DAYANANDA SAGAR COLLEGE OF ENGINEERING

(An Autonomous Institute affiliated to Visvesvaraya Technological University (VTU), Belagavi,
Approved by AICTE and UGC, Accredited by NAAC with 'A' grade & ISO 9001 – 2015 Certified Institution)
Shavige Malleshwara Hills, Kumaraswamy Layout, Bengaluru-560 111, India

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

Project Report on

Breaking the Carbon Curve: Advanced Forecasting of Global CO2 Emissions Using CNN-GRU

Submitted in partial fulfillment for the award of the degree of

Bachelor of Engineering
in
Computer Science and Engineering

Submitted by

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2024-25

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CERTIFICATE

Certified that the project report entitled "**Breaking the Carbon Curve: Advanced Forecasting of Global CO2 Emissions Using CNN-GRU**" carried out by **PRANAV J S [1DS21CS152], PRUDHVI RAJ R [1DS21CS160], PRANAV ARYA S [1DS21CS150], LOHISH VINAYAK YADAV [1DS21CS110]** a bonafide student of DAYANANDA SAGAR COLLEGE OF ENGINEERING, an autonomous institution affiliated to VTU, Belagavi in partial fulfillment for the award of Degree of Bachelor of Computer Science and Engineering during the year 2024-2025. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements with respect to the work prescribed for the said Degree.

Signature of the Guide	**Signature of the HOD**	**Signature of the Principal**
Dr. Annapoorna B.R **Assistant Professor** **Dept. of CSE, DSCE** **Bengaluru**	**Dr. Ramesh Babu D R** **Vice Principal & Head** **Dept. of CSE, DSCE, Bengaluru**	**Dr. B G Prasad** **Principal** **DSCE, Bengaluru**

Name of the Examiners	**Signature with date**
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2.	**...**

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DECLARATION

We, **Pranav J S (1DS21CS152), Prudhvi Raj R (1DS21CS152), Pranav Arya S (1DS21CS152) and Lohish Vinayak Yadav (1DS21CS152),** respectively, hereby declare that the project work entitled "Breaking the Carbon Curve: Advanced Forecasting of Global CO2 Emissions Using CNN-GRU" has been independently done by us under the guidance of **'Dr. Annapoorna B.R', Assistant Professor,** CSE department and submitted in partial fulfillment of the requirement for the award of the degree of **Bachelor of Computer Science and Engineering** at **Dayananda Sagar College of Engineering**, an autonomous institution affiliated to VTU, Belagavi during the academic year 2024-2025.

We further declare that we have not submitted this report either in part or in full to any other university for the award of any degree.

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PLACE:

DATE:

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We express our sincere thanks to Project Coordinator **Dr. Ramya R S, Assoc. Prof, Dr. Annapoorna B R Asst. Prof., Prof. Aparna M Asst. Prof and Prof. Kanchana M Dixit Asst. Prof of the Department of Computer Science and Engineering** for their continues support and guidance. We thank all teaching and non-teaching staff of the Department of Computer Science and Engineering for their kind and constant support throughout the academic Journey.

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ABSTRACT

In the 21st century, carbon dioxide (CO_2) emissions have emerged as a critical global concern, contributing to rising temperatures and severe climate change impacts. The melting of polar ice caps, flooding of coastal regions, and exposure to ancient pathogens are only some of the cascading consequences. These developments present significant socioeconomic risks that demand urgent mitigation. Traditional forecasting methods, while informative, often fall short in addressing the complexity of this global challenge due to their reliance on static data and manual analysis. To overcome these limitations, this paper proposes a hybrid model-based approach. The proposed system uses machine learning algorithms like Arima, LSTM, CNN-LSTM and CNN-GRU to predict and provide valuable macro and micro insights by achieving greater precision and adaptability. It not only predicts the CO_2 levels but also provides actionable recommendations for carbon neutrality and reduce emissions reduction rates. The framework of this innovative approach is to support global efforts to combat climate change. Decision-makers can access timely and accurate insights when they switch from conventional methods to hybrid-model driven forecasting. The CNN-GRU model shows the best performance among all other models. The development of adaptive systems marks a significant advancement in the fight against climate change, fostering resilience in the face of a global crisis. By the of ML algorithms, decision makers can optimize operations and promote sustainable practices.

Keywords: Cascading Consequences, Carbon Neutrality, Hybrid Model, Resilience, Reduction Rates.

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LIST OF ABBREVIATIONS

Abbreviation	Full Description
ARIMA	Auto Regressive Integrated Moving Average
LSTM	Long Short Time Memory
CNN	Convolutional Neural Network
GRU	Gated Recurrent Unit
RNN	Recurrent Neural Network
RMSE	Root Mean Square Error
PPM	Parts Per Million
SARIMAX	Seasonal Arima
TCN	Temporal Convolutional Network
S-CNN	Smoothed Convolutional Neural Network
MLP	Multi Layer Perceptron
LightGBM	Light Gradient Boosting Machine
RMSLE	Root Mean Squared Logarithmic Error
MAPE	Mean Absolute Error
APE	Absolute Percentage Error
LLM	Large Language Model
RAG	Retrieval Augmented Generation
FAISS	Facebook AI Similarity Search
ADF	Augmented Dicky Fuller Test
KPSS	Kwiatkowski-Phillips-Schimdt-Shin Test
ACF	Auto Correlation Function
PACF	Partial Autocorrelation Function

Chapter 1

Introduction

1.1 Overview

Climate change is one of the most urgent challenges facing humanity today. At the heart of this issue lies the rise in carbon dioxide (CO2) emissions, primarily fueled by human activities such as burning fossil fuels, clearing forests, and industrial production. Since the industrial revolution, CO2 levels have increased at an unprecedented pace, driving global warming and threatening ecosystems, economies, and communities worldwide.

Tackling this crisis requires a clear understanding of the problem, analyzing how emissions have changed over time and finding effective ways to predict and reduce them. This project focuses on addressing these needs by harnessing the power of advanced data analysis and machine learning. Using innovative hybrid models that combine Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and Gated Recurrent Units (GRUs), the project aims to create reliable tools for forecasting CO2 emissions trends.

In addition to developing these advanced models, the project compares their performance with traditional forecasting methods like ARIMA and standalone LSTMs to ensure a balanced, well-rounded approach. Beyond predicting emissions, this initiative also emphasizes individual action by introducing an AI-powered assistant to help people calculate and lower their carbon footprints. By combining large-scale insights with individual empowerment, the project seeks to make a meaningful contribution to global sustainability efforts.

1.2 Problem Statement

The relentless rise in CO2 emissions is a major environmental challenge that endangers the balance of natural systems, economic stability, and human well-being. Industrialization, urbanization, and unsustainable practices have significantly accelerated emissions growth, creating a pressing need for effective mitigation strategies.

However, many existing tools fall short. Traditional forecasting models like ARIMA and standalone LSTMs often struggle to capture the complex, non-linear patterns in emissions data. At the same time, there’s a lack of accessible tools that allow individuals to understand their carbon footprints and take meaningful steps to reduce them.

This project addresses these gaps by combining cutting-edge hybrid forecasting models with an easy-to-use AI-powered personal CO2 assistant. The goal is to provide accurate insights for policymakers and businesses while also enabling individuals to contribute to climate action through informed, practical choices.

1.3 Objectives

- **Analyze historical CO2 emissions data** to uncover key trends, anomalies, and contributions from different sectors.
- **Develop hybrid forecasting models** that leverage advanced machine learning techniques like CNN-GRU and CNN-LSTM to predict emissions more accurately.
- **Compare forecasting approaches**, including hybrid models, ARIMA, and standalone LSTM methods, to evaluate their strengths and limitations.
- **Ensure interpretability** by building explainable AI frameworks that clarify the predictions and make them more transparent.
- **Empower individuals** with an AI assistant to estimate and reduce their personal CO2 emissions.
- **Deliver actionable insights** that support effective policymaking, corporate sustainability strategies, and grassroots climate action.

1.4 Motivation

The rapid rise in CO_2 emissions and its devastating consequences—such as more frequent floods, wildfires, and droughts—serve as the driving force behind this project. Despite global efforts like the Paris Agreement, the gap between climate goals and actual progress remains significant. Bridging this gap requires innovative solutions that address the problem on both a large and small scale.

This project is fuelled by the belief that technology can be a powerful tool for change. By developing advanced forecasting models, it aims to give governments and businesses the insights they need to make informed decisions. At the same time, the inclusion of a personal CO_2 emissions assistant reflects a commitment to individual empowerment, recognizing that meaningful change begins with each person.

Ultimately, this project seeks to contribute to a future where communities, organizations, and individuals work together to achieve sustainability, driving collective action toward a carbon-neutral world.

Chapter 2

Literature Survey

[1] A comparative Analysis to forecast carbon dioxide emissions. This paper developed a comprehensive analysis of various time-series forecasting models applied to carbon dioxide emissions. The paper examines both traditional statistical models like ARIMA and advanced neural network models such as LSTMs, GRUs, and CNNs. ARIMA is highlighted for its simplicity and interpretability, while LSTMs and GRUs are noted for their ability to capture long-term dependencies in the data. CNNs, on the other hand, are shown to excel in feature extraction for multivariate time-series data. The paper emphasizes that although these models achieve high accuracy, they often lack explainability. The authors propose the development of a novel hybrid model that integrates the strengths of these approaches while explainability predictions features incorporating to make more transparent and actionable for stakeholders.

[2] Forecasting covid19 pandemic using Prophet, ARIMA, and hybrid stacked LSTM-GRU model in India. This paper developed a comprehensive model to forecast COVID 19 case trajectories in India, a country severely impacted by the pandemic. Despite advancements in medical and technological tools, accurately predicting the spread of the SARS-CoV-2 virus has proven challenging. Their study employs various predictive models such as RNN, GRU, LSTM, linear and polynomial regression, ARIMA, and Prophet to forecast confirmed and active cases, with a special focus on comparing outcomes. Among these, the stacked LSTM-GRU model demonstrated superior performance in terms of prediction consistency, R-square, and RMSE. This hybrid approach leverages the memory capabilities of LSTMs and the vanishing gradient resolution of GRUs, yielding higher ac curacy in forecasting virus transmission pathways. The findings underscore the stacked LSTM-GRU model’s effectiveness as a predictive analytic technique, aiding healthcare systems in anticipating future COVID-19 spread and resource needs.

