Hybrid Machine Learning and Generative AI Approach for Carbon Footprint Forecasting and Sustainable Policy Recommendations

Submitted by

Shakil Ahamed Riaz

221-35-995

Department of Software Engineering

Daffodil International University

Supervised by

Md. Shohel Arman

Assistant Professor

Department of Software Engineering

Daffodil International University

Bachelor of Science

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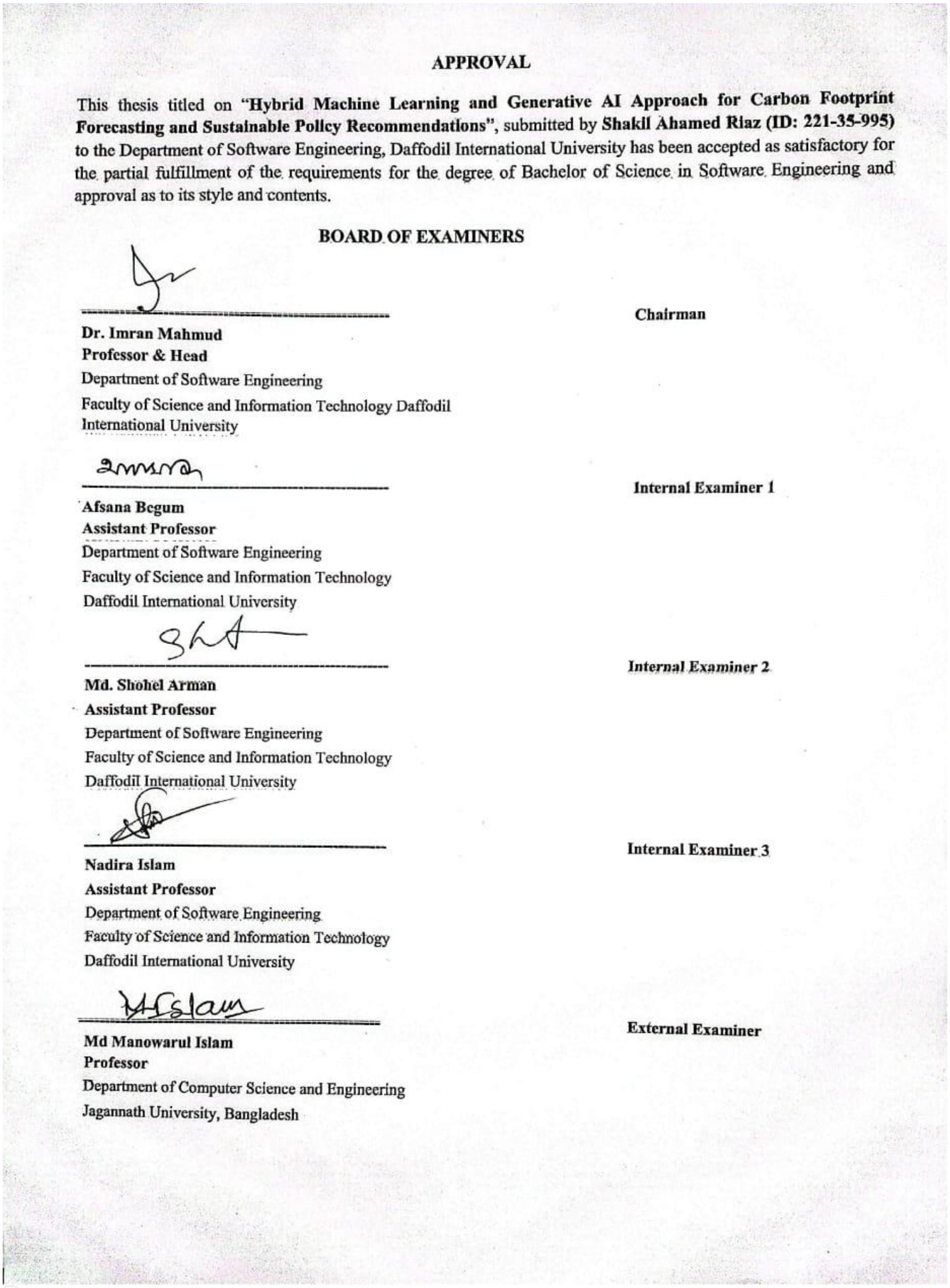

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ACKNOWLEDGEMENTS

I would like to sincerely thank my supervisor, Md. Shohel Arman, Assistant Professor in the Department of Software Engineering, for his unwavering support, helpful criticism, and direction throughout the writing of my thesis. His knowledge and words of support were essential to the project's successful conclusion.

