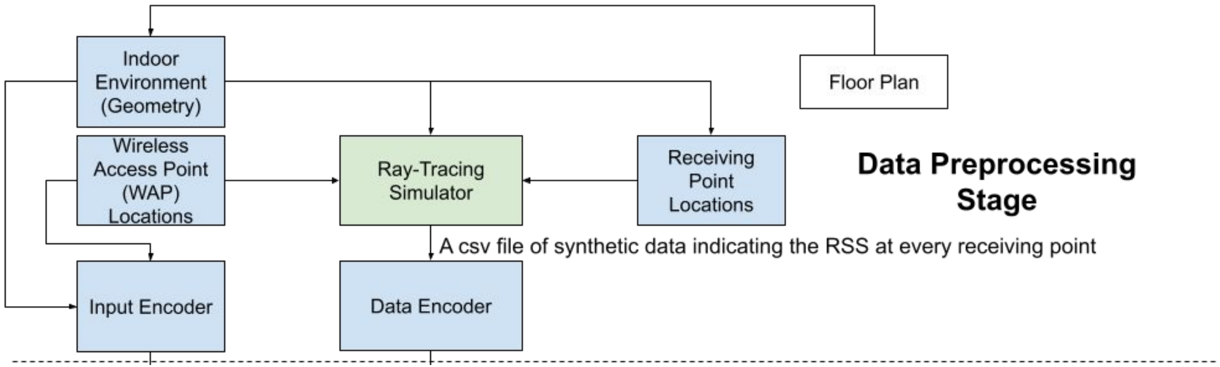
- Main Modules:
  - Generator Model (Trained)
  - Input Encoder
  - Pixel Decoder





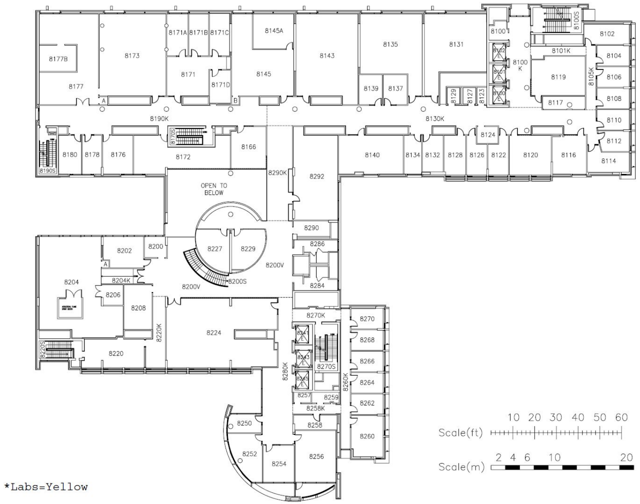
Data Preprocessing Stage

- Data Collection:
  - Ray-tracing simulator generating RSS data
- Encoding:
  - Data (Ground Truth) Encoder
    - Encoding collected RSS data into images
  - Input Encoder
    - Encoding WAP into images

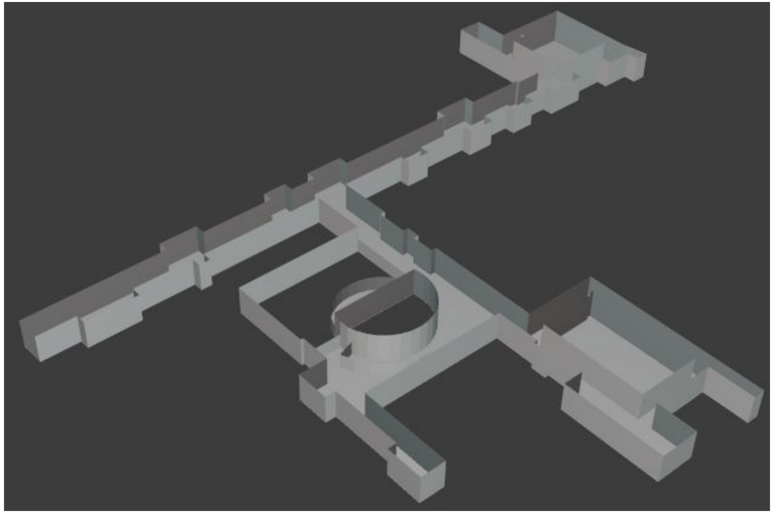


Data Collection

- Indoor environment for experiment: **the hallway of 8th floor, Bahen Centre for Information Technology, University of Toronto**
  - Generated a 3D geometry model based on its floor plan