[3] Forecasting and mitigation of global environment carbon dioxide emissions using machine learning technique. This paper developed models that aims to identify the year when CO2 levels will reach a critical threshold of 500 ppm and propose methodologies for reducing emissions to a safer level of 316 ppm. The research utilizes historical data from the United States to analyze annual carbon emissions and their relationship with various social and economic factors. By employing machine learning models, the authors seek to predict future CO2 emission values and identify crucial thresholds that must not be breached to avoid irreversible environmental damage. The paper emphasizes the importance of transitioning to renewable energy sources and sustainable practices to achieve carbon neutrality, highlighting the need for immediate action and further research in this domain.

[4] Machine learning based time series models for effective co2 emissions prediction in India. This paper developed models that aims to predict CO2 emissions over the next decade using univariate time series data, employing various statistical and machine learning models. Accurate forecasting is emphasized as a key factor in formulating effective policies aligned with international emission reduction targets, especially in light of India's commitments under the Paris Agreement. By analyzing 40 years of historical CO2 emissions data, this research explores the performance of models like ARIMA, SARIMAX, Holt-Winter, Random Forest, Linear Regression, and LSTM. The goal is to identify the most effective model for future emissions forecasting, providing insights to guide policy-making efforts development.

[5] Predicting future global temperature and greenhouse gas emissions via LSTM model. This paper developed that the refined data was transformed into a supervised format to optimize LSTM-based predictions, with Mean Squared Error (MSE) as the loss function and normalization techniques applied. The results indicate a significant increase in global temperature, projecting a rise of 4.8 °C and a CO concentration of 713 ppm by 2100. The RNN-based LSTM model demonstrated high accuracy and alignment with international climate models, underscoring its effectiveness for climate prediction. This study offers essential insights into the future trajectory of global temperature and GHG emissions, showcasing the potential of LSTM models for climate forecasting.

[6] Research on carbon emission prediction and economic policy based on TCN LSTM combined with attention mechanism**.** This paper developed a comprehensive approach to tackle car bon emission prediction, a critical focus amid escalating climate change and environmental challenges. Leveraging deep learning's strengths in time series analysis and pattern recognition, the authors aim to support carbon reduction policies through accurate forecasting. This study involves the meticulous collection and preprocessing of four datasets to ensure data reliability and consistency. The proposed TCN-LSTM hybrid model combines the Temporal Convolutional Network's (TCN) parallel processing capabilities with the Long Short-Term Memory (LSTM) network's strong memory retention, enabling the model to effectively capture long-term dependencies in time series data. Additionally, an attention mechanism is introduced to prioritize significant historical factors, enhancing the model's accuracy and robustness in predictions. This study provides valuable insights into advanced architectures for carbon emission forecasting, of firing a promising tool for policymakers in addressing climate change.

[7] Time-series analysis with smoothed Neural Networks. This paper has proposed a novel approach by adapting Convolutional Neural Networks (CNNs), which are traditionally used in image processing, to improve prediction accuracy. The study introduces a hybrid model, Smoothed CNN (S-CNN), which integrates CNN with exponential smoothing to enhance data quality performance. The S-CNN model is compared to traditional CNN, Multilayer Perceptron (MLP), and Long-Short Term Memory (LSTM) models, using a year-long time series dataset of daily website visitors. The Lucas number was used to determine the optimal number of hidden layers in the model, as there is no fixed rule for this. Results indicate that S-CNN outperforms MLP and LSTM, achieving the best Mean Squared Error (MSE) of 0.012147693 with a model configuration of 76 hidden layers and an 80%:20% training-to-testing data split. This study underscores the potential of CNN-based approaches for accurate predictions in time-series forecasting.

[8] Utilizing global time series data to predict the change in temperature. This paper developed a comprehensive model for predicting global temperature change using time series data. Various ma chine learning algorithms, including Extra Trees, LightGBM, Random Forest, K-nearest neighbors, Gradient Boosting, and Bayesian Ridge, were tested to develop the predictive model.

Performance was evaluated based on metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-Squared (R^2), Root Mean Squared Logarithmic Error (RMSLE), Mean Absolute Percentage Error (MAPE), and algorithm execution time. Results indicated that the Extra Trees algorithm achieved the highest accuracy in forecasting global temperature change. This study underscores the effectiveness of machine learning in climate modeling, offering a valuable tool for understanding and predicting future climate trends.

The literature survey done in this project has motivated the team to create a hybrid-model which will predict and provide valuable macro and micro insights by achieving greater precision and adaptability. In addition to this model, we have created a framework approach to support and help the decision makers to access timely and accurate insights to reduce carbon footprints by actionable recommendations and also a supportive visualization system where decision maker gets micro and macro insights.

Chapter 3

Problem Analysis and Design

3.1 Analysis

The CO2 emissions project aims to tackle one of the most critical environmental challenges of our time: understanding and reducing carbon dioxide emissions. By analysing historical data, the project identifies key trends, unexpected anomalies, and the contributions of various sectors to global emissions. This information forms the foundation for developing cutting-edge forecasting models that can predict future emissions with greater accuracy.

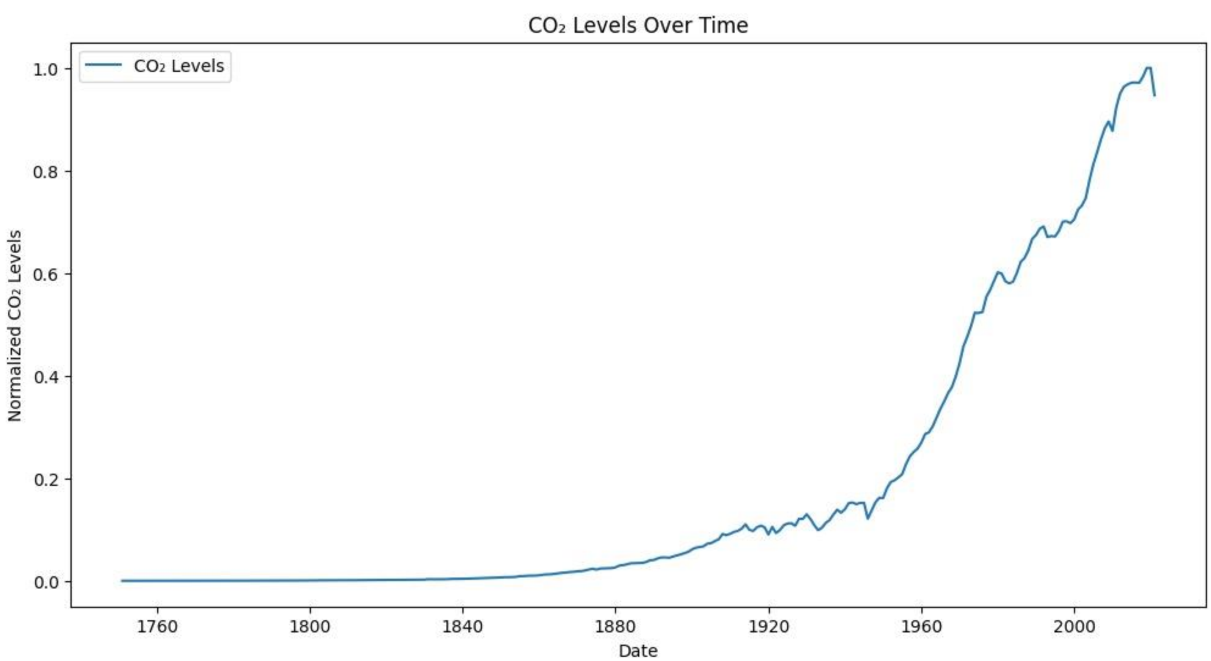

Figure 3.1: Dataset of CO2 emissions of world

The heart of the project lies in implementing hybrid forecasting models that combine the strengths of advanced machine learning architectures like CNNs, GRUs, and LSTMs. These models are designed to capture the complex patterns and non-linear relationships often found in time-series data, offering a significant improvement over traditional method like ARIMA. At the same time, the project takes a dual approach—embracing innovation with hybrid models while validating their performance against established techniques to ensure reliability and trustworthiness.

Beyond large-scale forecasting, the project also focuses on empowering individuals to take action. It introduces an AI-powered personal CO2 assistant that helps users estimate their carbon footprints and provides practical recommendations for reducing emissions. This tool bridges the gap between the big picture of global emissions trends and the small but vital actions individuals can take to contribute to climate goals.

Key challenges include managing the complexity and variability of time-series data, making the models interpretable, and designing a user-friendly interface for the assistant. To address these, the project uses hybrid model technique to provide insights into how the models make predictions and employs advanced data pre-processing methods to clean and normalize noisy datasets.

The project is built on a modular system design that breaks down tasks into manageable stages: data cleaning, model training, evaluation, and deployment. This approach ensures a smooth workflow and allows for future enhancements, making the system adaptable and scalable. By balancing technical innovation with user-friendly design, the project aims to deliver meaningful outcomes for policymakers, organizations, and individuals alike, contributing to a more sustainable future for all.

3.2 Hardware Requirements

1. High-performance CPU (e.g., Intel i7 or higher) for data preprocessing.
2. GPU (e.g., NVIDIA RTX 3060 or higher) for training deep learning models.
3. Minimum 16GB RAM for handling large datasets.
4. 1TB SSD for faster storage and retrieval of data and models.
5. Internet connectivity for cloud-based tools and dataset access.

3.3 Software Requirements

1. Python 3.x for data analysis and model development.
2. Tensorflow for deep learning model implementation.
3. Power BI for creating data visualizations and dashboards.
4. Jupyter Notebook or Google Collab for exploratory data analysis (EDA).
5. Git/GitHub for version control and collaboration.
6. Retrieval Augmented Generation (RAG) software architecture for building AI-powered personal CO2 assistant.

