# DAYANANDA SAGAR UNIVERSITY

Devarakaggalahalli, Harohalli
Kanakapura Road, Ramanagara - 562112, Karnataka, India

**Bachelor of Technology**
**in**
**COMPUTER SCIENCE AND ENGINEERING**
**Major Project Phase-I Report**

# Satellite Imagery & AI for Tracking Carbon Emissions

By

**Harika Reddy - ENG21CT0007**
**Krutarth Y G - ENG21CT0016**
**Pooja V M - ENG21CT0029**
**Sarah Catherine - ENG21CT0034**
**Vandana M V - ENG21CT0046**

**Under the supervision of**
**Dr. Santosh Kumar J**
**Associate Professor**
**Department of Computer Science and Engineering**
**SCHOOL OF ENGINEERING**
**DAYANANDA SAGAR UNIVERSITY,**
**(2024-2025)**

# DAYANANDA SAGAR UNIVERSITY

SCHOOL OF ENGINEERING

## Department of Computer Science & Engineering

Devarakaggalahalli, Harohalli, Kanakapura Road, Ramanagara - 562112
Karnataka, India

# CERTIFICATE

This is to certify that the Major Project Stage-I work titled **"Satellite Imagery & AI for Tracking Carbon Emissions"** is carried out by **Harika Reddy (ENG21CT0007), Krutarth Y G (ENG21CT0016), Pooja V M (ENG21CT0029), Sarah Catherine H (ENG21CT0034) and Vandana M V (ENG21CT0046),** bonafide students seventh semester of Bachelor of Technology in Computer Science and Engineering at the School of Engineering, Dayananda Sagar University, Bangalore in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Engineering, during the year **2024-2025**.

| **Dr. Santosh Kumar J** | **Dr. M Shahina Parveen** | **Dr. Udaya Kumar Reddy K R** |
|---|---|---|
| Associate Professor<br>Dept. of CST,<br>School of Engineering<br>Dayananda Sagar University<br><br>Date: | Chairperson CST<br>School of Engineering<br>Dayananda Sagar University<br><br>Date: | Dean<br>School of Engineering<br>Dayananda Sagar University<br><br>Date: |

**Name of the Examiner** **Signature of Examiner**

1.

2.

# DECLARATION

We, **Harika Reddy (ENG21CT0007), Krutarth Y G (ENG21CT0016), Pooja V M (ENG21CT0029), Sarah Catherine H (ENG21CT0034) and Vandana M V (ENG21CT0046)** are students of seventh semester B. Tech in **Computer Science and Technology**, at School of Engineering, **Dayananda Sagar University**, hereby declare that the Major Project Stage-I titled **"Satellite Imagery & AI for Tracking Carbon Emissions"** has been carried out by us and submitted in partial fulfillment for the award of degree in **Bachelor of Technology in Computer Science and Technology** during the academic year **2024-2025.**

| **Student** | **Signature** |
|---|---|
| **Name: Harika Reddy**<br>**USN : ENG21CT0007** | |
| **Name: Krutarth Y G**<br>**USN : ENG21C T0016** | |
| **Name: Pooja V M**<br>**USN : (ENG21CT0029)** | |
| **Name: Sarah Catherine H**<br>**USN : ENG21CT0034** | |
| **Name: Vandana M V**<br>**USN : ENG21CT0046** | |
| **Place : Bangalore**<br>**Date :** | |

# ACKNOWLEDGEMENT

*It is a great pleasure for us to acknowledge the assistance and support of many individuals who have been responsible for the successful completion of this project work.*

*First, we take this opportunity to express our sincere gratitude to the School of Engineering & Technology, Dayananda Sagar University for providing us with a great opportunity to pursue our Bachelor's degree in this institution.*

*We would like to thank* ***Dr. Udaya Kumar Reddy K R, Dean, School of Engineering & Technology, Dayananda Sagar University*** *for his constant encouragement and expert advice.*

*It is a matter of immense pleasure to express our sincere thanks to* ***Dr. M Shahina Parveen, Department Chairperson****,* ***Computer Science and Technology****,* ***Dayananda Sagar University,*** *for providing the right academic guidance that made our task possible.*