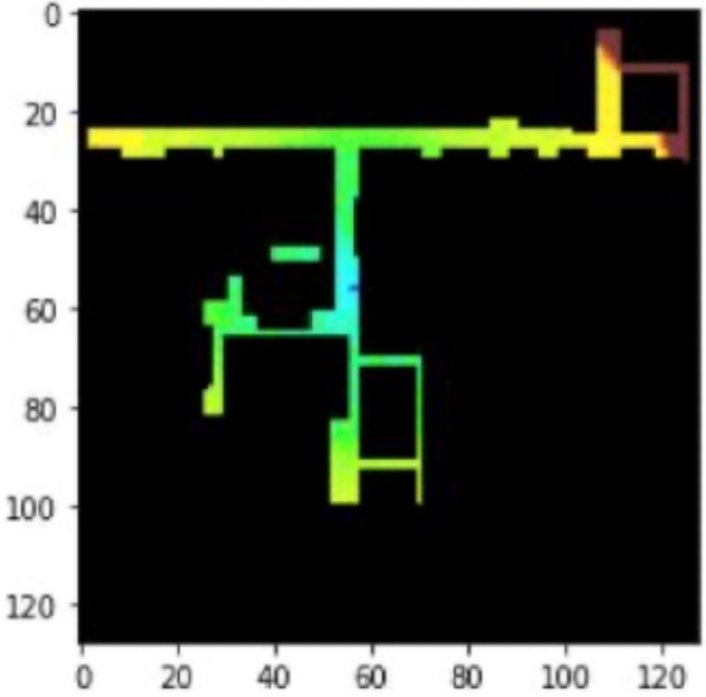
Floor Map of Indoor Environment



Generated 3D Geometry Model

Data Collection

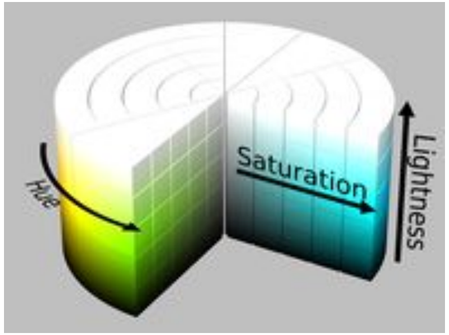
- Using a ray-tracing simulator
- Signal receiving points:
  - 0.625 m apart from each other
  - 1296 receiving points in total
- Properties for walls/boundaries:
  - Dielectric permittivity: 5 F/m
  - Dielectric conductivity: 0.1 S/m



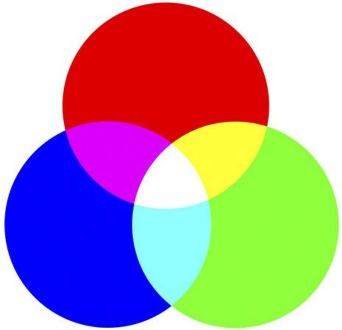
Power Map Visualization for Generated RSS Data

Encoding: Data (Ground Truth) Encoder

- **Raw Ground Truth RSS data → Pixel-Encoded Ground Truth Images**
  - Step 1: RSS-colour conversion
    - **RSS data in dBm** → hue in HSL
    - Fixed saturation and lightness level
    - HSL colour → **RGB colour pixels**



HSL Colour Scale [1]



RGB Colour Scale [2]

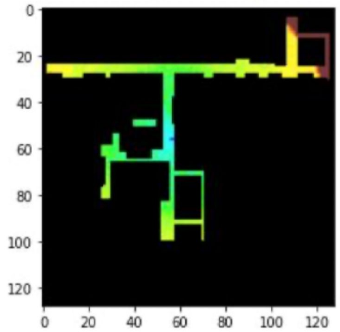
[1] J. J. Martín-Sotoca, A. Saa-Requejo, R. Moratiel, N. Dalezios, I. Faraslis, and A. M. Tarquis, “Statistical analysis for satellite-index-based insurance to define damaged pasture thresholds,” Natural Hazards and Earth System Sciences, vol. 19, no. 8, pp. 1685–1702, 2019.
[2] “RGB,” RGB (Red Green Blue) Definition. [Online]. Available: https://techterms.com/definition/rgb. [Accessed: 02-Nov-2021].

Encoding: Data (Ground Truth) Encoder

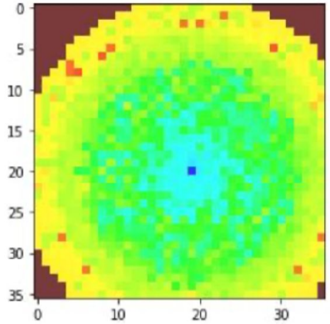
- **Raw Ground Truth RSS data → Pixel-Encoded Ground Truth Images**
  - Step 2: Physical-to-pixel coordinate mapping
    - WAP locations have unique pixel coordinates
    - For receiving points, calculate F_{recv}:

$$F_{recv} = \frac{RSS_{recv} - \min RSS}{\max RSS - \min RSS} - \frac{\|P_{recv} - P_{WAP}\|_2}{\max \|P - P_{WAP}\|_2}$$