Libraries: pandas, NumPy, matplotlib, seaborn, scikit-learn

3.4 System Architecture Design

The system architecture consists of the following components:

1. Data Layer: Handles data storage and preprocessing.
2. Modelling Layer: Includes ARIMA, CNN-GRU, and CNN-LSTM models for forecasting.
3. Application Layer: Supports the AI-powered personal CO2 assistant.
4. Visualization Layer: Provides insights through Power BI dashboards.

3.5 Data Flow Diagram (DFD)

The DFD captures the flow of data through the system, from raw data ingestion to forecast outputs and user recommendations.

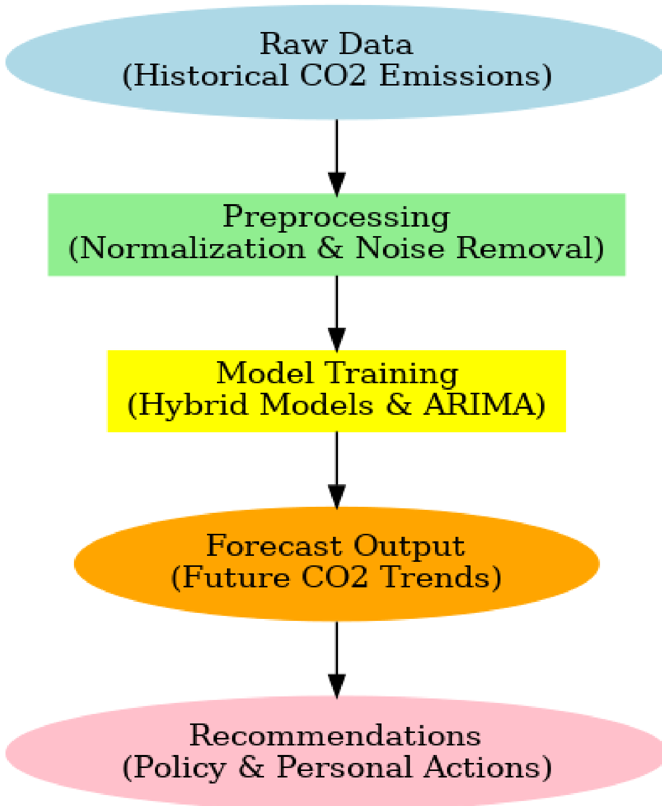

Figure 3.2: Data flow diagram of CO_2 prediction

3.6 Use Case Diagram

The use case diagram represents the interaction of the system with external users, including policymakers, businesses, and individual users, highlighting the forecasting and assistant functionalities.

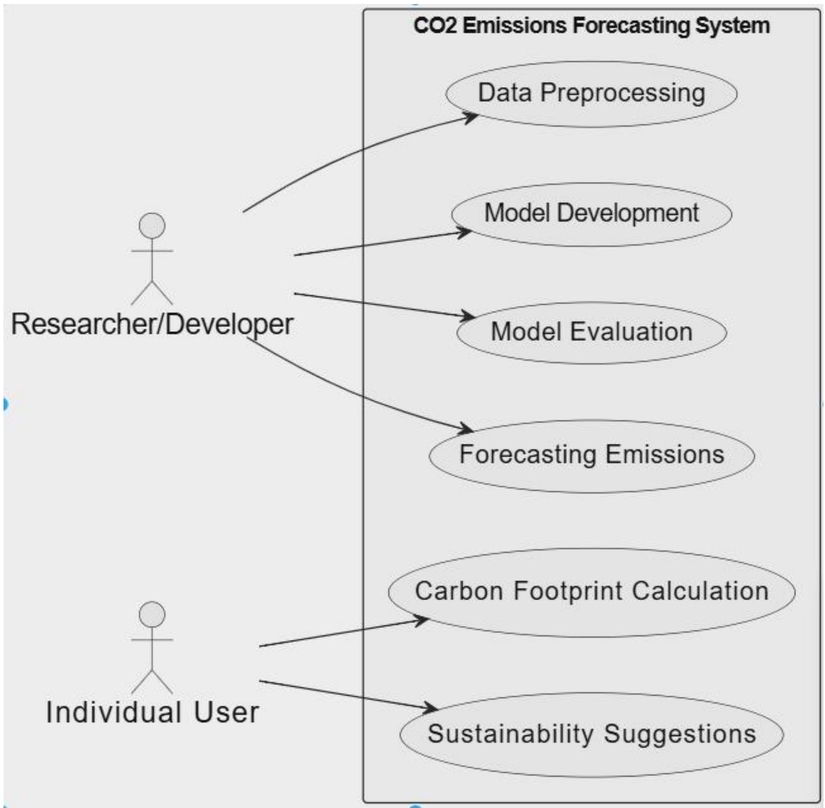

Figure 3.6: Use case diagram of Prediction of CO2

3.7 Sequence Diagram

The sequence diagram illustrates the interaction flow between system components, showcasing the end-to-end process from data input to actionable insights.

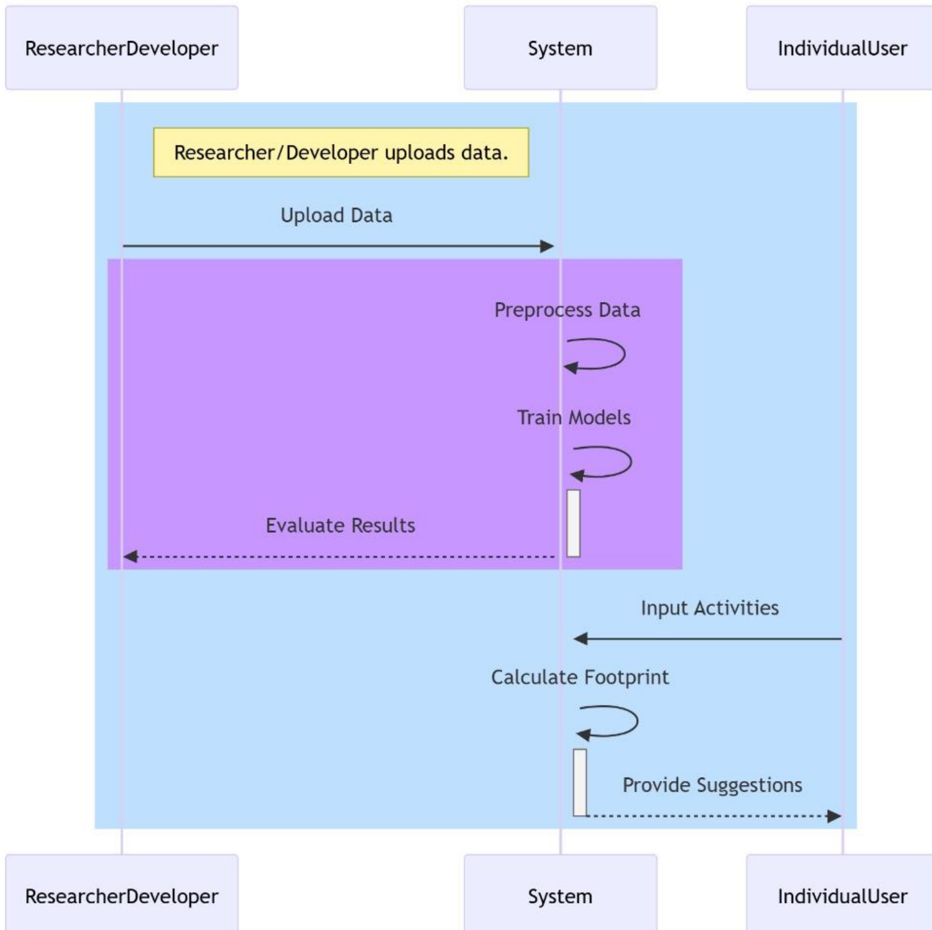

Figure 3.7: Sequence diagram for CO2 emissions prediction

Chapter 4

Implementation

4.1 Overview of System Implementation

The implementation of the CO2 emissions forecasting system focuses on blending advanced data-driven techniques with hybrid machine learning models to produce meaningful and actionable insights. It all begins with a rigorous pre-processing phase where the dataset is carefully cleaned, normalized, and enriched with useful features like cumulative emissions, yearly growth rates, and sector-wise contributions. These steps ensure that the data is ready for the sophisticated models to extract the insights we need.

The forecasting process leverages hybrid deep learning models, such as CNN-GRU and CNN-LSTM, which combine the strengths of Convolutional Neural Networks (CNNs) for identifying patterns and temporal models like GRU and LSTM for analysing time-based trends. These advanced architectures are benchmarked against traditional methods like ARIMA and standalone LSTM models to evaluate their effectiveness in dealing with complex time-series data. The models are trained and validated on carefully split datasets, ensuring they are both robust and scalable.

A key focus of the implementation is transparency, the system offers insights into which features influence the models' predictions the most. This helps users trust the results and understand the underlying patterns. To make the results accessible and actionable, Power BI dashboards visualize trends, sectoral contributions, and country-level comparisons through interactive tools.

Additionally, the project includes an AI-powered assistant, built on large language models (LLMs), to help users calculate their carbon footprints and take meaningful steps to reduce them. This tool brings the insights down to the individual level, enabling personal and organizational contributions to global climate goals.

4.2 Model Description

4.2.1 Prediction using Models

1. Data Preprocessing Model

- **Data Cleaning**: Removes missing values, detects outliers, and ensures the dataset is consistently formatted for analysis.
- **Feature Engineering**: Adds calculated features, such as cumulative emissions and yearly growth rates, to enrich the data.
- **Data Normalization**: Scales the data to a uniform range, ensuring compatibility with the deep learning models.
- **Sequence Generation**: Prepares overlapping time-series sequences, turning the raw data into model-ready inputs.