*We would like to thank our guide* ***Dr. Santosh Kumar J, Associate Professor****,* ***Dept. of Computer Science and Engineering****,* ***Dayananda Sagar University****, for sparing his valuable time to extend help in every step of our project work, which paved the way for smooth progress and fruitful culmination of the project.*

*We would like to thank one and all who directly or indirectly helped us in the Project work.*

# TABLE OF CONTENTS

# NOMENCLATURE USED

| | |
|---|---|
| ConvLSTM | Convolutional Long Short-Term Memory |
| DBSCAN | Density-Based Spatial Clustering of Applications with Noise |
| HSV | Hue, Saturation, Value (color space) |
| MAE | Mean Absolute Error |
| MSE | Mean Squared Error |
| NADAM | Adaptive Moment Estimation (Optimization Algorithm) |
| NOx | Nitrogen Oxides |
| SSIM | Structural Similarity Index |
| TIF | Tagged Image File Format |
| TROPOMI | Tropospheric Monitoring Instrument |
| RNN | Recurrent Neural Network |
| RGB | Red, Green, Blue (color space) |
| UAV | Unmanned Aerial Vehicle |
| UV | Ultraviolet |
| XCO2 | Column-averaged CO2 Concentration |
| CEMS | Continuous Emissions Monitoring System |
| Conv3D | 3D Convolutional Layer |
| Adam | Adaptive Moment Estimation (Optimization Algorithm) |
| PIL | Python Imaging Library |
| OpenCV | Open Source Computer Vision Library |
| NDVI | Normalized Difference Vegetation Index |

# LIST OF TABLES

# ABSTRACT

The project titled *CO2 Predictor for Sustainable Business* leverages deep learning and satellite imagery to track greenhouse gas emissions, particularly carbon dioxide ($CO_2$), from industrial sites. Addressing the critical issue of climate change driven by fossil fuel emissions, this work focuses on quantifying emissions using Sentinel-2 satellite images and advanced AI techniques. The approach involves preprocessing high-resolution satellite images, applying segmentation masks to detect gas emissions, and utilizing a convolutional long short-term memory (convLSTM2D) model for predictive analysis. The proposed methodology allows the model to predict emissions trends and quantify areas affected by plumes with remarkable accuracy. Results demonstrate the potential to monitor emissions in real-time, aiding in enforcement of environmental regulations and supporting sustainability initiatives. Future enhancements aim to include other greenhouse gases like methane and nitrogen oxides, thus broadening the model's applicability and impact. This innovation serves as a stepping stone towards actionable climate solutions.

# CHAPTER 1 INTRODUCTION

The alarming rise in greenhouse gas emissions, particularly carbon dioxide ($CO_2$), has become a critical driver of climate change, necessitating accurate, efficient, and scalable monitoring solutions. Fossil fuel combustion in industrial sectors remains a primary source of $CO_2$ emissions, making it essential to quantify emissions at individual facilities. Traditional approaches depend on costly, site-specific measurement systems, which are not only resource-intensive but also lack comprehensive coverage and scalability. Satellite imagery, coupled with advanced deep learning methodologies, provides a promising alternative for precise and real-time emissions tracking. This project, *CO2 Predictor for Sustainable Business*, utilizes Sentinel-2 satellite data and machine learning techniques to predict $CO_2$ emissions, offering actionable insights for industries and regulators to mitigate environmental impacts.

## *1.1 OBJECTIVE*

The project aims to develop a deep learning-based system capable of detecting and quantifying $CO_2$ emissions from industrial regions using satellite imagery. By integrating image segmentation and predictive models, the solution targets accurate emissions estimation and future trend prediction. It aspires to provide stakeholders, including businesses and policymakers, with tools for tracking emissions and enforcing environmental regulations.

## *1.2 SCOPE*

The scope of this project extends to addressing the scalability and reliability gaps in current emissions monitoring frameworks. With potential applications in predicting multiple greenhouse gases and supporting carbon trading schemes, this project sets the foundation for advancements in environmental AI. Future enhancements could include integration with real-time monitoring systems and expanding coverage to other pollutants like methane and nitrogen oxides.