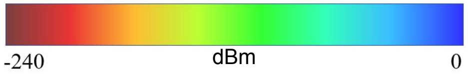
    - Higher F_{recv} value, pixel coordinate closer to WAP
  - Advantages:
    - All pixels in encoded images are useful
    - Observable patterns in encoded ground truth image



Power Map Visualization for Generated RSS Data

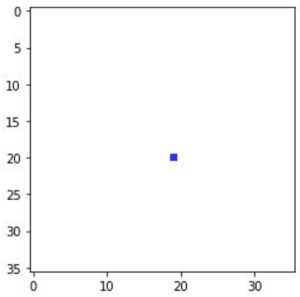


Encoded Ground Truth Image

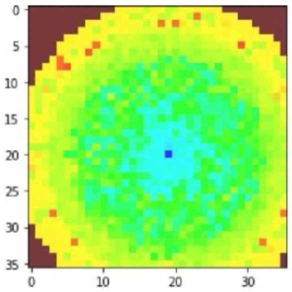


Encoding: Input Encoder

- **WAP Location → Pixel Encoded Input Images**
  - Each WAP location has a unique pixel coordinate
  - Same pixel coordinate as on the encoded ground truth image

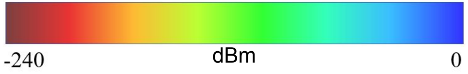


Encoded Input Image



Encoded Ground Truth Image

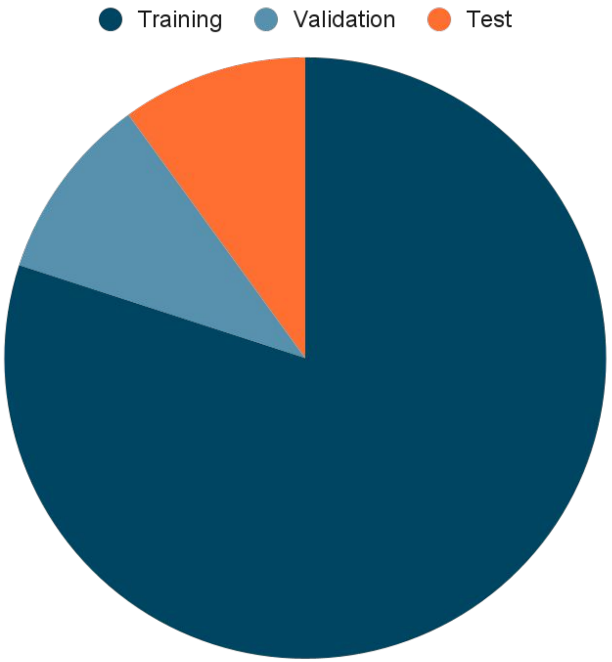
WAP Coordinate: (0.9375, -9.6875)



Dataset

Size of dataset: 1296

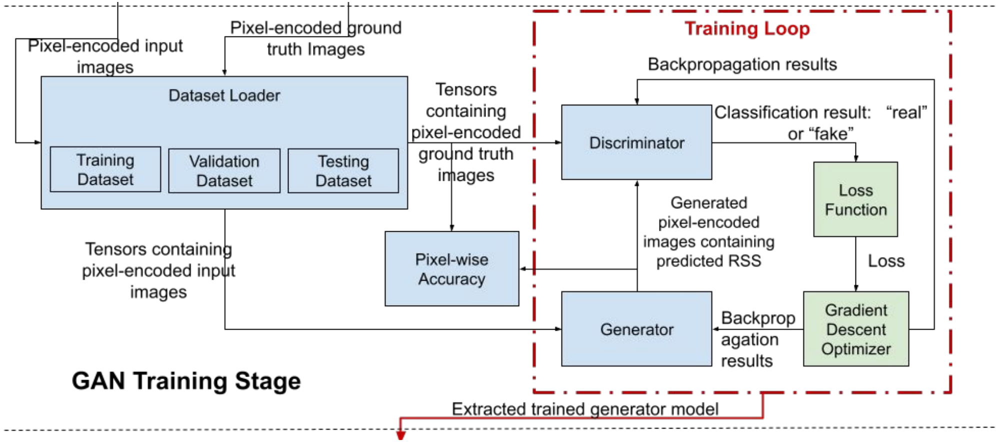
- Training dataset: 80%
- Validation dataset: 10%
- Testing dataset: 10%



GAN Training Stage: Deep Convolutional Generative Adversarial Network

- **Adversarial Training Strategy**
    - Competitions between models
- **Benefits**
    - Learn high resolution features from data
    - Generate high quality power maps

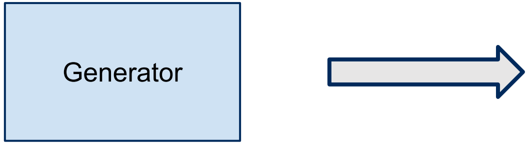
- **General Architecture**
    - Generator: Generate power maps
        - 6-Level U-Net [1]
    - Discriminator: Detect fake power maps
        - 4-Layer CNN
    - Loss Function: Binary cross entropy
    - Gradient Descent Optimizer: ADAM [2]

