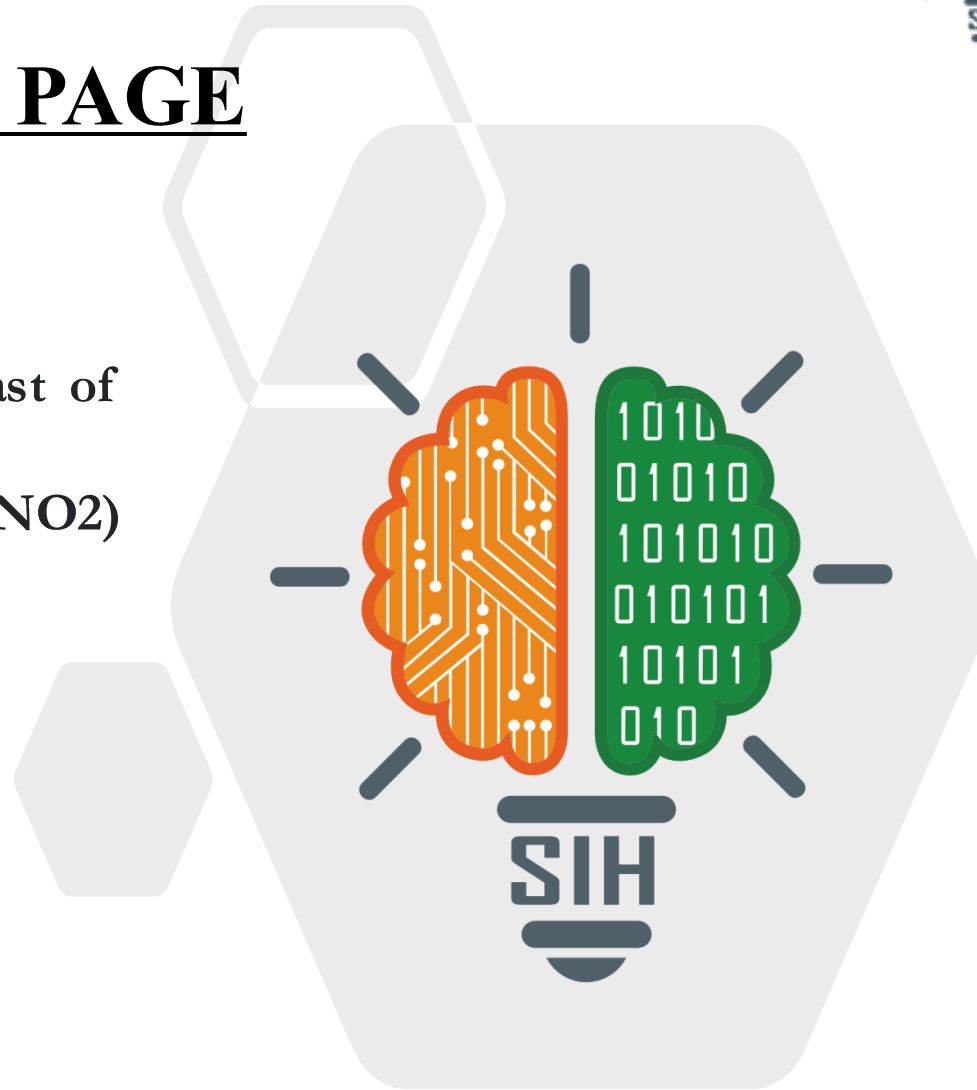


# SMART INDIA HACKATHON 2025



## TITLE PAGE

- Problem Statement ID – SIH25178
- Problem Statement Title- Short term forecast of gaseous air pollutants (ground-level O3 and NO2) using satellite and reanalysis data.
- Theme- Space Technology
- PS Category- Software
- Team ID- 117392
- Team Name- VyomCoders