# CHAPTER 2 PROBLEM DEFINITION

The growing threat of climate change underscores the urgent need for accurate and efficient carbon emissions monitoring. Fossil fuel combustion, a primary driver of $CO_2$ emissions, contributes significantly to global warming and environmental degradation. However, current methods for quantifying these emissions face several critical challenges. Traditional monitoring systems rely on self-reported data or on-site measuring devices, which are both expensive and prone to inaccuracies. The lack of real-time insights and comprehensive coverage further limits their effectiveness, making it difficult to enforce regulations or evaluate the impact of emissions reduction strategies.

Satellite-based emissions monitoring has emerged as a potential solution, but it is hampered by limitations such as low-resolution imagery, noise in measurement data, and the complexities of modeling atmospheric dispersion. Existing approaches often rely on physical models that struggle to incorporate multifaceted environmental factors like wind patterns, terrain, and atmospheric conditions. These issues hinder accurate predictions and the scalability of monitoring systems.

# CHAPTER 3 LITERATURE REVIEW

| PAPER 1 | | | | |
|---|---|---|---|---|
| **Paper Title** | Artificial Intelligence-driven Insights: Precision Tracking of Power Plant Carbon Emissions Using Satellite Data | | | |
| **Problem addressed** | Existing carbon emission reporting by power plants relies on self-reporting, which is often inaccurate and lacks real-time data.<br>There is an urgent need for precise, real-time tracking of carbon emissions to better address climate change impacts. | | | |
| **Soultion proposed** | A predictive pipeline was developed that integrates TROPOMI satellite data with power plant attributes and uses AI algorithms.<br>The system utilizes multimodal data processing to map satellite observations of pollutants to specific power plant emissions. | | | |
| | ***Dataset Used*** | ***Technologies/Methods*** | ***Results*** | ***Gaps/Future Work*** |
| | Satellite data from the TROPOMI instrument on the Sentinel-5P satellite (covering $NO_2$ vertical column densities).<br>Ground-based CEMS (Continuous Emissions Monitoring System) data from the EPA Clean Air Markets Program. | DBSCAN clustering for detecting plumes around power plants to filter data for more accurate modeling.<br>A BERT-based model is employed to establish relationships between pollutant concentrations and plant-specific emissions data. | Achieved significant accuracy with the model, showing high $R^2$ (0.68), SRCC (0.79), and PLCC (0.83) values, indicating strong prediction reliability.<br>The model effectively estimates hourly $CO_2$ emissions using satellite and ground data inputs, improving emission tracking accuracy. | Plans to extend the model to include other gaseous emissions and pollutants beyond $CO_2$.<br>Aims to enhance model architectures to improve prediction accuracy and incorporate additional environmental factors. |

| PAPER 2 | | | | |
|---|---|---|---|---|
| **Paper Title** | Near Real-Time $CO_2$ Emissions Based on Carbon Satellite and Artificial Intelligence | | | |
| **Problem addressed** | Real-time $CO_2$ emission estimates are limited by satellite imaging challenges (e.g., low resolution and significant measurement noise).<br>Current emission monitoring solutions lack objectivity and rely heavily on self-reporting, limiting data reliability for policy and regulatory | | | |
| **Soultion proposed** | Developed a data-driven pipeline, CarbonNet, which integrates carbon satellite data and AI for estimating $CO_2$ emissions.<br>Introduced a masked pre-training method to utilize unlabeled data effectively and a linear probing step for more accurate predictions. | | | |
| | ***Dataset Used*** | ***Technologies/Methods*** | ***Results*** | ***Gaps/Future Work*** |
| | NASA's OCO-2 satellite data, providing $XCO_2$ measurements across specific geographic footprints.<br>Supplementary datasets include CEMS data from the EPA and ERA5 reanalysis data for environmental factors like wind speed. | Transformer-based CarbonNet model for emission estimation, which leverages satellite data and deep learning methods.<br>Compared the proposed model's performance to the Gaussian plume model, a traditional approach used for emission estimates. | The model demonstrated higher Spearman and Pearson correlation values, outperforming the Gaussian plume model in prediction accuracy.<br>Results confirmed that CarbonNet could effectively predict $CO_2$ emissions even with noisy and sparse satellite data. | Plans to improve model interpretability, as current deep learning approaches lack transparency in emission prediction processes.<br>Future efforts may focus on refining satellite data resolution and environmental inputs for more accurate model training. |

