AI-Augmented Radiation Field Reconstruction via Minimal Drone Exploration

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Introduction

Locating radiation sources and understanding field distributions are essential tasks in nuclear safety, emergency response, and remote site inspection. However, collecting complete radiation measurements across large or hazardous areas is often impractical.

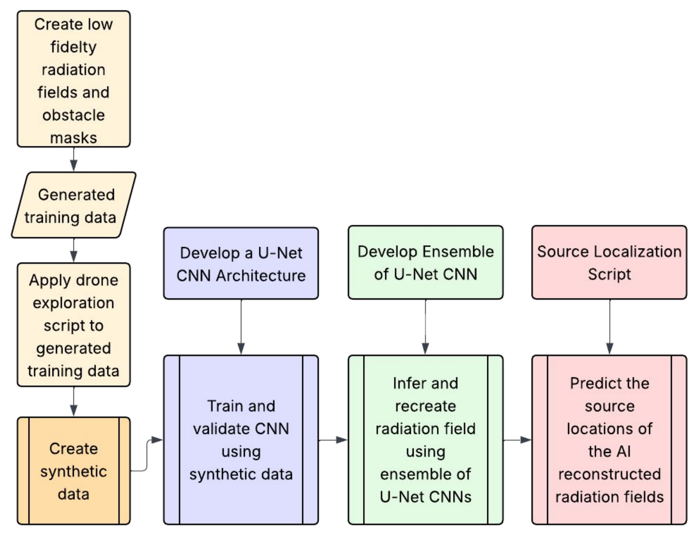
This project focuses on recreating full radiation maps using only limited data collected by a drone that measures radiation over a small portion of the area. A machine learning model was trained to predict the entire field from these partial measurements, along with information about visited locations and obstacles. Once the full field is predicted, a separate algorithm identifies likely source locations by detecting peak radiation areas.

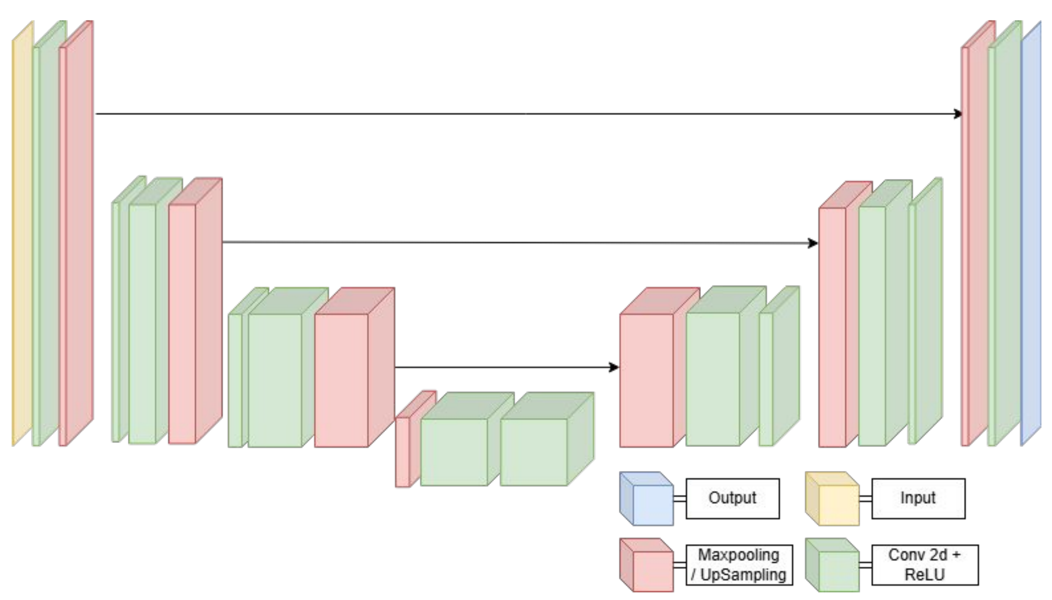
The method enables both radiation field estimation and source localization using as little as 20% coverage, supporting faster and safer assessments in environments where full access is not possible.

Methods

Data Generation:
Synthetic 100×100 radiation fields were generated using randomized point sources with inverse-square decay. Binary obstacle masks were applied to simulate occlusion. All fields were log-transformed as $\log_{10}(x + 1)$.

Drone Coverage:
Drone paths were simulated using a waypoint-hopping strategy, limited to 20% spatial coverage. Each traversal yielded partial radiation data and a binary mask of visited grid cells.