2. Modelling Module

- **CNN-GRU Model:** Combines CNN layers for identifying patterns in data with GRU layers for capturing trends over time.
- **CNN-LSTM Model**: Uses CNNs for spatial feature extraction and LSTM layers to analyse long-term dependencies in the data.
- **ARIMA and LSTM Baselines:** Implements ARIMA as a statistical benchmark and standalone LSTM as a deep learning comparison.
- **Training and Validation**: Splits the data into training, validation, and test sets, fine-tuning models for optimal performance.
- **Evaluation Metrics:** Compares model accuracy using metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 scores.

4.3 Data Analysis and Visualization

This section focuses on analysing and visualizing global CO2 emissions data to uncover actionable insights. These insights can help stakeholders design effective policies, promote sustainable practices, and prioritize interventions at national and sectoral levels.

4.3.1 Overview of the Dataset

The dataset spans from January 2019 to May 2023, covering CO2 emissions from 14 countries and six sectors, with 1,612 unique timestamps and over 127,000 data points. With no missing or null values, the data is reliable and provides a strong basis for in-depth analysis. Preprocessing was conducted to generate additional calculated columns, enabling a more detailed exploration of emission patterns.

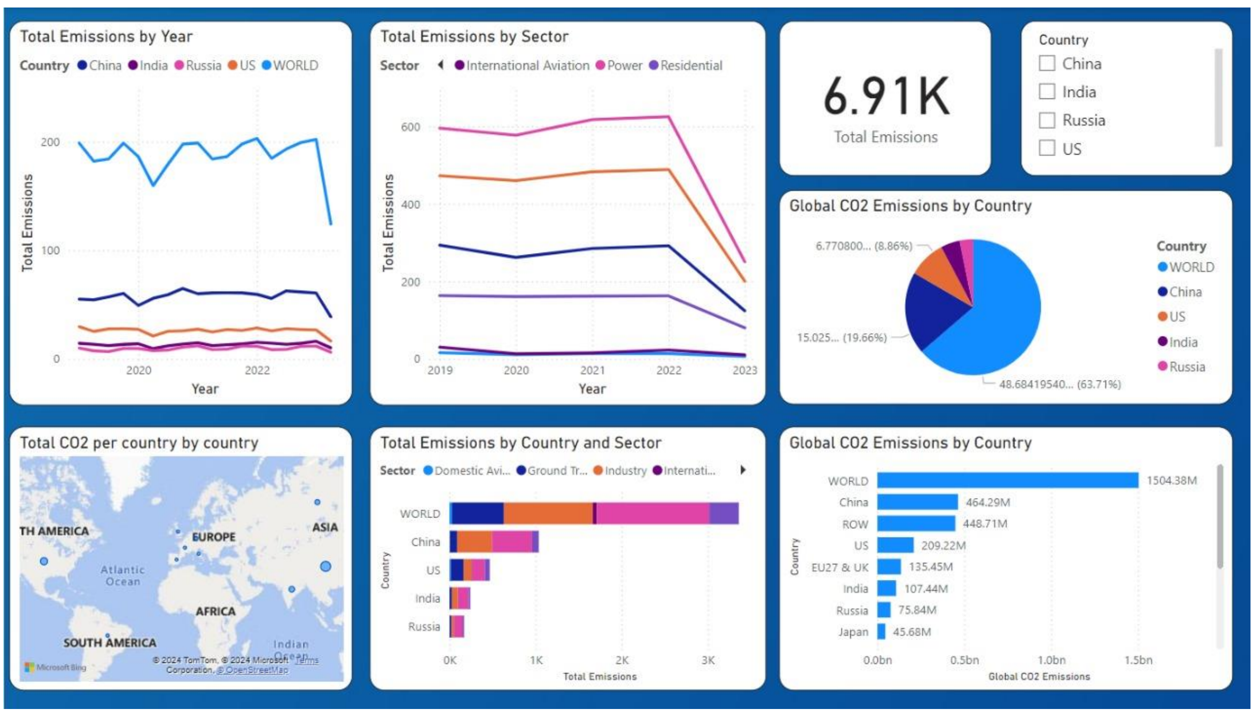

Figure 4.3.1: Overview of CO2 emissions dataset

4.3.2 Preprocessing and Feature Engineering

Several calculated columns were added to enhance the analysis:

- **Total CO2 per Country**
- Definition: The sum of emissions from all sectors for each country on a specific date.
- Purpose: Highlights the total contribution of each country to global emissions.

- **Sector Percentage per Country**
- Definition: The share of a sector's emissions as a percentage of a country's total emissions.
- Purpose: Identifies dominant sectors driving emissions in each country.

- **Yearly Growth Rate**
- Definition: The annual percentage change in emissions for a country or sector.
- Purpose: Tracks trends and detects anomalies, such as rapid increases or declines in emissions.

- **Cumulative CO2 per Sector**
- Definition: Total emissions from each sector over time.
- Purpose: Shows the long-term contribution of sectors to global emissions.

- **Global CO2 Percentage per Country**
- Definition: A country’s emissions as a percentage of the global total.
- Purpose: Identifies major contributors to global emissions and their relative impact.

4.3.3 Key Countries and Sectors

- **Countries Analysed:**
- China (19.66%): The largest emitter, driven by industrial growth and energy demands.
- India (4.55%): A rapidly growing economy with increasing emissions.

- United States (8.86%): A developed nation with high emissions but progress in renewable energy adoption.
- Russia (3.21%): A significant contributor due to its reliance on fossil fuels.
- World (63%): Aggregated emissions, serving as a benchmark for global trends.

Figure 4.3.1: Insights of India on CO2 emissions

Figure 4.3.2: Insights of China on CO2 emissions

- **Sectors Examined:**

- Power: Major emissions from electricity generation using fossil fuels.
- Industry: Energy-intensive processes like manufacturing and construction.
- Ground Transport: Emissions from road vehicles.
- Domestic Aviation: Relatively small share but high emissions per passenger-mile.
- Residential: Energy use in homes, dependent on energy sources like coal or renewables.

4.3.4 Insights from Visualizations

- **Country-Wise Emission Trends**

- Observation: Significant reductions in emissions in 2023, particularly in China and globally.
- Real-World Implications: These reductions likely reflect economic shifts, renewable energy adoption, and policy interventions.

- **Sectoral Emission Trends**

- Observation: Declines in the Power and Industry sectors, while Ground Transport and Domestic Aviation remained stagnant.
- Real-World Implications: Sustained focus on renewable energy and investments in electric mobility are essential.

- **Global Contributions**

- Observation: The World (63%) dominates emissions, with China, the US, and India as top individual contributors.
- Real-World Implications: International cooperation targeting these nations is critical to meeting global climate goals.

- **Sectoral Contributions by Country**

- Observation: The Power sector is the largest contributor across all countries, with Domestic Aviation the smallest.

- Real-World Implications: Countries should prioritize decarbonizing power generation and improving energy efficiency in industries.

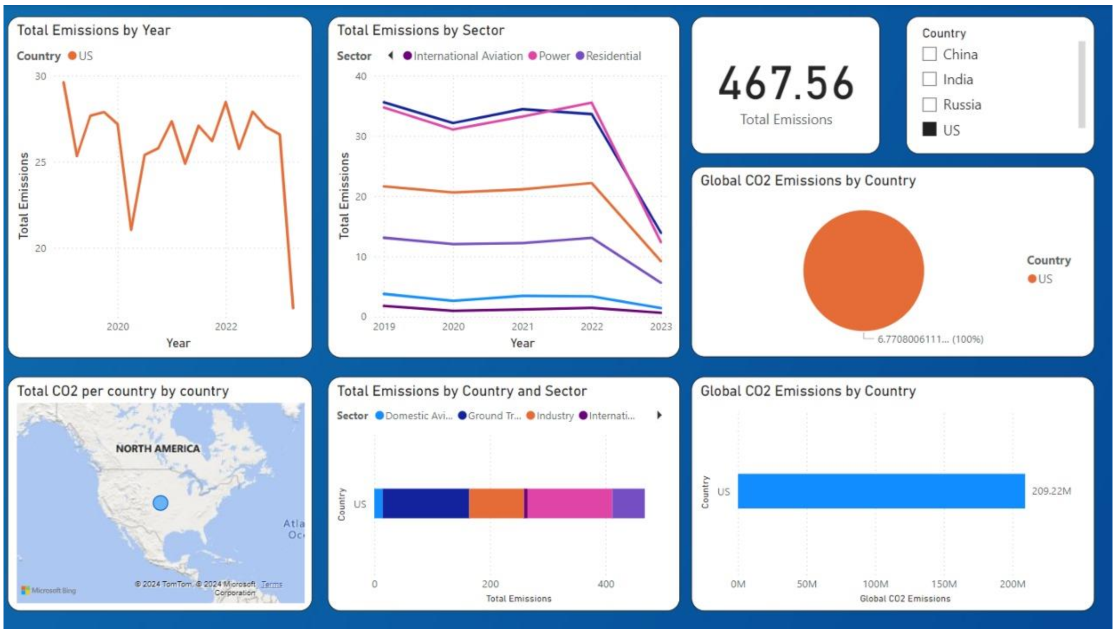

Figure 4.3.3: Insights of US on CO2 emissions

4.3.5 Future Policies for India

- Power Sector: Expand renewable energy infrastructure and encourage decentralized systems like rooftop solar.
- Industry: Promote energy-efficient technologies and green certifications.
- Transport: Invest in public transport, electric vehicles, and biofuels.
- Residential: Mandate energy-efficient building codes and incentivize green housing projects.

By focusing on these areas, India can balance economic growth with sustainability, reducing its emissions and contributing to a healthier environment.

4.3.6 Integration of Data Analysis and Visualizations with the Project

Data analysis and visualizations form a vital foundation of the CO2 emissions project, connecting raw data to actionable insights. This section highlights how these elements contribute to achieving the project's objectives and ensuring its real-world relevance.