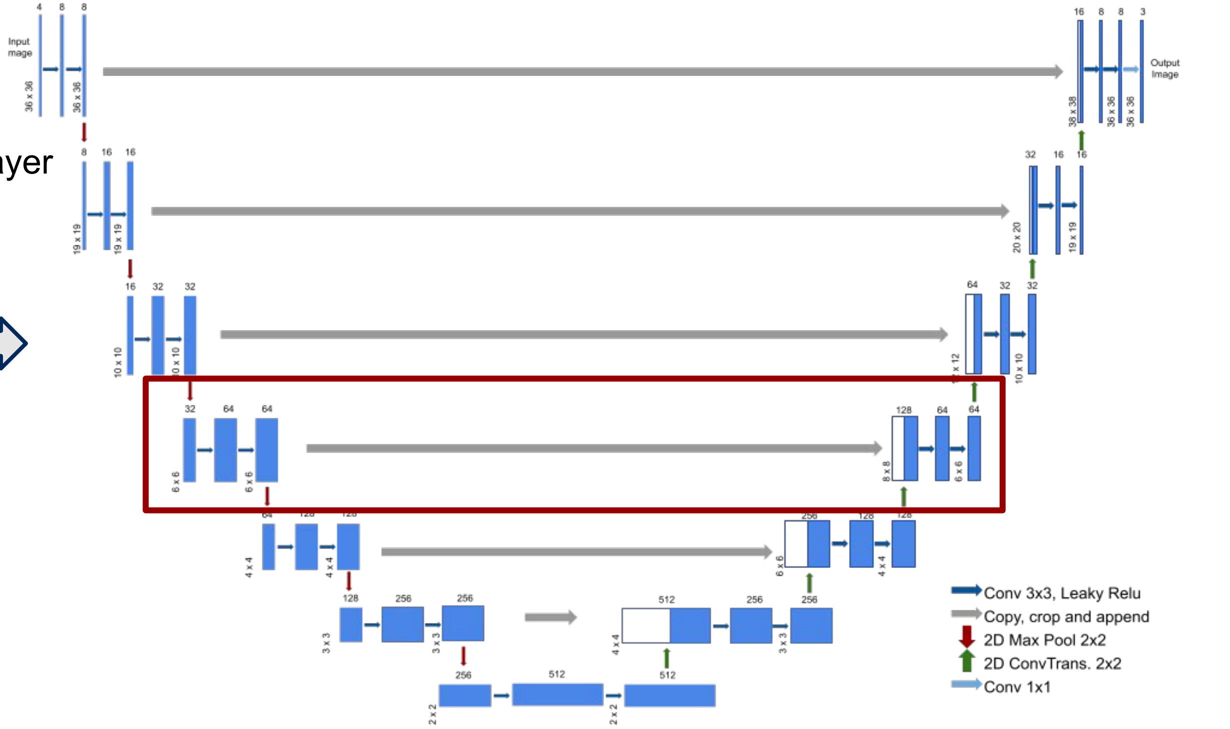


[1] O. Ronneberger, P. Fischer and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation", Computer Science Department and BIOSS Centre for Biological Signalling Studies, University of Freiburg, Germany, 2015.
[2] D. Kingma and J. Ba, "ADAM: A METHOD FOR STOCHASTIC OPTIMIZATION", 2017

Generator: 6-Level U-Net

- **Down Sampling: 6 Levels**
  - Max-pooling layer
- **Up Sampling: 6 Levels**
  - Transpose convolutional layer