I thank Dr. Imran Mahmud sir, Head of the Department of Software Engineering, Daffodil International University, for his advice and inspired me in life, and also created a very good environment conducive for me in my research work. My parents, Rafiqul Islam and Khaleda Begum Rekha, have my utmost regard; their unwavering encouragement, support, and prayers served as the cornerstones of my academic career. Their unwavering confidence in me inspired me to do this.

I am very grateful to the professors, friends, and well-wishers who helped me a lot during the thesis writing.

ABSTRACT

Mitigation of global climate change depends on accurate carbon emission forecasting and implementation of actionable, data-supported policy frameworks. This thesis proposes a unique hybrid architecture that blends state-of-the-art machine-learning techniques with Generative AI to pursue this purpose. Via an ambitious global sustainable energy dataset, we implement a multi-step approach to analyze country-level CO_2 emissions' estimations and predictions. The authors first develop time-series forecasting models such as ARIMA, XGBoost, and Long Short-Term Memory (LSTM) networks to capture emissions trends for the period 2026-2035. The second step clusters countries into different sustainability archetypes using K-Means, making judgments based upon selected economic, energy, and emission indices. Lastly, the study harnesses the predictive insights and the profile information obtained from the clustering via the Large Language Model (LLM) to create context-driven and professionally articulated mitigation strategies. Results show that the non-linear models, particularly XGBoost and LSTM, exhibit much better performance than the classical statistical baselines in relating complex emission dynamics. The XGBoost model has shown high predictive accuracy of the R^2 scored 0.998 and Mean Absolute Percentage Error of (MAPE) 1.38 while LSTM model performed fairly well with an R^2 of 0.987 and MAPE of 3.50. Moreover, through the effective Generative AI application, quantitative forecasts were turned into qualitative policy propositions, which immensely suit high-impact sectors. Thus, this dissertation showcases how the hybrid AI systems may actually change the game by linking raw environmental data with strategic decision-making to provide a sturdy instrument for policymakers in achieving the global sustainable development goals.

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Chapter 1

Introduction

1.1 Background of the Study

Greenhouse gas emissions tend to cause climate change when overloads occur. Currently, the ever-increasing emission of carbon dioxide, one of the greater constituents of greenhouse gases, constitutes one of the greatest challenges for the modern world. As nations direct an effort into the international climate agreements, the need for developing advanced computational tools in environmental sciences is ever increasing. AI and ML emerge as strong contenders in this field, finding uses and deployable abilities far beyond simple statistical analysis. Hence, with intelligent systems to optimize energy distributions and real-time tracking of emissions, AI has found a place in the ever-expanding arsenal of future CDR technologies cited in the recent literature [2][16].

For example, the focus of AI on sustainability was the optimization of supply chains to minimize wastage and emissions [8], while at the same time developing advanced frameworks for consumer low-carbon lifestyles [12]. AI has advanced to incorporating the branches of Natural Language Processing and Generative AI, which are used to estimate industrial carbon footprints from unstructured data sources, such as bank transactions [9]. This rare convergence of an advanced predictive analytic along with generative capability will be the research anchor in this study, attempting to utilize hybrid methods to forecast country-level carbon.

1.2 Importance of Carbon Footprint Forecasting

Accurate forecasting of CO_2 emissions is, therefore, not only of theoretical importance but has become a prerequisite to policymaking and even survival. Studies say that without reductions, the important 500 ppm-threshold, which is seen as the "point of no return" to irreversible climate change-would be reached as early as 2047 [4]. Consequently, all predictions on the emission pathways must be made with high accuracy, as this is vital for determining the rates of reversal that need to be achieved in order to reach safe atmospheric concentrations.