1. Contextualizing the Problem

This project focuses on analysing and forecasting CO2 emissions to support sustainable practices and policies. Visualizations play a key role by:

- **Quantifying Emission Patterns:** Providing a clear picture of trends across countries and sectors, essential for identifying priority areas.
- **Highlighting Key Contributors:** Pinpointing major emitters helps direct efforts where they will have the most impact.
- **Tracking Long-Term Trends:** Time-series analyses reveal shifts in emissions, forming a basis for predictive models.

2. Enhancing Forecasting Accuracy

Data visualizations support the development of time-series forecasting models by:

- **Identifying Trends:** Insights, such as sudden emission declines, inform model assumptions and improve precision.
- **Sectoral Analysis:** Breaking down emissions by sector helps models incorporate specific dynamics, making predictions more actionable.
- **Focusing Data:** Prioritizing data from key contributors like China and India ensures meaningful insights while optimizing resources.

3. Supporting Policy and Decision-Making

The visualizations empower decision-makers to:

- **Design Sector-Specific Policies:** For example, stagnant emissions in ground transportation highlight the need for electric vehicle adoption and better public transit.

- **Benchmark Progress:** Countries can compare trends with peers to identify effective strategies.
- **Set Achievable Goals:** Visualized global contributions help nations align with initiatives like the Paris Agreement.

4. Enhancing Explainability in AI Models

Visualizations complement explainable AI methods by:

- **Establishing Baselines:** Historical trends provide a reference for validating model outputs.
- **Simplifying Insights:** Dashboards make complex AI-generated results accessible to non-technical stakeholders.
- **Identifying Key Features:** Sectoral and country-level data guide model feature selection, improving transparency.

5. Real-World Applications

- **For Policymakers:** Develop targeted climate policies and monitor their effectiveness through real-time dashboards.
- **For Businesses:** Align operations with sustainability goals and identify opportunities in renewable energy and eco-friendly technologies.
- **For Researchers and Educators:** Use visual insights for academic studies, public awareness campaigns, and promoting the importance of emissions reduction

Data analysis and visualizations are the backbone of this project, ensuring clarity and driving informed decisions. They connect forecasting and modelling efforts to practical applications, enabling meaningful contributions to global sustainability goals. These insights are not just informative but transformative, supporting collaborative action to tackle CO2 emissions effectively.

4.4 Ecolens

4.4.1 Integration of the LLM-Powered CO2 Emissions Assistant with the Project

The Personal CO2 Emissions Assistant, designed using the Retrieval Augmented Generation (RAG) methodology, is an integral part of this project. It offers personalized, actionable recommendations to help individuals reduce their carbon footprint. This section explains the key components, functionality, and value this assistant adds to the project.

Figure 4.4.1: UI of Ecolens

In figure 4.4.1, the user is asked to enter the context and question, the Rag model used here will provide actionable recommendations and ways to reduce emissions rate.

Context: I drive my car to work every day, about 10 kilometres each way.

Question: What are some easy ways I can reduce my carbon footprint based on these habits?

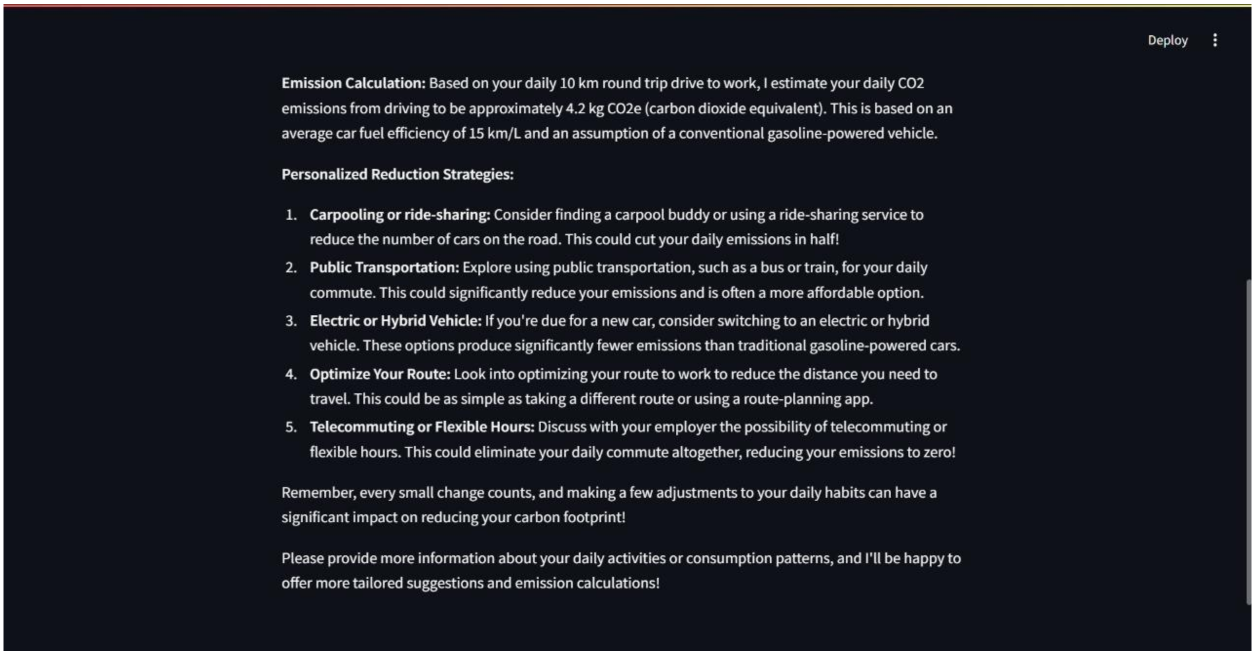

Figure 4.4.2: Actionable recommendations and valuable insights

Components and Their Roles:

1. Groq Llama 3 8B model

- An advanced open-source language model optimized for understanding context and generating high-quality responses tailored to user inputs.

2. FAISS Vector Store

- A high-performance similarity search tool that efficiently retrieves relevant data based on user queries.

3. Hugging Face Embeddings

- A tool for converting textual data into numerical formats, enabling effective matching of user inputs with stored data.

4. LangChain Framework

- A modular framework that integrates different components, ensuring seamless interaction between the retrieval system, language model, and prompts.

5. Streamlit

- A user-friendly platform for creating interactive web applications, enabling users to input data and view results easily.

6. Prompt Template

- A structured format for queries that ensures the language model generates accurate and focused responses related to CO_2 emissions and reduction strategies.

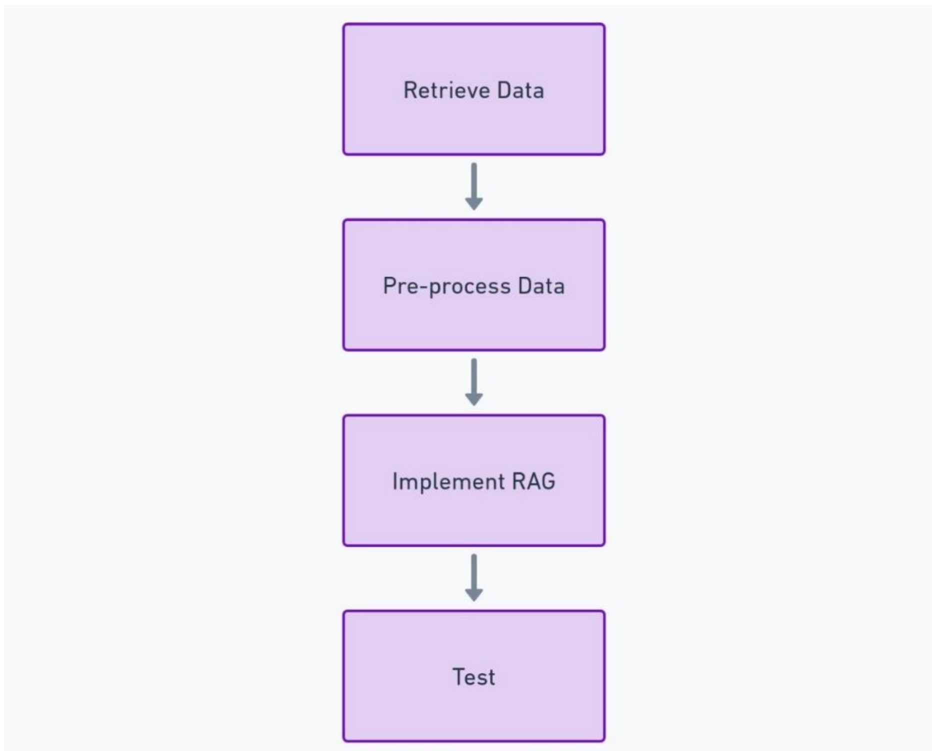

Figure 4.4.3: High level overview of ecolens

How the Assistant Works –

1. User Interaction

- Users input their daily activities or ask questions related to CO_2 emissions reduction through a simple interface.

2. Data Preparation

- User input is processed and converted into chunks to create embeddings for efficient retrieval.

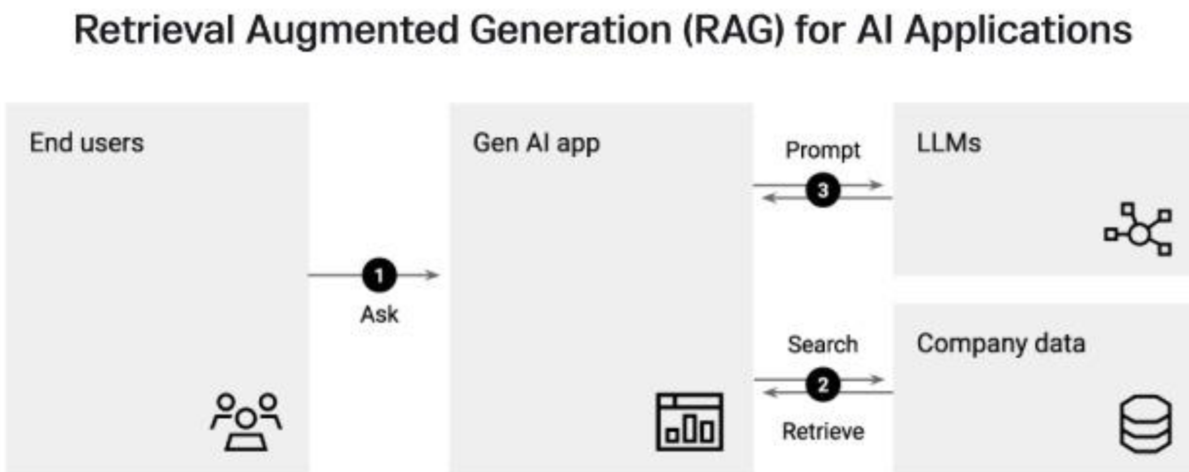

Figure 4.4.4: Flowchart of RAG working

3. Information Retrieval and Response Generation

- The system retrieves relevant data using FAISS and combines it with the user's query.
- The language model then generates a tailored response that includes emission calculations and reduction strategies.