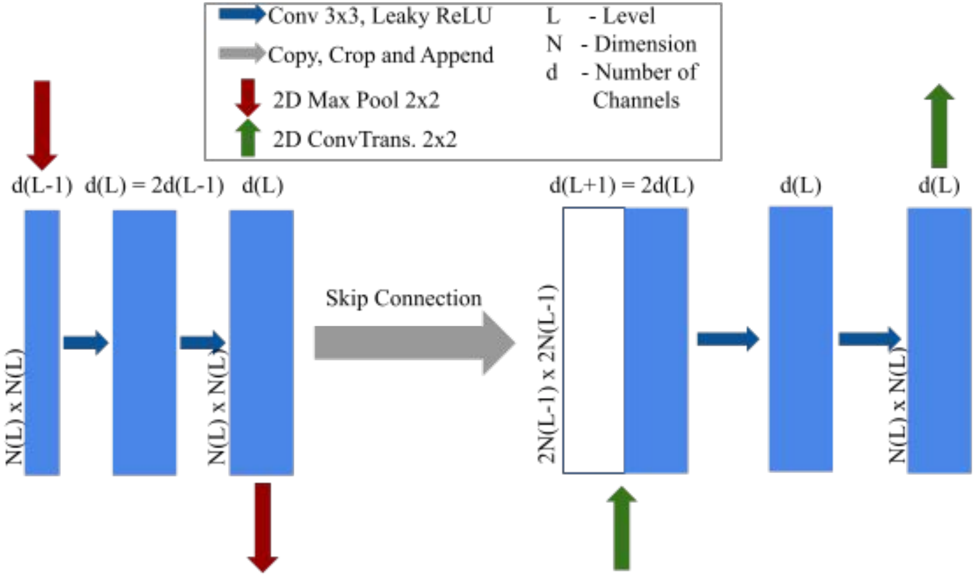




Architecture of 6-Level U-Net

Generator: 6-Level U-Net

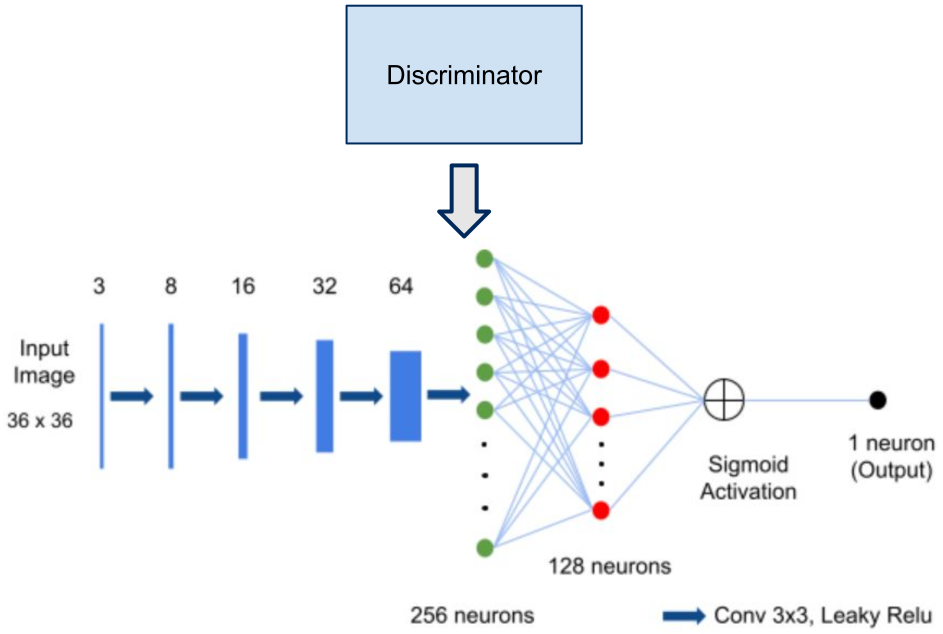
- **Double Convolutional Layers**
  - Extracts important features
  - Batch Normalization
    - Stabilizes the learning process
  - Leaky ReLU
    - Avoids vanishing gradient
- **Down Sampling Layer**
  - 2D Max Pool
    - Extracts sharp features
- **Up Sampling Layer**
  - 2D Conv Trans
    - Increase dimension
- **Skip Connection**
  - Preserve high-resolution features



Per-level architecture of U-net

Discriminator: 4-Layer Convolutional Neural Network

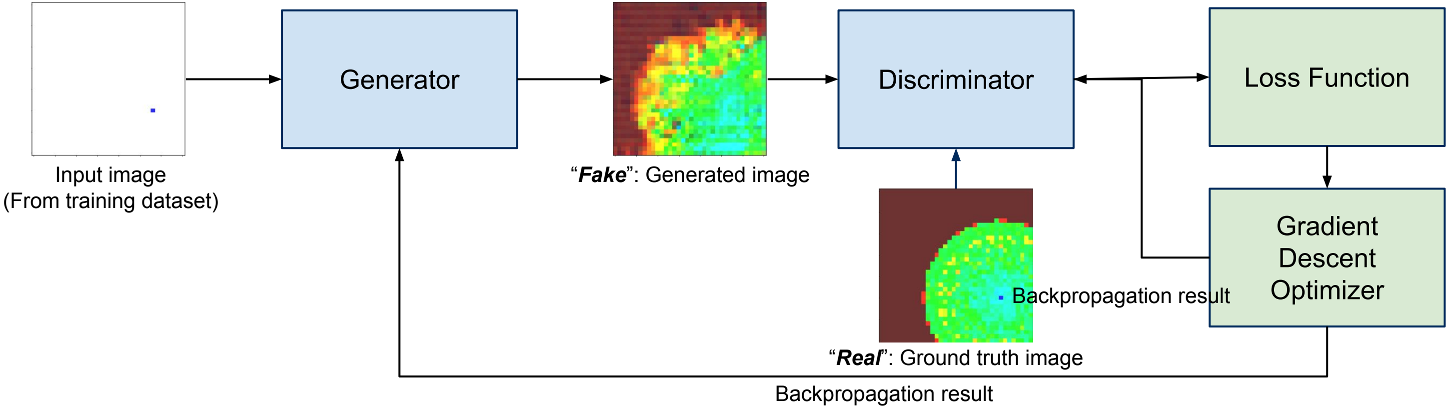
- **2D Convolutional Layers**
  - Feature learning
  - Batch Normalization
    - Stabilizes the learning process
  - Leaky ReLU
    - Avoids vanishing gradient
- **Linear Layers**
  - Classification process
- **Sigmoid Activation Function**
  - Return value in the range from 0 to 1
  - $$S(x) = \frac{1}{1 + e^{-x}}$$