Predictive strategies offer opportunities for proactive interventions. For instance, one of the use cases for global supply chains by data-driven predictive modeling would be to identify key drivers of environmental impacts and thus allow considerable emissions reductions in operations [8].

Recent studies draw upon SARIMAX models and demonstrate that valid predictions allow for the appraisal of long-term trends in emissions affected by major global incidents like the COVID-19 pandemic [15]. Without valid forecasting, the policy-makers will not have the empirical basis to set real NDCs and overall achieve a high implementation efficiency in mitigation actions.

1.3 Limitations of Existing Methods

Despite very many advances made in environmental modeling, some specific methodological gaps still exist. Traditional econometric models and some standalone machine learning algorithms have not been able to model the complex non-linear interrelationships of generation of global emissions.

1. Inability to Handle Non-Linearity: Conventional state estimation techniques often fail when the applied to highly non-linear systems. Research suggests that hybrid approaches, such as combining Extended Kalman Filters with Artificial Neural Networks (ANNs), are necessary to reduce all estimation errors and unlock the full potential of sustainable technologies align with them [3].

2. Data Gaps and Complexity: Existing tools often face challenges regarding the data quality and the diversity of emission sources. Like, in the domain of geopolymer concrete, the lack of accurate predictive models necessitated the development of ensemble learning frameworks to account for complex and chemical variables [1].

3. Lack of Explainability: While Deep Learning(DL) models like Convolutional Neural Networks (CNNs) offer high accuracy, they often function as "black boxes," some lacking the interpretability scenario required for stakeholder trust [8].

4. Static Policy Generation: Most of forecasting studies stop at numerical types prediction. There is a major notable scarcity sof frameworks that translates quantitative data into qualitative way, actionable sustainable policy recommendations. While Generative AI has shown promise in recommending emission factors for Life Cycle Assessments (LCA) [5], its application in generating all country-specific macro-economic policy remains underexplored.

1.4 Research Motivation

This thesis motivation lies in the impatience between high-precision forecasts and policy synthesis actions. Studies focus on ML for certain industrial applications [1][7]. Meanwhile, studies on global forecasts utilize singular architectures [15][16]. There is a dearth of frameworks that would integrate predictive capacity of Hybrid Machine Learning with its possible interpretive power in Generative AI[20].

This research is based on the hypothesis that combining ensemble methods such as XGBoost with deep learning techniques such as LSTM would give rise to improved forecasting accuracy by these methods as compared to baseline traditional methods. This will also provide a possible solution for dealing with the "interpretability gap" by including a feature of Large Language Models (LLMs) in terms of translating raw forecasts into far more professional, context-aware policy recommendations. This also conforms to the ongoing trend towards the enhancement of decision making through AI technologies [13] and aims to develop an all-in tool for policymakers towards visualising future scenarios and implementing data-supported strategies towards sustainable futures [24].

Chapter 2

Literature Review

2.1 Introduction

The world of environmental science has undergone a dramatic paradigm shift from static, retrospective analysis to dynamic, predictive modeling driven by artificial intelligence (AI). As the sense of urgency to mitigate climate change quickly accelerates, researchers are turning to computational methods to estimate carbon footprints and optimize energy systems. This chapter discusses the evolution of carbon forecasting methodologies from classical econometric models to advanced machine learning (ML) and deep learning (DL) architectures. The chapter also discusses the nascent yet disruptive potential of generative AI (GenAI) in sustainability while exposing existing research gaps requiring the hybrid framework proposed here.

2.2 Traditional and Statistical Forecasting Methods

Statistical time series models have been the workhorse for the prediction of carbon emissions from ancient times. These methods presume that future trends are linear functions of the historical data. A prime candidate for this has been Autoregressive Integrated Moving Average (ARIMA) and its seasonal variant (SARIMAX). Meng and Noman [15] advertised the use of SARIMAX for modeling global CO_2 emissions, with special reference to its usefulness in separating the impacts of exogenous shocks like the COVID-19 pandemic or other microeconomic factors. With improved optimization of seasonal parameters, the study was able to achieve a calculated Mean Absolute Percentage Error (MAPE) of 0.09, thus establishing the fact that statistical models are still an even better baseline for stable time series-like data.