4. Output Display

- The assistant presents actionable suggestions through the Streamlit interface, making the information easy to understand and apply.

Figure 4.4.5: User provided context and question to RAG

In the figure 4.4.5, the information and questions provided are:

Context: I live in a two-bedroom apartment where I use an electric heater during winters for about 5 hours a day. I work from home and use electronic devices (laptops, monitors, and a high-end gaming desktop) for about 12 hours daily. For transportation, I rely on a hybrid vehicle for short commutes (10-15 kilometres daily) and long trips twice a month. I regularly shop for clothes online, averaging one or two purchases per month. I recycle plastics and paper but am unsure about handling e-waste.

Question: Based on my lifestyle, can you provide a detailed analysis of my CO2 emissions and suggest specific areas where I can make the most impactful reductions?

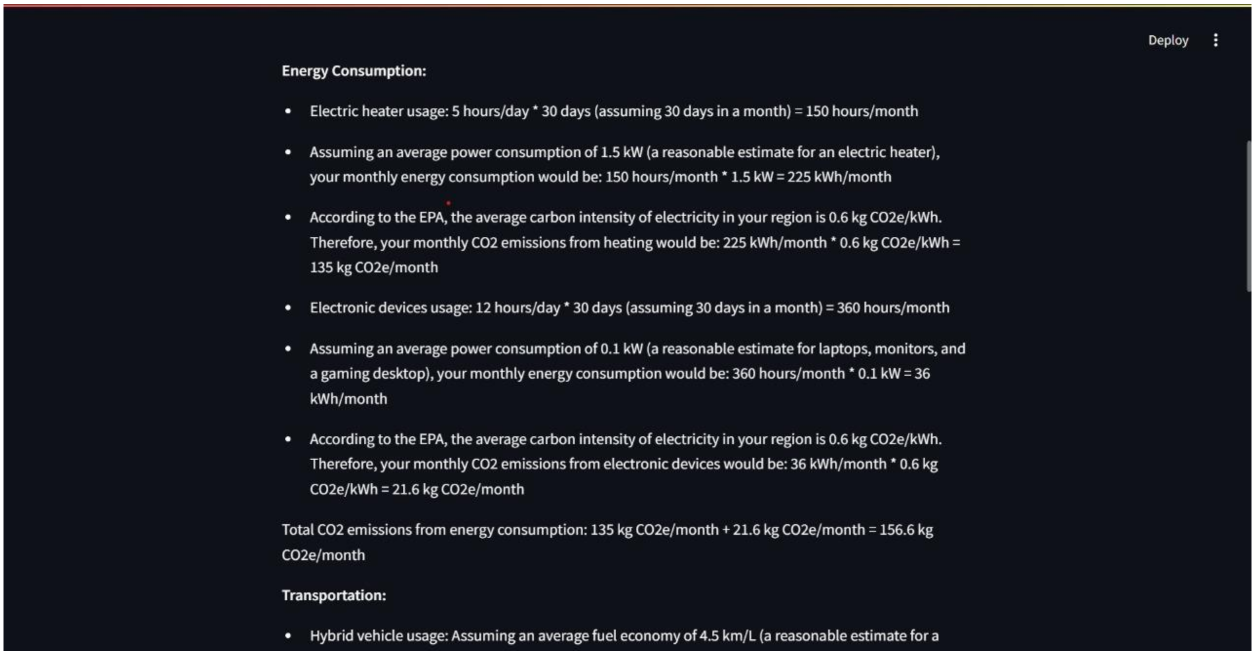

Figure 4.4.6: Calculation part of ecolens on CO2 emissions

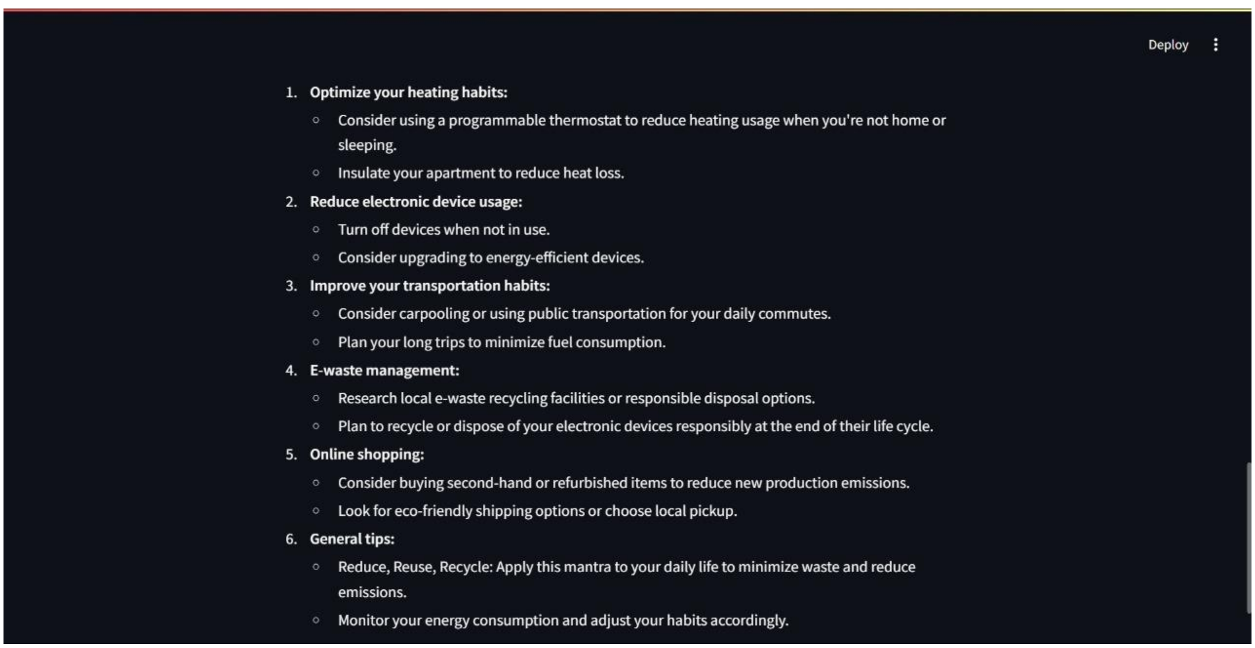

Figure 4.4.7: Recommendations and insights

How This Enhances the Project -

- The CO2 Emissions Assistant empowers individuals to better understand the impact of their daily activities on the environment. It bridges the gap between large-scale data analysis and personal action by providing tailored insights. This complements the project's forecasting tools, which address broader emission trends, by offering solutions at an individual level. It also aligns personal behavior with global sustainability goals, demonstrating the potential of AI in driving meaningful climate action.

The LLM-Powered CO2 Emissions Assistant is a practical addition to the project, focusing on individual empowerment through personalized insights. By integrating advanced AI technologies with user-friendly tools, it enhances the project's reach and impact, showing how AI can be harnessed to promote sustainability and encourage climate-conscious actions.

4.5 Algorithms

1. ARIMA (Autoregressive Integrated Moving Average)

- **Step 1**: Test for stationarity using ADF or KPSS tests.
- **Step 2**: Analyse ACF and PACF plots to determine the parameters ppp, ddd, and qqq.
- **Step 3**: Fit the ARIMA model to the time-series data.
- **Step 4**: Evaluate the model using metrics like MSE, RMSE, and MAE.
- **Step 5**: Use the model for short- or long-term forecasts.