U-Net CNN Model Visual Representation

U-Net Architecture:
A U-Net CNN reconstructed full radiation fields from three input channels:

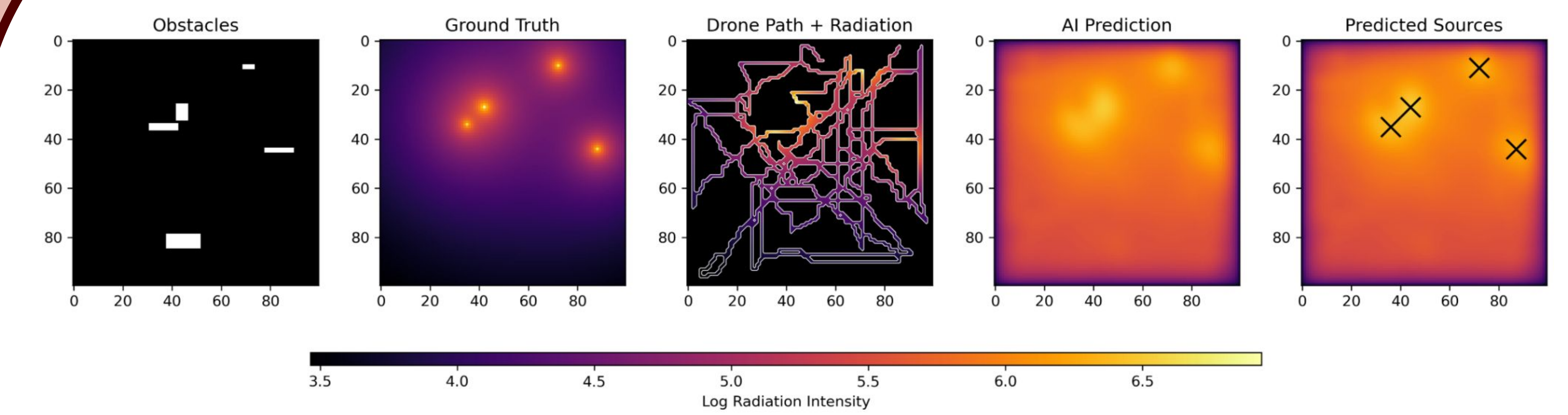
1. Partial radiation data
2. Visited mask
3. Obstacle mask

Skip connections were used to preserve spatial detail during reconstruction.

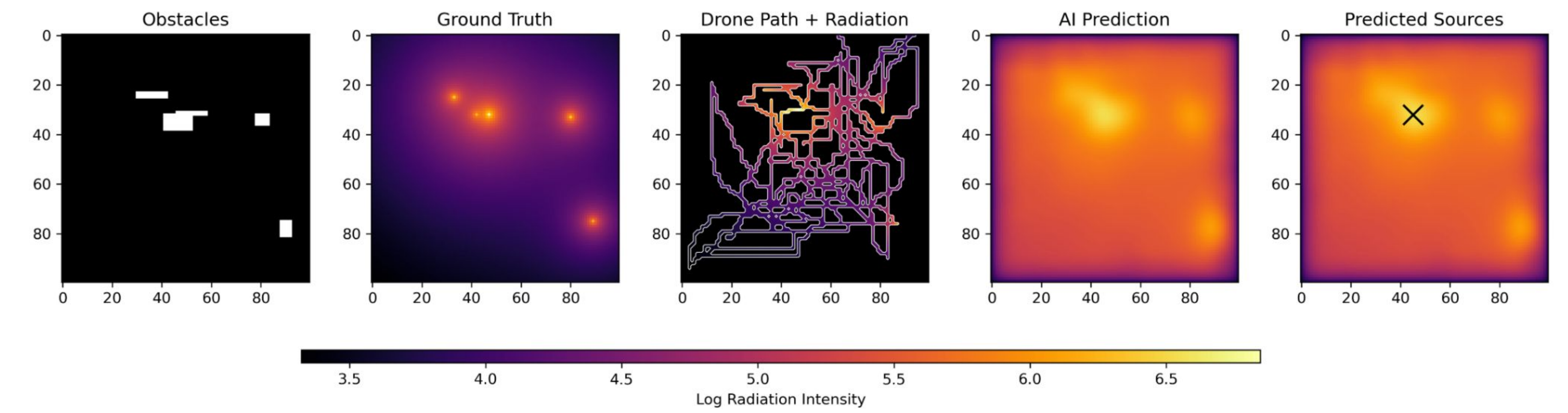
Training:
The model was trained for 30 epochs using RMSE loss on 1000 field-mask pairs. Optimization was performed using the Adam algorithm. No data augmentations were applied.