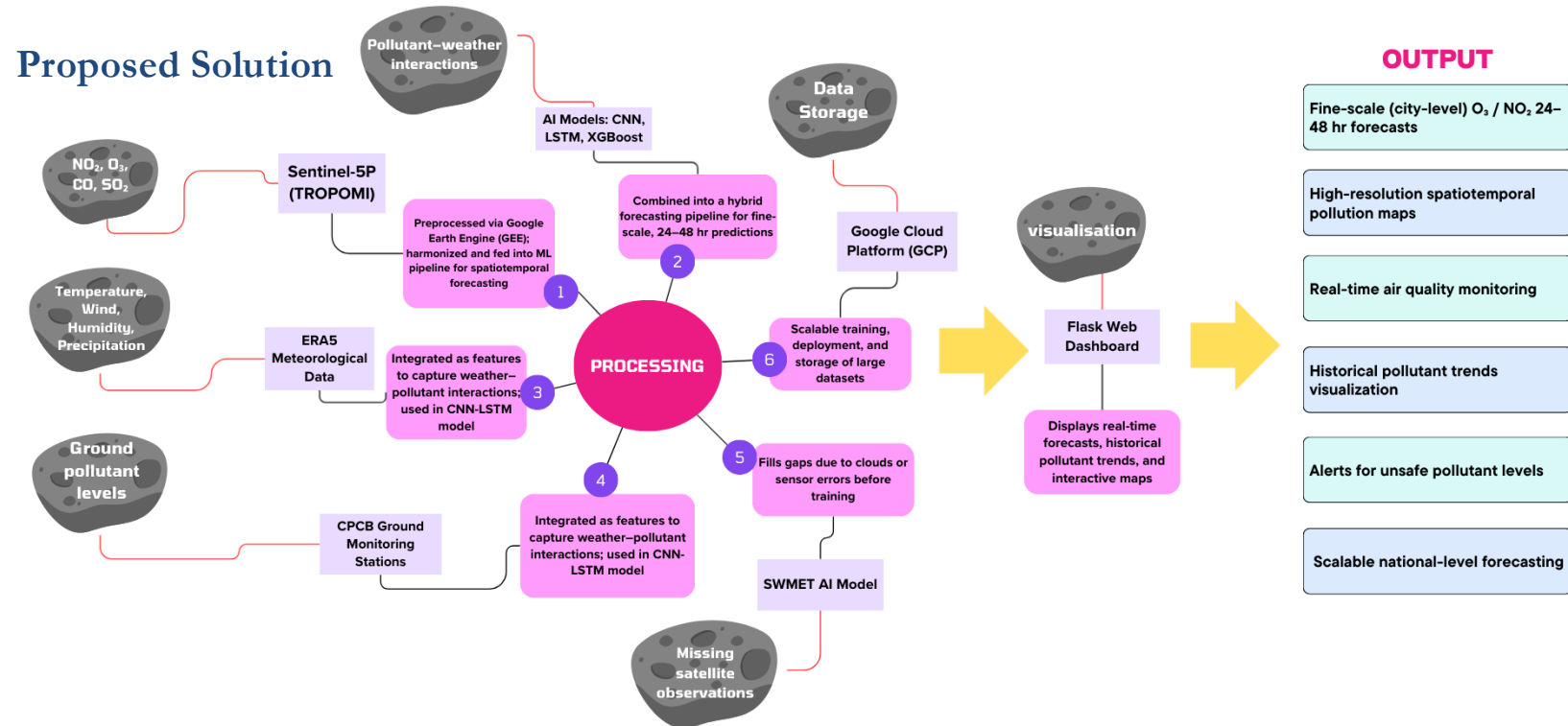
# Short term forecast of gaseous air pollutants (ground-level O<sub>3</sub> and NO<sub>2</sub>) using satellite and reanalysis data.

An **advanced machine learning framework** for short-term forecasting of ground-level O<sub>3</sub> and NO<sub>2</sub> concentrations in Delhi. The solution leverages **satellite data and meteorological reanalysis** to build accurate 24-hour ahead predictions at hourly intervals. We developed an **advanced machine learning framework** for short-term forecasting of ground-level O<sub>3</sub> and NO<sub>2</sub> concentrations in Delhi. The solution leverages **satellite data and meteorological reanalysis** to build accurate 24-hour ahead predictions at hourly intervals.