Whatever. Traditional models are found to be poor with high dimensional data with nonlinear characteristics. According to Liang et al. [3], conventional state estimation techniques fail in complex sustainable energy systems. Their study indicates that relying on purely linear assumptions can bring about large state estimation errors, thus requiring the application of non-linear approximation techniques to effectively harness environmental technologies.

2.3 Machine Learning Approaches in Environmental Science

One of the most significant aspects of a modern transformation in which Machine Learning has been incorporated to break away from the constraints of statistical linearity is that it models intricate input-output relationships. Bhatt et al. [4] have trained a package of machine learning algorithms to predict the global CO_2 concentrations. Some of these algorithms include Support Vector Machines (SVM) and K-Nearest Neighbours (KNN). Researchers specified that such ML techniques can very accurately forecast critical thresholds, such as the 'point of no return' at 500 ppm, for vital data with respect to reversal rates: [25].

Among various ML techniques, ensemble methods showed improved performance. Al-Fakih et al. [1] projected the carbon footprint of geopolymer concrete using a stacking ensemble model. Their work has evaluated single models like Decision Trees and Neural Networks, while ensemble one (including Gradient Boosting) produced lower prediction error. This validates the effort of the boosting algorithms such as XGBoost for carbon footprint tasks that are characterized by a rather complex feature interaction. Similarly, Lang et al. [7] applied Random Forest regression to assess product carbon footprints, surpassing analytical calculations and showcasing the capacity of ML to manage data scarce in industrial applications.

2.4 Deep Learning and Time-Series Forecasting

Long Short-Term Memory (LSTM) Networks are Deep Learning (DL) architectures that represent the best technology for sequential data with long-term dependencies. Unlike regular Recurrent Neural Networks (RNNs), they are designed to address the vanishing gradient problems and, therefore, to support effective multi-year climate forecasting [18] [21].

Intervention areas of Huang and Mao [8] in supply chain management through a convolutional neural network with deep learning revealed some critical drivers of environmental impact and yielded high prediction accuracy. Also, González-González et al. [9] related to the use of LSTM and Natural Language Processing (NLP) to derive industrial bank transaction data. Their studies show the versatility of the approach in dealing with unstructured sequential data which makes the use of LSTM justifiable for emission forecasting at country levels since time patterns are critical.

2.5 Generative AI and Policy Modeling

Generative AI (GenAI) is now tackling methodologically correct responses whereas predictive-AI is working on what happens next. Environmental science and the introduction of LLMs for that purpose form a new frontier of research. Balaji et al. [5] described "Parakeet"-a system using LLMs combined with Retrieval-Augmented Generation (RAG)-to recommend emission factors for Life Cycle Assessments (LCA). The study demonstrated that GenAI can accurately bridge the gap between technical data and expert decision-making by interpreting extremely complicated technical descriptions. [19][20, 22].

In addition to, Li et al. [2], spotted the integration of AI along with several Carbon Dioxide Removal (CDR) technologies and threw light on advantages of using AI for optimizing the deployment of removal facilities. Nonetheless, they point to a glaring critical gap in the absence of decision support tools that confront uncertainty and regulatory hurdles. Evidence is strong that AI has, indeed, made wonderful strides in decision making with respect to supply chains designed for sustainability[9]. However, the much-needed systems for deciphering stakeholder evaluation were brought forth as a crucial gap. A very recent addition by Hasan [13].

2.6 Research Gaps

Despite all these advancements, the literature reveals gaps:

1. Fragmentation of Methods: Most of the studies focus either on statistical forecasting [15] or industrial-specific Machine learning dirven applications [1][7]. There is a lack of integrated actual frameworks that combine the interpretability of ensemble learning methods (XGBoost) with the temporal power of Deep Learning (LSTM) for country-level carbon analysis [17].

2. Interpretability Gap: While models like ANNs and CNNs can offer high accuracy outcomes, they lack explainability or recommendation [3][8]. Stakeholders and policymakers require qualitative context, not just numerical outputs for this.