Architecture of Discriminator

Neural Network Training: Adversarial Training Strategy

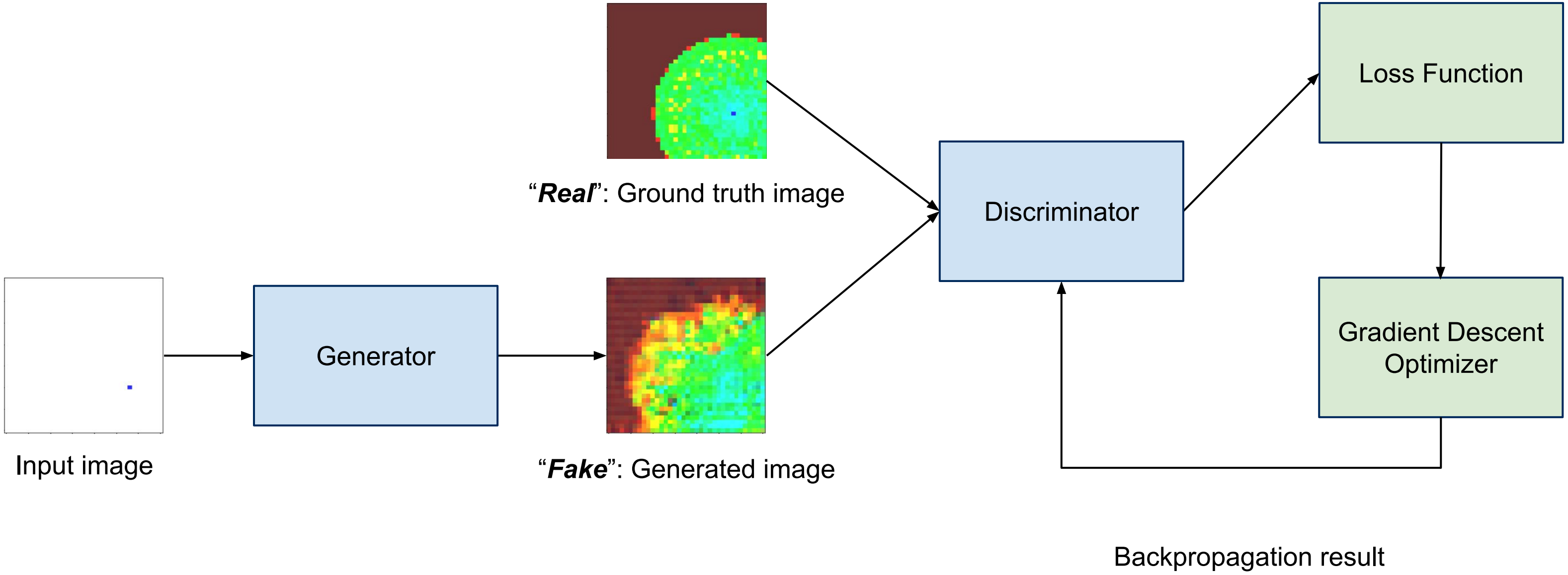
- Two players play a **Minimax** game:
  - **Discriminator**
    - maximizes its probability of classifying “real” and “fake” images correctly
  - **Generator**
    - maximizes the probability that discriminator labels generated images as “real”
  - **Minimax Loss Function** [1]
    - $$\mathcal{L}_{minimax} = \mathbb{E}_x[\log(D(x))] + \mathbb{E}_z[\log(1 - D(G(z)))]$$



[1] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. and Bengio, Y., 2014. *Generative Adversarial Networks*. [online] arXiv.org. Available at: <https://arxiv.org/abs/1406.2661?source=post_page-----b665bbae3317--------------------> [Accessed 1 November 2021].