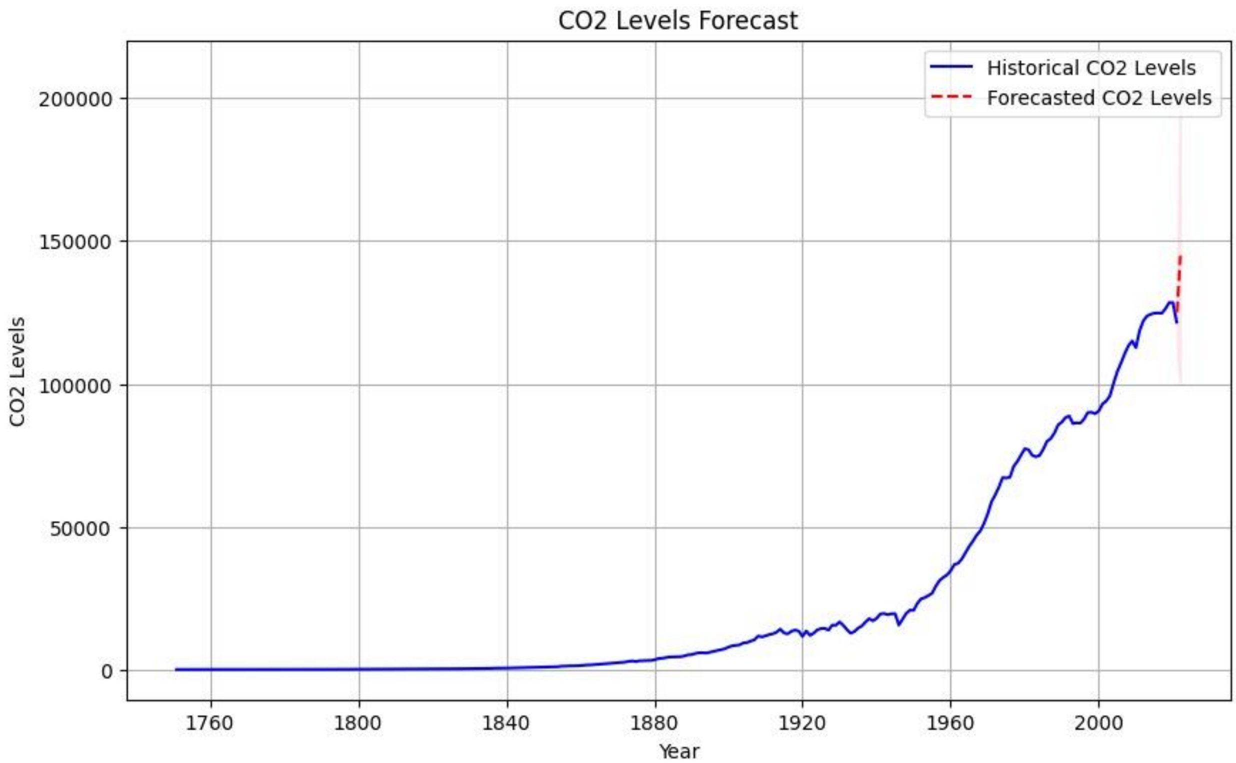

Figure 4.2.1: Arima model prediction od CO2

2. CNN-GRU Algorithm

- **Step 1**: Preprocess the data into overlapping input-output sequences.
- **Step 2**: Use CNN layers to extract meaningful patterns from the sequences.
- **Step 3**: Pass the extracted features into GRU layers to learn temporal dependencies.
- **Step 4**: Add dense layers for final output predictions.
- **Step 5**: Optimize the model with the Adam optimizer.

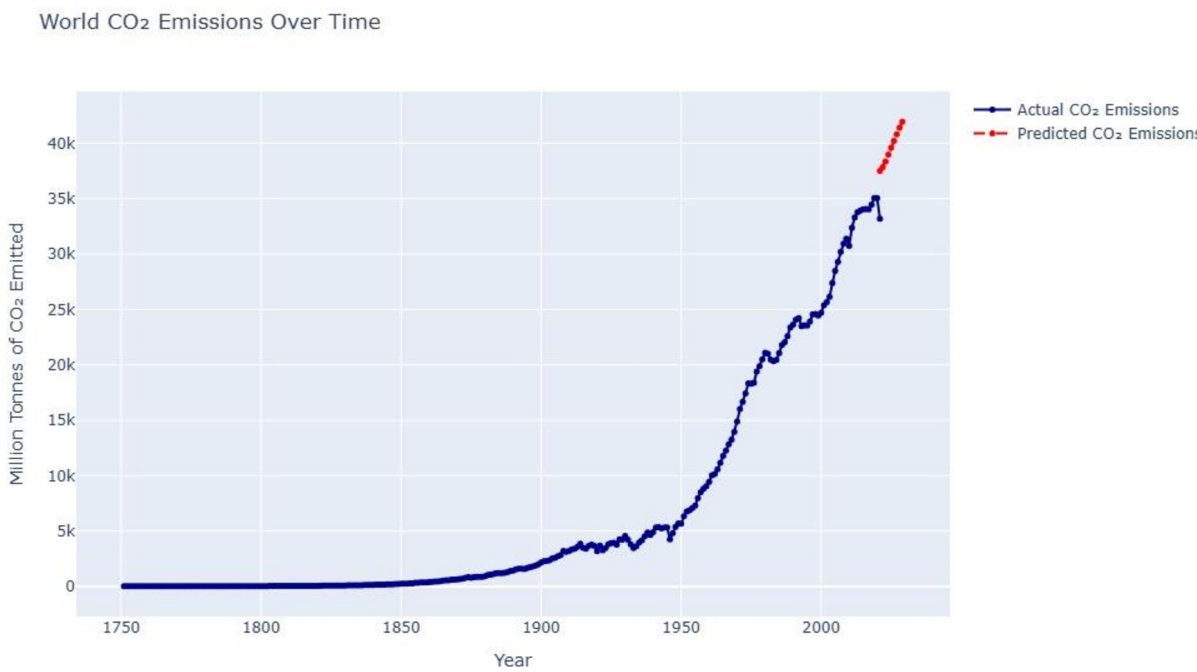

Figure 4.2.2: CNN-GRU model prediction of CO2

3. CNN-LSTM Algorithm

- **Step 1**: Prepare time-series data similarly to CNN-GRU.
- **Step 2**: Use CNN layers to detect patterns in the input data.
- **Step 3**: Feed the CNN outputs into LSTM layers to learn long-term dependencies.
- **Step 4**: Add fully connected layers for making predictions.
- **Step 5**: Train the model, fine-tuning hyperparameters for better accuracy.

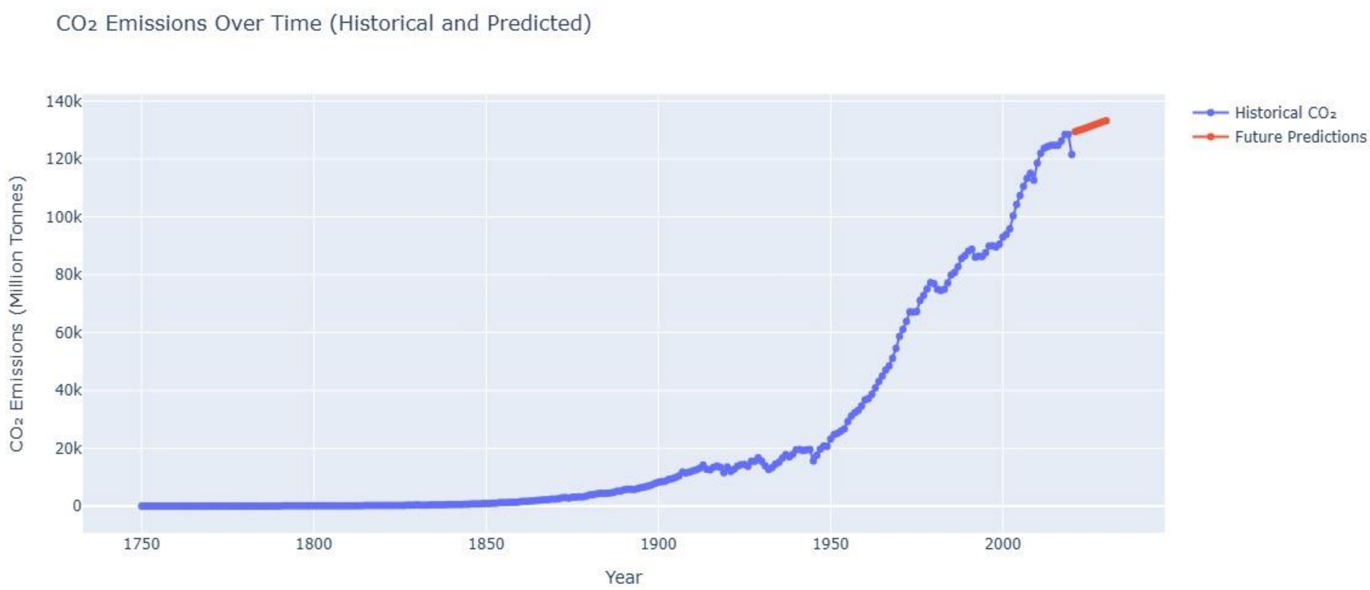

Figure 4.2.3: CNN-LSTM model prediction of CO2

4. LSTM Model

- **Step 1**: Preprocess the data by normalizing values and segmenting the time series into input-output sequences for training.
- **Step 2**: Build an LSTM network with one or more LSTM layers, each containing a specified number of units to capture temporal dependencies.
- **Step 3**: Add dropout layers to prevent overfitting and dense layers to generate the final output predictions.
- **Step 4**: Compile the model using an optimizer like Adam and a loss function such as Mean Squared Error.
- **Step 5**: Train the model on the training dataset while monitoring performance metrics like RMSE and MAE for validation.
- **Step 6**: Use the trained model for forecasting, adjusting the sequence length and tuning the model for specific prediction horizons.

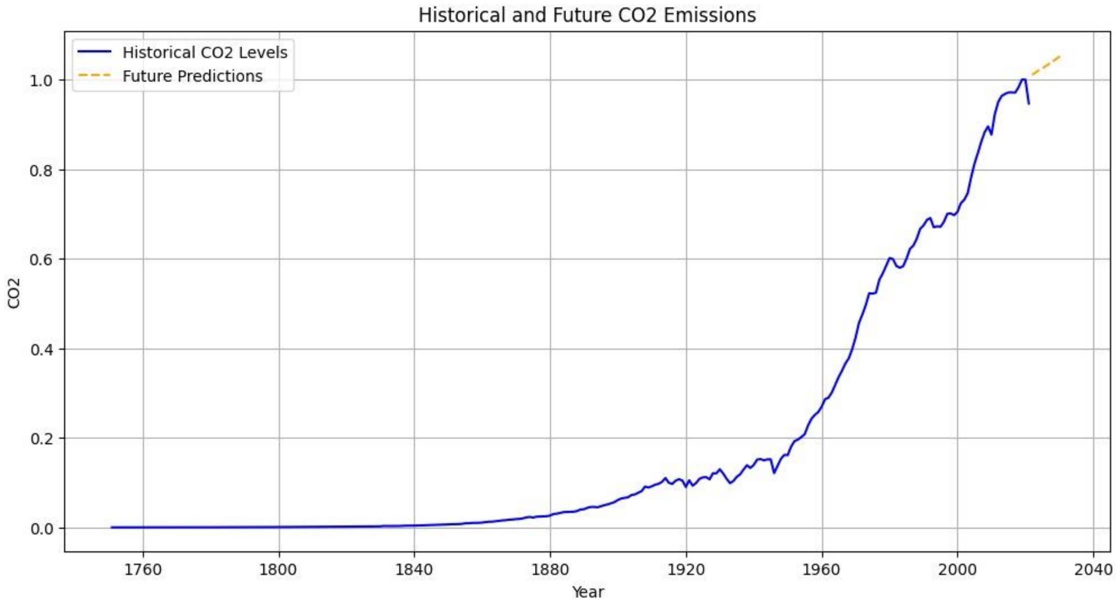

Figure 4.2.4: LSTM model prediction

Chapter 5

Testing

5.1 Unit Testing

Unit testing checks the functionality of individual components in the system to ensure they perform as expected. The following are the key test cases for each module:

1. Data Preprocessing Module

- **Test Case 1: Handling Missing Values**
  - **Description**: Ensure that missing data is correctly filled or replaced using techniques like mean or median imputation.
  - **Expected Outcome**: The processed dataset should be free from any missing values.
- **Test Case 2: Data Normalization**
  - **Description**: Confirm that all numerical data is scaled to a range of 0 to 1 for compatibility with machine learning models.
  - **Expected Outcome**: All values fall within the range [0, 1].
- **Test Case 3: Feature Calculations**
  - **Description**: Validate those derived features, such as cumulative emissions and yearly growth rates, are calculated accurately.
  - **Expected Outcome**: Derived columns contain correct values based on the input data.