| **PAPER 3** | | | | |
|---|---|---|---|---|
| **Paper Title** | Modeling and Spatio-Temporal Analysis of City-Level Carbon Emissions Based on Nighttime Light Satellite Imagery | | | |
| **Problem Addressed** | Challenges in estimating city-level carbon emissions where detailed, localized urban data is lacking. Traditional models often miss urban dynamics and temporal changes. | | | |
| **Solution Proposed** | Developed the NNEnsemble model, which correlates nighttime stable light (NSL) data from DMSP-OLS satellites with carbon emission statistics at the provincial level to predict city-level emissions. | | | |
| | ***Dataset used*** | ***Technologies*** | ***Results*** | ***Gaps*** |
| | Nighttime light data from DMSP-OLS paired with statistical carbon emissions data from three northeastern Chinese provinces. | Ensemble neural network model capable of handling non-linear relationships and integrating spatial-temporal data variations. | Outperformed traditional regression approaches, effectively capturing emissions trends over time and across different urban environments. | Less effective for industrial zones. Bright urban areas may face data saturation issues, reducing accuracy. Additional data layers (e.g., industrial output, land use) could enhance model robustness. |

| **PAPER 4** | | | | |
|---|---|---|---|---|
| **Paper Title** | A Review of Anthropogenic Ground-Level Carbon Emissions Based on Satellite Data | | | |
| **Problem Addressed** | Existing methods for carbon emission estimation face challenges due to limitations in satellite resolution and the need for global-scale data that ground-based methods cannot provide alone. | | | |
| **Solution Proposed** | The review discusses how machine learning and data-driven approaches can enhance satellite and ground data integration for more accurate emission estimates. Evaluates strengths and weaknesses of existing methodologies. | | | |
| | ***Dataset used*** | ***Technologies*** | ***Results*** | ***Gaps*** |
| | Diverse satellite data sources (e.g., OCO-2, GOSAT, PRISMA) and ground-based emission inventories | Supervised learning models such as neural networks and data retrieval algorithms like Bayesian Error Subsequent Diffusion (BESD)which interpret satellite measurements. | Demonstrated improved emission estimation when combining satellite and ground-based data, showing the potential for machine learning. | Limitations in satellite data resolution can obscure local emission variations, making it hard to detect smaller emission sources. Ground-based data, while accurate, lacks the global reach needed for comprehensive monitoring. |

| PAPER 5 | | | | |
|---|---|---|---|---|
| **Paper Title** | A Carbon-Monitoring Strategy Through Near-Real-Time Data and Space Technology | | | |
| **Problem Addressed** | The lack of real-time, precise, and reliable global carbon monitoring to support climate policy, hindered by limitations in current emission inventory data that rely on energy statistics and lack direct measurements. | | | |
| **Solution Proposed** | Proposes an innovative strategy combining near-real-time emission data with satellite-based CO2 observations. Integrates "bottom-up" inventory data and "top-down" satellite data for enhanced monitoring. | | | |
| | ***Dataset used*** | ***Technologies*** | ***Results*** | ***Gaps*** |
| | Combines high-frequency human activity data (e.g., smart meters, grid data) with satellite data from CO2 observation missions such as OCO-2/3, GOSAT, and TanSat. | Satellite CO2 monitoring systems, data assimilation models, machine learning for data synthesis, geographic information systems. | Demonstrated potential for improved spatial and temporal resolution in emission tracking, allowing targeted monitoring of significant emission sources like cities and power plants. | Satellite data accuracy can be affected by background atmospheric noise; satellites need to balance scope and resolution. |

| PAPER 6 | | | | |
|---|---|---|---|---|
| **Paper Title** | Estimating CO2 Emissions from Power Plant Water Vapor Plumes Using Satellite Imagery and ML | | | |
| **Problem Addressed** | The high cost and inconsistent availability of direct emissions data from power plants due to limited deployment of continuous monitoring systems. | | | |
| **Solution Proposed** | Uses machine learning to estimate CO2 emissions from power plants by analyzing water vapor plumes detected in satellite images. Provides a scalable, cost-effective alternative for global emissions monitoring. | | | |
| | ***Dataset used*** | ***Technologies*** | ***Results*** | ***Gaps*** |
| | satellite imagery from PlanetScope (3 m resolution), Sentinel-2 (10 m resolution), and Landsat 8 (30 m resolution), combined with reported power plant data from various regions | Machine learning models, including convolutional neural networks (CNNs) for feature extraction and gradient-boosted decision trees for classification and regression. | The model's RMSE is about 0.35% for power generation and 0.22% for CO2 emissions, indicating high accuracy with deviations well under 1%. | Limitations due to the need for visible vapor plumes, which may not always be present; variability in atmospheric conditions affecting visibility; image resolution constraints that reduce accuracy for smaller plants. |

