# **SMART INDIA HACKATHON 2024**



## TITLE PAGE

• **Problem Statement ID:** 1734

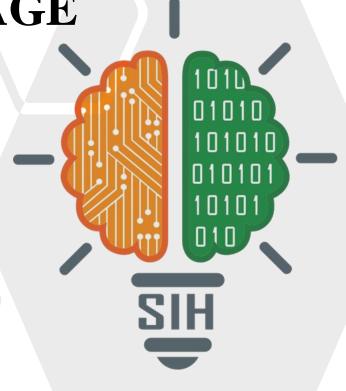
• **Problem Statement Title:** Downscaling of Satellite based air quality map using AI/ML

• Theme: Clean & Green Technology

• **PS Category:** Software

• Team ID:

• **Team Name:** Tech Titans





## **IDEA TITLE**



### **Proposed Solution:**

#### 1. Data Collection & Preprocessing:

Acquiring NO2 data from satellites (e.g., Sentinel-5P) and handle gaps with imputation techniques.

#### 2. Model Development:

• Training a Machine Learning model (e.g., Random Forest) to downscale satellite data to fine resolution.

#### 3. Validation:

Apply cross-validation and test with independent data to ensure accuracy.

#### 4. Deployment:

• Deploy as a web tool for real-time NO2 monitoring with a user-friendly interface for researchers and government bodies.

**How it Addresses the Problem:** Provides detailed local NO2 maps, improving air quality assessments.

<u>Innovation & Uniqueness:</u> Combines satellite and ground data with advanced ML for accurate, real-time air quality mapping and no comprehensive solution exists like this.



**Data Acquisition** 

•API: Accessed via Sentinel Hub using specific coordinates and date range.

•Token: Used for API authentication.

### **Data Processing**

•Script: Extracted NO2 levels in floating-point format.

•Request: Retrieved NO2 data for the region.

#### Visualization

•Output Grid: Displays NO2 levels per pixel, with a color bar indicating concentration levels (dark = low, light = high).

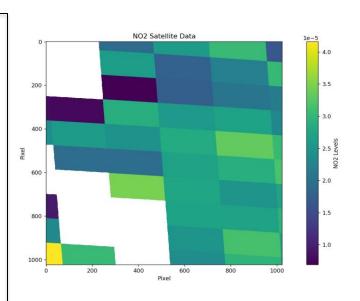


Fig 1. Snap of dataset



## TECHNICAL APPROACH



## **\*** Technologies to be Used

Programming Languages: Python

**Database:** MongoDB

Frameworks & Libraries: TensorFlow, PyTorch, Scikit-

Learn, GeoPandas, Matplotlib, Pandas

## Methodology & Process for Implementation

**Data Collection**: Satellite data ,data from air quality monitoring stations

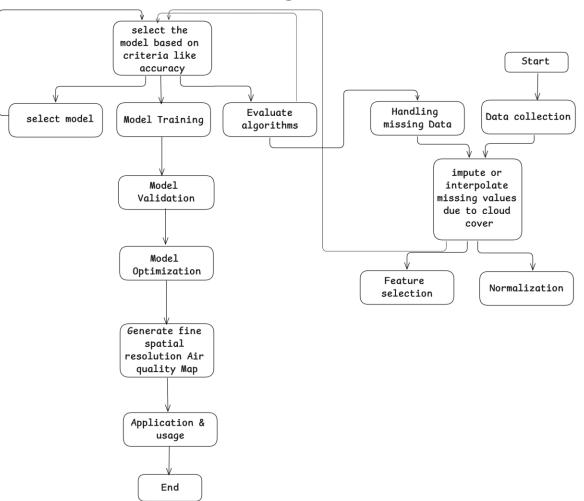
**Data Preprocessing:** Handling gaps in data, Extracting relevant environmental features

**Algorithm Selection**: Random Forest, CNN, GBM

**Training**: data to train the model

Validation: Independent dataset validation, cross-validation

## **Block Diagram**



# FEASIBILITY AND VIABILITY



## **Feasibility**

- Data Availability: Abundant satellite and ground data, though preprocessing is needed.
- Technical Maturity: Reliable AI/ML algorithms and robust libraries are available.
- Computational Resources: Requires high-performance computing or cloud solutions.

### **Challenges & Risks**

- **Data Gaps**: Missing or noisy data could lead to inaccurate maps.
- Model Complexity: Balancing model sophistication with risk of overfitting or underfitting.
- Scalability: Managing large datasets might cause performance slowdowns.
- Validation: Ensuring the model works well across different regions.
- Interpretability: Complex models might be difficult for stakeholders to understand.

## **Strategies**

- Data Gaps: Implement cloud masking, interpolation, and data augmentation.
- **Model Complexity**: Start with simpler models, use cross-validation, and combine model for better accuracy.
- Scalability: Leverage cloud computing and parallel processing to handle big data efficiently.
- Validation: Use diverse and independent datasets to ensure the model generalizes well.



## IMPACT AND BENEFITS

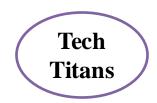


## **Target Audience:**

- •Researchers: Access to high-resolution data improves the quality and scope of environmental research.
- •Government Bodies: Enhanced capabilities for real-time air quality monitoring and rapid response to pollution events.
- •Public: Better access to localized air quality information empowers individuals to make informed health and lifestyle decisions.

### **Benefits:**

- •Health Improvements: Facilitates early warning systems for air pollution, reducing health risks and chronic diseases.
- •Community Engagement: Fosters community involvement in environmental issues through accessible data and visualization tools.
- •Targeted Pollution Control: Enables precise targeting of pollution sources, leading to more effective cleanup and mitigation efforts.
- •Enhanced Environmental Policies: Provides data-driven evidence to support stringent air quality regulations and compliance with environmental standards.
- •Sustainable Development: Supports green initiatives and sustainable practices by offering insights into pollution trends and impacts.



# RESEARCH AND REFERENCES



#### RESEARCH

- "NASA Worldview," NASA Earth Observing System Data and Information System. [Online]. Available: Link.
- "IHME Cloud Storage," Institute for Health Metrics and Evaluation. [Online]. Available: Link.

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- K. L. Chan, E. Khorsandi, S. Liu, F. Baier, and P. Valks, "Estimation of Surface NO2 Concentrations over Germany from TROPOMI Satellite Observations Using a Machine Learning Method," *Remote Sens.*, vol. 13, no. 5, p. 969, Mar. 2021, doi: 10.3390/rs13050969.
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- P.S. Kanaroglou, N.A. Soulakellis., N.I. Sifakis., Improvement of satellite derived pollution maps with the use of a geostatistical interpolation method. International Journal of Geographical Systems. (4); pp. 2002, 193-208.