## Current systems Limitations:

- Satellite data cover large areas but miss local urban details and rapid changes.
- Available systems like MODIS AOD provides proper forecasts but lacks accuracy due to challenges like cloud and low sensitivity to surface pollution.
- Most models alone can't capture complex interactions between weather and multiple pollutants at fine scales.

## Proposed Solution



## 1. Data Sources:

**Sentinel-5P (TROPOMI):** Satellite-based measurements of NO<sub>2</sub>, O<sub>3</sub>, CO, and SO<sub>2</sub>. Daily high-resolution data (~3.5 × 5.5 km) for forecasting air quality.

**ERA5 Meteorological Data:** Temperature, wind, humidity, and precipitation to capture weather effects on pollutants.

**Ground Stations (CPCB, optional):** Real observed data to validate predictions.

## 2. Platforms:

**Google Earth Engine (GEE):** Access, preprocess, and analyze satellite data.

**Google Cloud Platform (GCP):** Cloud storage and scalable compute for training and deployment.

## 3. AI Models:

**XGBoost:** Regression model for baseline prediction and feature importance.

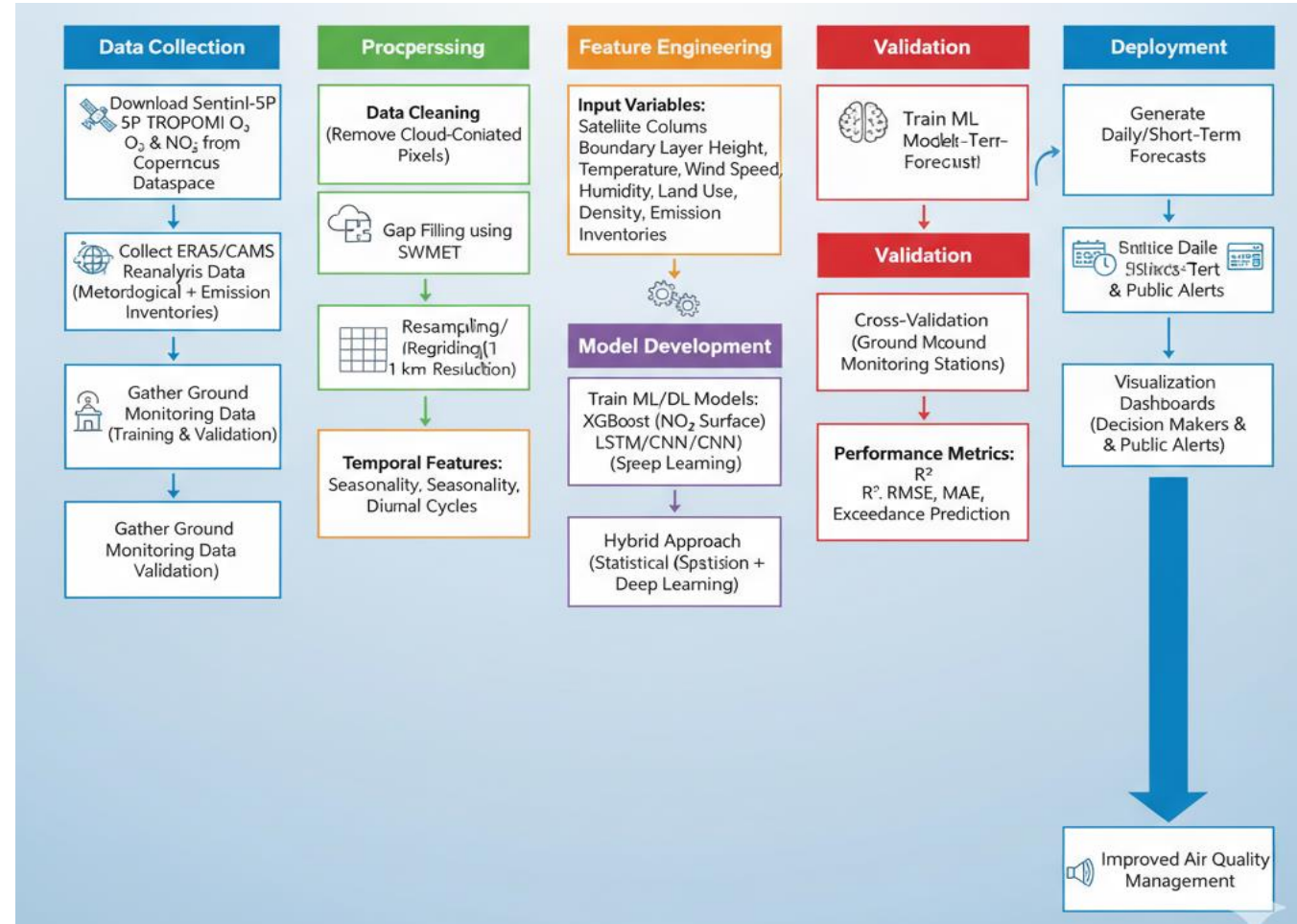
**LSTM:** Captures temporal patterns in pollutant levels.