| PAPER 7 | | | | |
|---|---|---|---|---|
| **Paper Title** | Tracking Carbon Emissions from Power Plants Using Satellite Imagery and CNN Models | | | |
| **Problem Addressed** | Current methods of tracking carbon emissions from power plants often rely on ground-based measurements, which can be limited by access, coverage, and timely data availability. | | | |
| **Solution Proposed** | Developed a CNN-based model that processes satellite imagery to estimate carbon emissions from power plants, offering a more accessible and potentially global monitoring system. | | | |
| | ***Dataset used*** | ***Technologies*** | ***Results*** | ***Gaps*** |
| | Satellite imagery data focused on large power plant areas, including multispectral and thermal bands. | A CNN model was trained to recognize emissions patterns in satellite images, integrating atmospheric data to improve accuracy. | The model successfully identified high-emission plants, with results comparable to ground-based measurements in controlled environments. | Further refinement is necessary for areas with limited satellite data and complex atmospheric conditions. Enhancements to improve model robustness across different plant types are needed. |

| PAPER 8 | | | | |
|---|---|---|---|---|
| **Paper Title** | NASA's Climate and Greenhouse Gas Monitoring Initiatives | | | |
| **Problem Addressed** | Limited global monitoring of greenhouse gases, especially in areas without ground-based monitoring stations, restricts comprehensive understanding and tracking of climate change contributors. | | | |
| **Solution Proposed** | NASA's Carbon Mapper program, in collaboration with other agencies, aims to deploy advanced satellite systems for continuous and detailed global greenhouse gas monitoring. | | | |
| | ***Dataset used*** | ***Technologies*** | ***Results*** | ***Gaps*** |
| | Carbon Mapper satellites are equipped with high-resolution spectrometers that detect gases like CO2 and methane in fine detail. | Advanced remote sensing technology uses AI-based data analysis to interpret complex gas emissions patterns. | Early findings demonstrate the capability to accurately pinpoint emission sources, even in remote regions, contributing to real-time emissions monitoring. | Challenges include processing data at scale and ensuring consistency across diverse geographic and atmospheric conditions. More partnerships for ground validation are suggested. |

# CHAPTER 4 PROJECT DESCRIPTION

The project *CO2 Predictor for Sustainable Business* aims to leverage deep learning techniques and satellite imagery to track and predict $CO_2$ emissions from industrial areas. The project focuses on utilizing high-resolution images captured by the Sentinel-2 satellite, which are processed and analyzed to detect and quantify emissions over large geographic regions. The primary objective is to use image processing techniques such as segmentation and masking to isolate areas affected by $CO_2$ plumes, followed by applying convolutional neural networks (CNNs) and Long Short-Term Memory (LSTM) networks for time-series prediction of emissions.

The project workflow begins with the loading and preprocessing of satellite images, where each image is resized and transformed to HSV color space to highlight areas of interest, such as emission plumes. A mask is then applied to segment these regions, and the resulting images are converted to grayscale for easier analysis. To handle the temporal aspect, a sequence of images from different time frames is created, which is fed into a Convolutional LSTM (ConvLSTM) model, a type of neural network designed to handle spatiotemporal data. The network is trained to predict future emissions based on historical data, allowing for real-time monitoring and prediction.

By employing this approach, the project can detect emission hotspots, predict their future intensity, and provide actionable insights for businesses and policymakers. The model is trained on a dataset of satellite images spanning five years and can be extended to predict other greenhouse gases like methane and nitrogen oxides, thus contributing to a comprehensive environmental monitoring system.