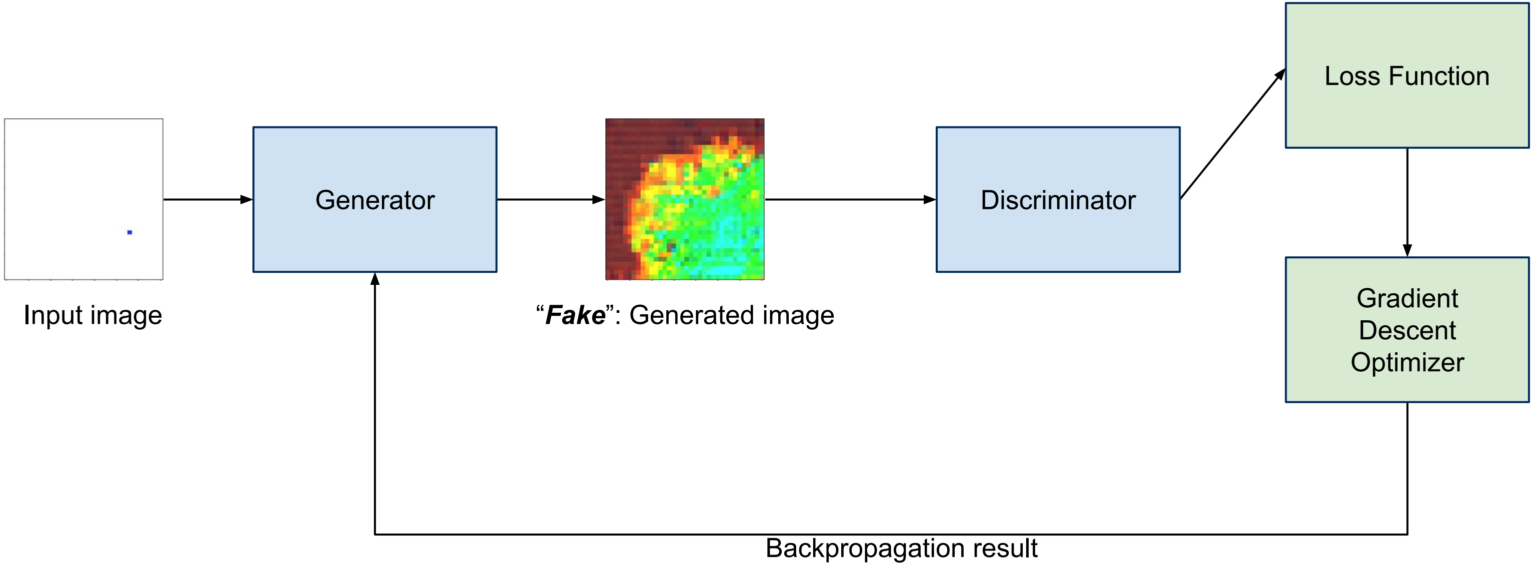
Training Procedures:

1. Discriminator Training

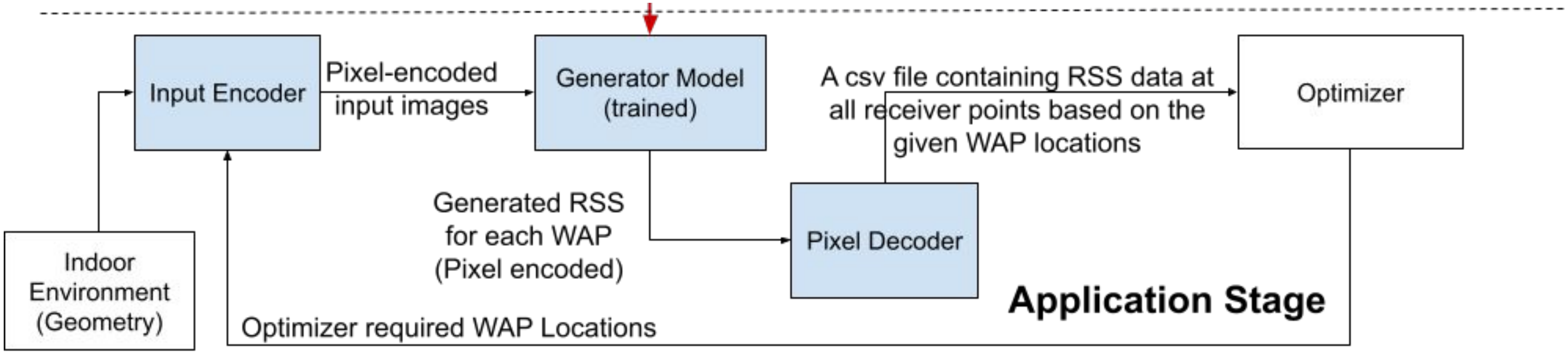


Training Procedures:

2. Generator Training



Application Stage:



- **Pixel Decoder: Pixel-Encoded Output Images → Output RSS data**
  - Reverse process of the Data Encoder
  - The decoded data can then be used for further applications
- **Simulation Process**