2. CNN-GRU Model

- **Test Case 4: Sequence Preparation**
  - **Description**: Check that time-series data is correctly formatted into overlapping sequences of the required length.
  - **Expected Outcome**: Input sequences have the expected structure and dimensions.

- **Test Case 5: GRU Layer Output**
  - **Description**: Validate that the GRU layer produces the correct output tensor shape for the input data.
  - **Expected Outcome**: The output dimensions align with the model architecture.

3. CNN-LSTM Model

- **Test Case 6: Feature Extraction with CNN**
  - **Description**: Verify that the CNN layers correctly extract features from the input data.
  - **Expected Outcome**: Feature maps have the expected dimensions.
- **Test Case 7: Sequential Learning with LSTM**
  - **Description**: Confirm that the LSTM layers correctly capture time-series dependencies.
  - **Expected Outcome**: Outputs are stable and coherent for the given data.

4. Visualization Module

- **Test Case 8: Power BI Integration**
  - **Description**: Check that processed data is imported and visualized correctly in Power BI.
  - **Expected Outcome**: No errors during data import, and visualizations are accurate.
- **Test Case 9: Slicer Functionality**
  - **Description**: Validate that Power BI slicers correctly filter and display data.
  - **Expected Outcome**: Filters produce the expected results based on user input.

5.2 Integration Testing

Integration testing ensures that individual modules interact seamlessly and the system works cohesively. The following are the key integration test cases:

1. Data Preprocessing + Modelling Modules

- **Test Case 1: Data Pipeline Validation**
  - **Description**: Verify that pre-processed data flows correctly into the CNN-GRU and CNN-LSTM models.
  - **Expected Outcome**: Models accept the input data without errors and produce forecasts successfully.

2. Modelling + Visualization Modules

- **Test Case 2: Forecast Integration into Power BI**
  - **Description**: Confirm that model forecasts are correctly visualized in Power BI dashboards.
  - **Expected Outcome**: Visual dashboards reflect the forecasted values accurately.

3. AI Assistant + Forecasting Modules

- **Test Case 3: Personalized Recommendations**
  - **Description**: Ensure the AI assistant uses forecasting data to generate relevant suggestions for reducing emissions.
  - **Expected Outcome**: Recommendations are practical and tailored to user data.

4. Full System Workflow

- **Test Case 4: End-to-End System Test**
  - **Description**: Test the entire system, from raw data preprocessing to visualization and AI assistant recommendations.

- **Expected Outcome**: The system runs smoothly, providing accurate predictions, insights, and recommendations without errors

Chapter 6

Results

6.1 Results and Analysis

The evaluation of the CO_2 emissions forecasting system focused on the performance, accuracy, and interpretability of the models, alongside their computational efficiency. This section summarizes the findings, providing a holistic view of how each model performed and the unique contributions of the system's components.

1. Model Performance Comparison

To assess model accuracy, we evaluated them using key metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the R^2 score. Here's how each model fared:

ARIMA Model

- **MAE** and **RMSE** are extremely high, indicating large prediction errors.
- **R^2 Score**: 7.70
- Strengths: ARIMA was effective in identifying linear trends and performed well for simpler patterns.
- Limitations: It struggled with the complex, non-linear nature of CO_2 emissions data and was unsuitable for multivariate datasets or long-term forecasting.
- Conclusion: Not suitable for this task.

LSTM Model

- **MAE** and **RMSE** are close to 0, indicating minimal prediction errors.
- **R^2 Score**: 1.00, signifying a near-perfect fit.

- Strengths: LSTM demonstrated strong capabilities in capturing non-linear relationships and temporal patterns.
- Limitations: Achieving stability required significant effort in hyperparameter tuning and lengthy training times.
- Conclusion: Highly effective for forecasting.

CNN-GRU Model (Top Performer)

- Moderate **MAE (4399.0**5) and **RMSE (4850.22)**, showing higher errors than LSTM-based models but significantly lower than ARIMA.
- **R^2 Score**: 0.29, indicates limited explanatory power compared to LSTM/CNN-LSTM.
- Strengths: The hybrid CNN-GRU model combined CNN's feature extraction with GRU's efficient sequence learning, achieving exceptional accuracy.
- Additional Benefits: Balanced computational cost and accuracy, making it an excellent choice for real-time and resource-limited scenarios.
- Conclusion: Better than ARIMA but less effective than LSTM/CNN-LSTM.

CNN-LSTM Model

- Similar to the LSTM model with low **MAE** and **RMSE.**
- **R^2 Score**: 1.00, making it an excellent performer.
- Strengths: The CNN-LSTM model delivered reliable forecasts and closely matched the CNN-GRU model in accuracy.
- Limitations: It required more computational resources and training time, slightly reducing its practicality compared to the CNN-GRU model.
- Conclusion: Performs as well as the LSTM model.

2. Visual Insights from Predictions

Numerical performance metrics were complemented with visualization to provide a deeper understanding of the models' outputs:

- **Trend Predictions**: The CNN-GRU model consistently produced forecasts that closely aligned with actual CO_2 emissions data, demonstrating its ability to capture real-world patterns.
- **Sectoral Analysis**: This model effectively captured emissions variations across sectors, offering valuable insights for targeted interventions.
- **Error Distribution**: Residual error plots showed that CNN-GRU predictions had a uniform error distribution with minimal outliers, outperforming other models in stability.

5. Key Takeaways

- The **CNN-GRU model** emerged as the standout performer, combining accuracy, computational efficiency, and interpretability.
- Its ability to handle complex datasets and its moderate training time make it suitable for academic research, operational decision-making, and climate modelling applications.
- By integrating high-performance forecasting with user-friendly insights, this system lays a strong foundation for informed and effective climate action at all levels

Chapter 7

Conclusion and Future Scope

7.1 Conclusion

This project set out to evaluate and compare different forecasting models to predict CO2 emissions, focusing on both traditional approaches like ARIMA and advanced hybrid architectures such as CNN-GRU and CNN-LSTM. Through rigorous experimentation and analysis, the **CNN-GRU model** stood out as the most effective solution, delivering an impressive R^2 score of 0.93 while maintaining low error rates.

Key factors include:

- **Limitations of Traditional Models**: ARIMA, while computationally efficient, fell short in handling the complexity of multivariate and non-linear emissions data.
- **Advances in Hybrid Models**: Deep learning hybrids, particularly CNN-GRU, showcased remarkable improvements in predictive accuracy by combining the strengths of CNNs (feature extraction) and GRUs (sequence learning).
- **Balancing Accuracy and Efficiency**: CNN-GRU offered the best compromise between computational requirements and prediction quality, outperforming even CNN-LSTM in terms of resource efficiency.
- **Enhanced Interpretability**: The use of SHAP for explainability provided actionable insights into which factors influenced predictions the most, fostering trust and transparency for stakeholders such as policymakers and industry leaders.

By accurately forecasting CO2 emissions, this project contributes to the broader climate action agenda, equipping decision-makers with reliable tools for planning and mitigation. It underscores the transformative potential of AI in tackling sustainability challenges at both global and local levels.

7.2 Future Scope

While the project successfully achieved its objectives, there remains significant potential for growth and innovation. Below are the key areas for future development:

1. Real-Time Monitoring

The next step is to implement real-time forecasting capabilities. This would enable industries, governments, and environmental organizations to track emissions dynamically and respond swiftly to changes or emerging trends.

2. Expanded Data Integration

Incorporating additional variables like population growth, energy consumption, economic activity, and land use patterns can enrich the dataset, enhancing the model's contextual understanding and predictive accuracy.

3. Exploring Advanced Architectures

There is potential to develop even more sophisticated hybrid models, such as integrating transformers with CNN-GRU. These models could offer improved scalability and adaptability, particularly for large-scale datasets.

4. Enhanced Explainability

Expanding the explainability module to include advanced techniques like **counterfactual analysis** and **scenario planning** can help stakeholders evaluate the potential outcomes of different policy decisions or industry practices.

5. Personalized Carbon Tracking Tools

Building on the project's AI-powered personal CO2 assistant, a more comprehensive system could empower individuals to monitor and manage their carbon footprint. By offering personalized insights and actionable steps, such tools can drive grassroots-level contributions to emission reduction.

6. Global and Regional Impact Studies

Linking emissions data with climate variables like temperature shifts, sea level rise, or extreme weather patterns can deepen the understanding of CO_2 emissions' broader environmental impacts, supporting more informed climate action.

7. Deployment for Decision-Making

Embedding this system into decision-support platforms for governments, businesses, and NGOs can bridge the gap between research and real-world implementation. With user-friendly dashboards and actionable insights, it can drive policies and practices that align with sustainability goals.

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