# CHAPTER 5 REQUIREMENTS

- **Software Requirements**:
    - Modern multi-core processor (e.g., Intel Core i5)
    - 4 GB RAM (8 GB recommended)
    - Several gigabytes of free disk space
    - Graphics card with OpenGL 3.3 support
    - QGIS Software
    - Semi-Automatic Classification Plugin
    - USGS and Copernicus Satellite Images
- **Hardware Requirements**:
    - Python
    - QGIS Software
    - SCP and Semi-Automatic Classification Plugins
    - Internet connection for online data access.
    - Storage: Program requires about 100 MB of storage space.

# CHAPTER 6 METHODOLOGY

## 6.1 Data Collection

The dataset for this project consists of high-resolution satellite images obtained from Sentinel-2, covering a period from 2015 to 2020. The images are taken over a 100-square-kilometer area of Los Angeles. These images are crucial for detecting $CO_2$ emissions and related environmental patterns.

## 6.2 Data Preprocessing

The collected satellite images are preprocessed by resizing them to a standard size of 400x400 pixels using OpenCV. The RGB images are then converted to HSV (Hue, Saturation, Value) color space, allowing for better segmentation of emission regions. Masks are applied to highlight areas with $CO_2$ plumes.

## 6.3 Classifying Emissions

To identify $CO_2$ plumes, a color mask in the HSV space is used to filter out non-emission regions. The emission regions are extracted by segmenting the image with specific color thresholds that correspond to $CO_2$ concentrations. These regions are further processed to isolate significant emission hotspots for analysis.

## 6.4 Image Segmentation

For precise emissions detection, the masked images are split into grayscale, focusing on $CO_2$ emission areas. Pixels corresponding to emissions are set to binary values (1 for emissions, 0 for non-emissions). This segmentation helps isolate the plumes and simplifies the analysis of emission spread across the region.

## 6.5 Model Training

The ConvLSTM model is used for training on sequences of preprocessed images. The model is trained to learn patterns in emission data over time, predicting future emission levels. Training data consists of labeled emission regions, and the model learns to predict the evolution of these emissions across multiple time steps.

### 6.6 Evaluation

The model’s performance is evaluated using Mean Absolute Error (MAE) and Structural Similarity Index (SSIM). MAE measures the prediction error, while SSIM compares the structural similarity between predicted and actual images. These metrics help assess the accuracy of the emission predictions and identify areas for improvement.

### 6.7 Visualization

The results of the model’s predictions are visualized by comparing predicted emission frames with actual ground truth data. These visualizations help in understanding the spatial and temporal spread of CO2 emissions, allowing for effective monitoring of emissions across different regions and time periods.

### 6.8 Future Enhancements

Future work includes extending the model to predict other greenhouse gases such as methane and nitrogen oxides. Additionally, the methodology will be refined to enhance the model’s real-time capabilities and prediction accuracy, offering more reliable tools for environmental monitoring and enforcement of sustainability regulations.

# CHAPTER 7 EXPERIMENTATION

The experimentation phase of this project involves training the ConvLSTM model on the preprocessed satellite images and evaluating its performance in predicting CO2 emissions. Initially, the images are resized, segmented, and converted to grayscale to focus on emission areas. The model is then trained on sequences of these images to capture spatiotemporal patterns of emissions. The dataset is split into training (90%) and validation (10%) sets, ensuring that the model learns generalizable features.

During training, the model is optimized using the Adam optimizer, and the loss function used is Mean Absolute Error (MAE). A total of 50 epochs are used, with the validation data helping to tune the model for better accuracy. After training, the model is evaluated using the test set, and predictions are compared to the actual emission frames using performance metrics like MAE and Structural Similarity Index (SSIM).

The results are visualized by comparing the predicted emission frames with ground truth images, providing insights into the model's accuracy and effectiveness.