**CNN:** Extracts spatial features from gridded data.

## 4. Tools

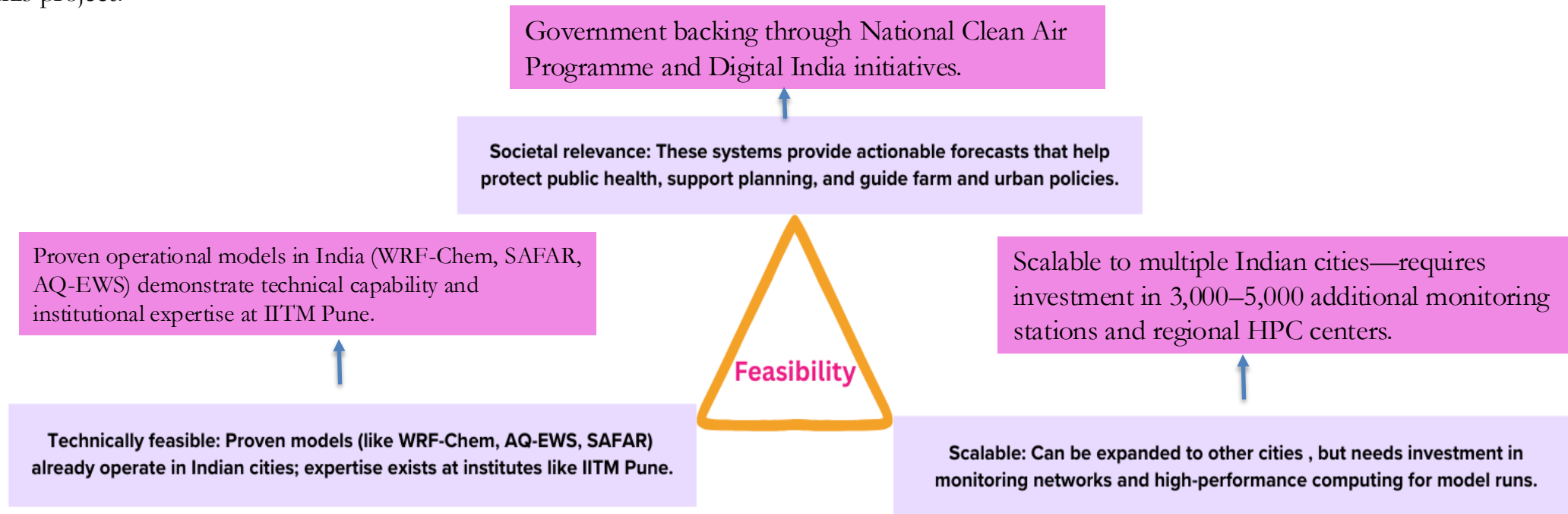


## METHODOLOGY AND PROCESS OF AIR QUALITY FORECASTING IMPLEMENTATION



What makes this solution out of the Box:

- **Seamless Multimodal Fusion:** Integrates TROPOMI satellite data, ECMWF forecasts, and ground stations for unparalleled spatial-temporal coverage.
- **Advanced Deep Learning:** Employs CNN-LSTM with attention mechanisms to capture nonlinear pollutant–meteorology interactions at urban scales.
- **Real-Time Operational Design:** Cloud-native architecture and optimized inference enable sub-hourly, city-wide forecasts for immediate public health and policy action.
- **Human resource:** Along with the smart tech developers, on site industry experts have been involved in the development and research of this project.