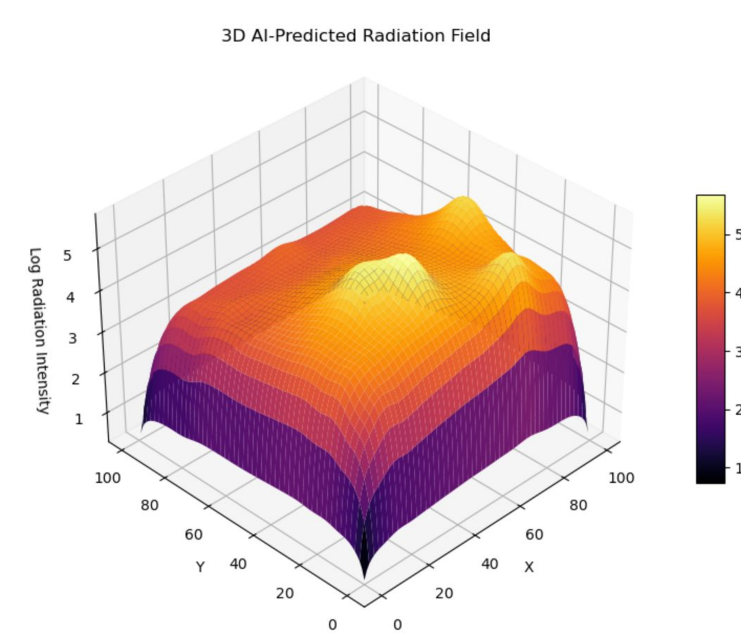
Source Localization:
A peak detection algorithm was used to identify radiation sources in reconstructed fields. Local maxima were filtered using suppression to avoid redundant detections.

Results and Discussion



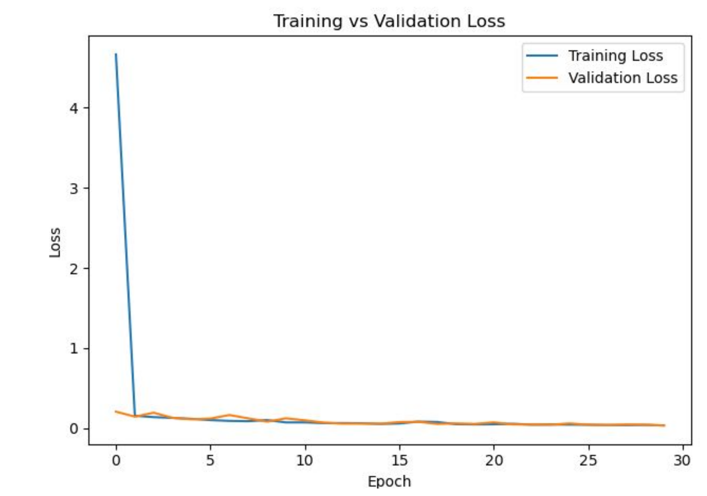
Data Set below is an example of a known limitation:

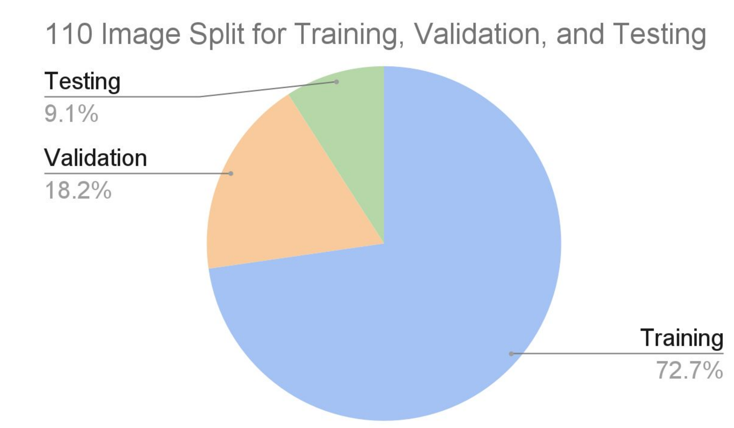




3D Radiation Field Topography for top row of data

3D Reconstruction Visualization:
Regions of elevated intensity on the heatmap correspond to potential radiation source locations. The terrain-style visualization offers an intuitive interpretation of spatial radiation gradients, capturing both distinct point sources and gradual background variations.





Reconstruction Accuracy:
The AI model reconstructs radiation fields using only 20% drone coverage. It captures general source locations and intensity gradients.

Localization Performance:
Source localization identifies the correct number of sources in most cases, especially when sources are spaced apart.

Observed Limitation:
When multiple sources are closely clustered, the algorithm may merge peaks or miss some entirely. This results in undercounting and positional inaccuracies.

Failure Case Example:
The lower row illustrates a scenario where overlapping sources were incorrectly detected as a single central source.

Gradient Behavior:
The model learns a general decay pattern but tends to over-smooth unvisited regions, resulting in uniform predicted gradients (e.g., log-scale values between 5.2 and 5.9) rather than a sharply defined source-driven decay.

Future Work

- Generate higher fidelity data for training and testing that includes realistic attenuation of radiation intensity given the obstacle in question.
- Transition from a single drone to a multi-drone system capable of coordinated operation.
- Display more accurate data for the edges of the area.
- Enhance gradient behavior of AI predictions.
- Adjust U-Net parameters to boost performance without extending inference time..
- Deploy the model in real drone systems to evaluate performance in field conditions.

References

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