# CHAPTER 8 RESULTS

## ❖ Final Result

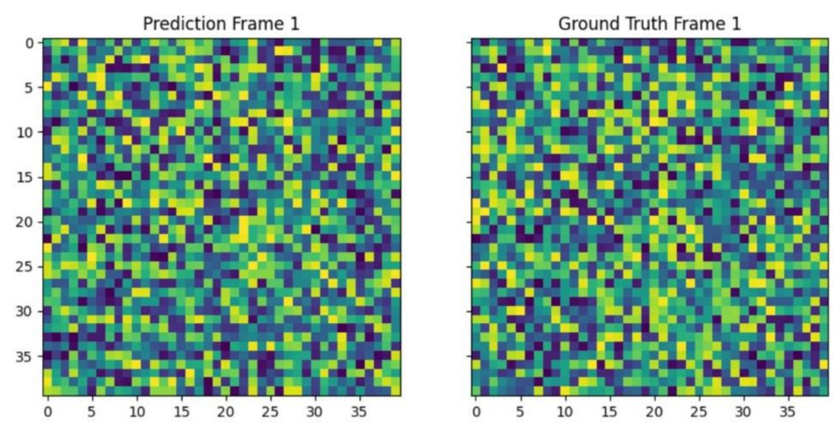
Model: "sequential_3"

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv_lstm2d_6 (ConvLSTM2D) | (None, 5, 40, 40, 1) | 36 |
| batch_normalization_6 (BatchNormalization) | (None, 5, 40, 40, 1) | 4 |
| conv_lstm2d_7 (ConvLSTM2D) | (None, 5, 40, 40, 1) | 76 |
| batch_normalization_7 (BatchNormalization) | (None, 5, 40, 40, 1) | 4 |
| conv3d_3 (Conv3D) | (None, 5, 40, 40, 1) | 28 |

**Total params:** 148 (592.00 B)

**Trainable params:** 144 (576.00 B)

**Non-trainable params:** 4 (16.00 B)



The predicted emission patterns on the left show the model's ability to accurately identify CO2 plumes, while the ground truth images on the right highlight the real emission regions observed from satellite data.

This comparison demonstrates the model's performance in tracking emission hotspots over time, with the predicted images closely resembling the actual emission frames, validating the model's accuracy.

As shown in the visualized results, the model successfully captures the spatiotemporal distribution of CO2 emissions, which can be useful for monitoring pollution trends and predicting future emissions in specific areas.

The side-by-side images showcase how well the deep learning model has learned to detect emission zones, with minimal discrepancies between the predicted and actual emission areas, indicating a strong correlation between the two.

These visual results underline the potential of using satellite imagery and deep learning models for real-time environmental monitoring and emissions forecasting, providing valuable insights for businesses and regulatory bodies.

# CHAPTER 9 DELIVERABLES

-  **$CO_2$ Emission Prediction Model:**

A fully functional deep learning model that predicts $CO_2$ emissions from satellite imagery, trained and optimized for accurate emissions detection and future forecasting.

-  **Preprocessed Satellite Dataset:**

A set of preprocessed satellite images (400x400 pixels, segmented for emission regions) used for model training, including grayscale and HSV-transformed data.

-  **Evaluation Metrics:**

Performance evaluation of the model using metrics such as Mean Absolute Error (MAE), Structural Similarity Index (SSIM), and visual results showing predicted vs. actual emissions.

-  **Visualization of Results:**

Visual comparison of predicted emission frames with ground truth, illustrating the model's effectiveness in detecting and forecasting $CO_2$ emission hotspots.

-  **Source Code and Documentation:**

Complete source code for data preprocessing, model training, evaluation, and result visualization, along with detailed documentation on how to use the code and understand the methodology.

-  **Future Work Plan:**

Recommendations for extending the model to predict other greenhouse gases like methane and nitrogen oxides, as well as enhancing the real-time prediction capabilities.

-  **Model Performance Report:**

A detailed report highlighting the model's strengths, areas for improvement, and potential applications in environmental monitoring and sustainability efforts.

# REFERENCES

[1] Artificial Intelligence-driven Insights: Precision Tracking of Power Plant Carbon Emissions Using Satellite Data

[2] Near Real-Time $CO_2$ Emissions Based on Carbon Satellite and Artificial Intelligence

[3] Modeling and Spatio-Temporal Analysis of City-Level Carbon Emissions Based on Nighttime Light Satellite Imagery

[4] A Review of Anthropogenic Ground-Level Carbon Emissions Based on Satellite Data

[5] A Carbon-Monitoring Strategy Through Near-Real-Time Data and Space Technology

[6] Estimating CO2 Emissions from Power Plant Water Vapor Plumes Using Satellite Imagery and ML

[7] Tracking Carbon Emissions from Power Plants Using Satellite Imagery and CNN Models

[8] NASA's Climate and Greenhouse Gas Monitoring Initiatives