Results: Accuracy and Runtime

- Use pixel-wise accuracy as the quantitative approach to evaluate:

$$A_{pixelwise} = 1 - \frac{\sum_{i=1}^{N_i} \sum_{p=1}^{N_{sp}} |p_t - p_g|}{N_i \times N_{sp} \times 255}$$

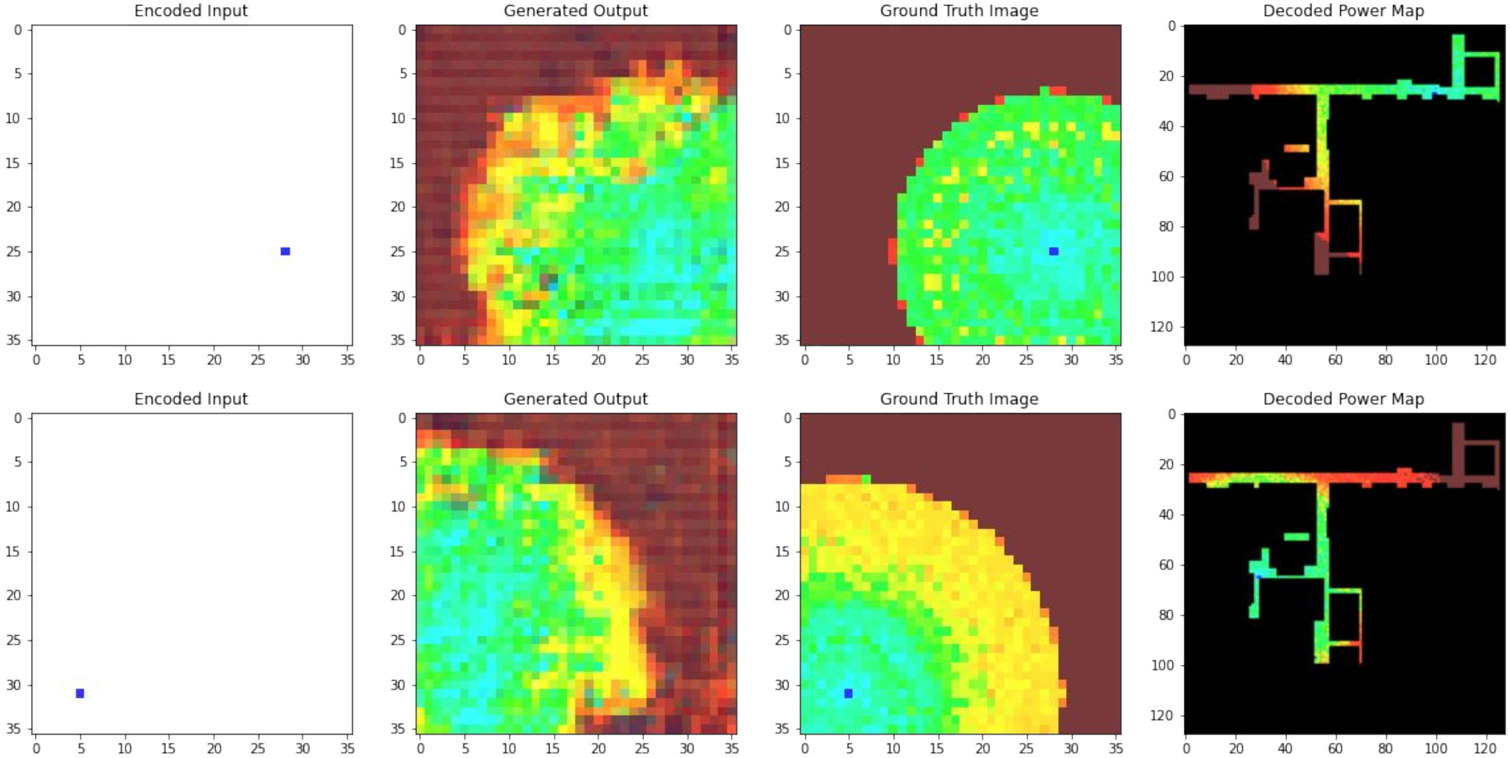
Datasets	Training	Validation	Testing
$A_{pixelwise}$ (%)	79.00	78.84	**78.02**

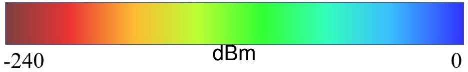
	Ray-Tracing Simulator	DCGAN Model
Average Runtime (s)	43.03	**0.42**

Results: Sample Test Cases

WAP:
(-17.2, 17.2)

WAP:
(6.5,-26.5)





Summary

- **Highlights**
  - Applied machine learning methods to predict RSS in an indoor environment
  - Unique data processing approach to encode data for machine learning operations and training
  - Reduce runtime by 99.02%, while maintaining a high level of accuracy

- **Future work**
  - Continue training with larger datasets
  - Improve generalization with different indoor environments