## Our approach stands out because:

### Current available system

- 1.SAFAR
- 2.AQ-EWS
- 3.AeroVision

**SAFAR:** 10km regional resolution, limited to 4 cities  
**AQ-EWS:** 400m only for Delhi-NCR, no national coverage  
**AeroVision:** 25km grid resolution

### Our Proposed Solution Advantage:

- TROPOMI satellite data at 3.5×7km resolution combined with ERA5 at 31km provides consistent high-resolution national coverage
- Unified framework scalable across all Indian megacities simultaneously
- Hourly forecasting at sub-urban scale vs. current daily/3-day systems

### AI/ML Integrity:

- 1.CNN-LSTM hybrid architecture capturing complex spatiotemporal relationships vs. traditional regression.
2. Attention mechanisms for automatic feature importance weighting.
- 3.Multi-task learning for simultaneous O<sub>3</sub>/NO<sub>2</sub> prediction with shared meteorological drivers

### Benefits to the users

### Data Integration Deficiencies

- 1.TROPOMI provides daily global coverage with superior sensitivity to NO<sub>2</sub>/O<sub>3</sub> compared to MODIS
- 2.Real-time meteorological fusion using ECMWF operational forecasts (1-hour latency) vs. ERA5's 5-day delay
- 3.Ground-satellite-model triangulation compensating for individual data source limitations

### Accuracy and Performance Issues:

- 1.Literature demonstrates  $R^2 > 0.84$  for satellite-based CNN-LSTM models
- 2.RMSE improvements of 20-40% over traditional CTM approaches
- 3.Multi-pollutant validation with European CAMS achieving  $> 0.9$  correlation after post-processing



- **Wang, Y., et al. (2021).** *Short-term forecasting of air pollutants: A comprehensive review of data sources, methods, and applications.* *Science of the Total Environment*, 775, 145944. Elsevier.
  - ♦ **Why used:** This paper provides a detailed review of different approaches and data sources for short-term air pollutant forecasting, which supports the methodology section of the presentation. [ScienceDirect Link](#)
- **Giani, P., Anav, A., De Marco, A., & Sicard, P. (2022).** *Air pollutant forecasting: Short-term prediction of O<sub>3</sub> and NO<sub>2</sub> using satellite and reanalysis data.* *Frontiers in Environmental Science*.
  - ♦ **Why used:** This research focuses specifically on forecasting ozone (O<sub>3</sub>) and nitrogen dioxide (NO<sub>2</sub>) using satellite and reanalysis datasets, which directly aligns with the pollutants studied in this project. [PMC Link](#)
- **Zhang, Y., et al. (2020).** *Deep Learning for Air Quality Forecasts: A Review.* *Current Pollution Reports*, 6, 399–415.
  - ♦ **Why used:** This review highlights how deep learning techniques (CNN, RNN, LSTM) are applied for air quality prediction, supporting the technical framework and AI-based methodology in the PPT. [ResearchGate Link](#)
- **European Centre for Medium-Range Weather Forecasts (ECMWF). (2025).** *ERA5: Fifth Generation of ECMWF Atmospheric Reanalyses of the Global Climate*
  - ♦ **Why used:** ERA5 reanalysis dataset provides global-scale historical weather and atmospheric data, which is essential as an input dataset for pollutant forecasting models. [ERA5 Reference](#)

## Comparative Insight:

Unlike traditional models (**ARIMA**, **CTMs** like **SAFAR**, or ensemble systems such as **CAMS**), our solution directly learns from **satellite** and **reanalysis data**—eliminating dependence on emission inventories or dense sensor networks. This enables faster, scalable, and region-specific air quality forecasting with minimal computational cost.