
SMARTi
EVERYONE DESERVES TO BE CONNECTED.

Meet Our Team

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Introduction

1

Problem Statement:

Many underserved regions lack internet, limiting education, healthcare, and economic growth. Our AI-driven project optimizes TVWS network placement, predicts failures, and enhances efficiency. By improving connectivity, we help bridge the digital divide and drive progress.

2

Objective:

- Use AI and ML to find optimal locations for TVWS base stations.
- Predict network failures and recommend solutions using LLMs.

TV White Space (TVWS)

What is TV White Space (TVWS)?

TV White Space (TVWS) refers to the unused or underutilized spectrum in the television broadcasting bands (VHF and UHF). These frequencies, originally allocated for TV channels, can be repurposed for broadband internet and wireless communication, especially in rural and underserved areas.

Why TVWS for Connectivity?

- Long-Range Coverage: TVWS signals can travel long distances (up to several kilometers) and penetrate obstacles like buildings and trees, making them ideal for remote areas.
- Cost-Effective: Utilizing existing spectrum reduces the need for expensive infrastructure like fiber-optic networks.
- Dynamic Spectrum Access: TVWS can adapt to available channels, ensuring efficient spectrum usage and minimizing interference.

How We Use TVWS in Our Project?

- Optimizing TVWS Base Station Locations: Using ML algorithms to determine the best placement for TVWS towers to maximize coverage.
- Predicting Network Failures: Analyzing historical data to forecast interference and station outages.
- AI-Driven Decision Making: Leveraging LLMs to suggest proactive solutions for network resilience.

Datasets Used

Elevation Data (Open Elevation):

Helps assess terrain impact on signal propagation, ensuring TVWS base stations are placed in locations that maximize coverage and minimize interference.

TV Spectrum Data (Synthetic):

Simulated spectrum availability data to model real-world scenarios, optimize frequency allocation, and avoid interference with existing networks.

Schools Data (GIGA):

Provides the locations of schools in Lesotho, helping identify underserved educational institutions that need better connectivity. This ensures that TVWS stations are optimally placed to support digital learning.

Towers Data (OpenCell ID):

Contains information on existing telecom infrastructure, allowing us to analyze network coverage gaps and determine where additional TVWS stations are needed to enhance connectivity

Demographic Data (Our World in Data):

Offers insights into population distribution, enabling targeted network expansion in high-density areas while ensuring remote communities are not left behind.

Methodology

1 Data Preprocessing (Manually + Python Libraries)

Cleaned and structured datasets using Pandas, NumPy, and OpenRefine.
Handled missing values, removed duplicates, and formatted data for consistency.

2 Optimization Model (ML-Based Location Selection)

Applied K-Means Clustering, RandomForestRegressor, and GridSearchCV to determine ideal TVWS station locations.
Used GeoPandas and Shapely for geospatial processing.

3 Simulation & Visualization

(Cesium, Leaflet, Flask Backend, JavaScript, Matplotlib, Plotly, Folium)

Mapped TVWS stations, towers, and school coverage using CesiumJS and Leaflet for interactive web-based visualization.
Used Matplotlib, Plotly, and Folium to visualize network coverage and failure predictions.

4 Failure Prediction

(ARIMA, RandomForestRegressor, Mean Absolute Error - MAE, Scikit-learn, Statsmodels)

Used ARIMA for time-series interference prediction. Applied RandomForestRegressor to model future network failures. Evaluated model accuracy using Mean Absolute Error (MAE).

5 AI-Powered Recommendations

(LLM – Gemini Open Source Flash, LangChain, Flask API)

Integrated Gemini Open Source Flash for AI-driven recommendations. Used LangChain for generating network optimization insights.Deployed recommendations via Flask API for real-time decision-making.

Demonstration

Map Simulation:

Visualizing base stations, towers, and coverage areas.

Prediction Dashboard:

ML-powered insights on interference and failures.

LLM-based AI Recommendations:

Suggested actions for network resilience.

Conclusion & Future Work

01

Scalability:

Expand the model to new regions, adapting to diverse connectivity challenges.

02

Integration:

Implement AI-driven recommendations into real-time network management with dynamic bandwidth allocation and policy-based optimization.

03

Continuous Learning:

Enhance AI models with real-time data for adaptive decision-making.

04

Vision:

Develop a fully autonomous AI system for smart, resilient, and policy-driven connectivity.

05

Procurement & Cost Efficiency:

Optimize infrastructure deployment with data-driven procurement strategies, ensuring cost-effective and sustainable expansion.

Acknowledgment & Thank You

Thank you for your time! We are excited to bring this vision to life

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