3. Absence of Automated Policy Synthesis: Current GenAI applications in sustainability are largely limited to classification or retrieval tasks [5][9]. There is a scarcity of research utilizing GenAI to synthesize macro-economic policy recommendations based on predictive clusters, which is the primary contribution of this thesis [20] [23].

2.7 Summary

The literature confirms that, although ARIMA and other traditional models form a baseline necessary for any forecasting model, hybrid and ensemble approaches in ML provide better forecasting accuracy for complex environmental data. In addition, the upcoming capabilities of Generative AI provide birth to new ways of converting these quantitative voices to qualitative actions. This thesis attempts to address the gaps above by developing a unified framework.

Chapter 3

Methodology

3.1 Research Framework and System Architecture

We're speaking here of a hybrid AI model which has brought statistical time-series analysis, supervised machine learning, unsupervised clustering, and LLMs (Large Language Models) into a singular framework. This is in order to address as comprehensively as possible all of the different facets through which carbon emission may be mitigated. Data are the starting point here, from which actionable insights for global energy policy are sought after, in this methodology represented as a multi-stage pipeline. The process has three phases of work: (1) Data Engineering and Exploratory Data Analysis, which harmonizes and augments historical data; (2) Predictive Modelling and Clustering, where forecasts of future emission trajectories and country-specific sustainability archetypes are created; (3) Synthesis for Policy, where the quantitative predictions are transformed by generative AI into qualitative professional policy recommendations.[20][21]. The conformative advantage of this holistic approach is that far from being theoretical, the final recommendations would be based on rigorous data-driven forecasts and steeped in country-specific economic and energy indicator realities.

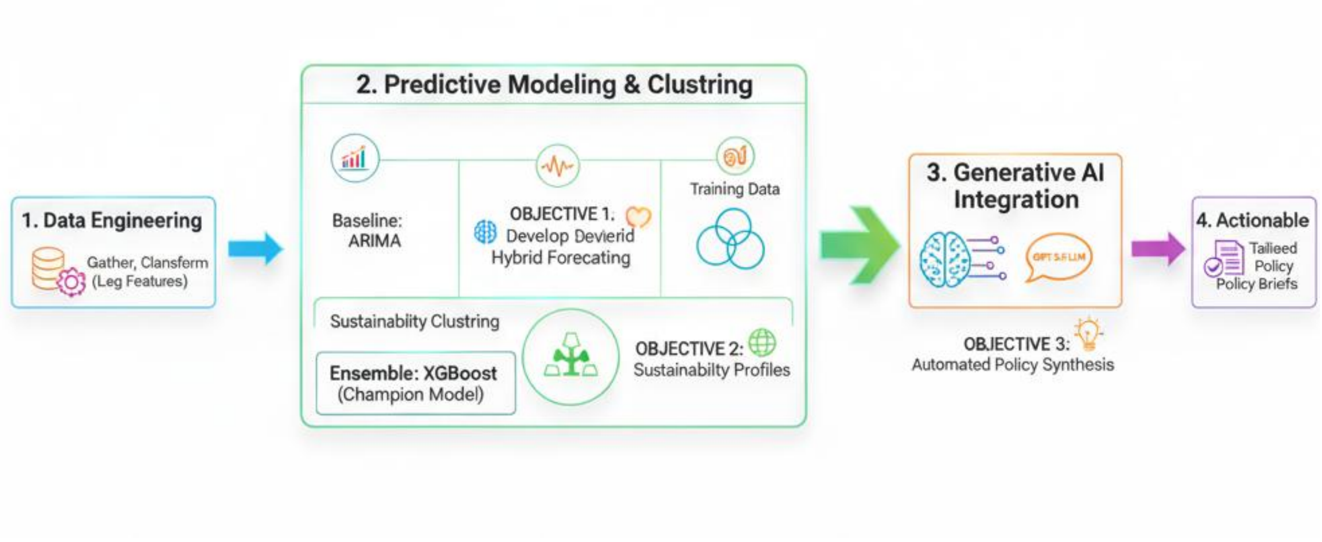


Fig 1: Proposed Hybrid Machine Learning & Generative AI Methodology Framework

3.2 Data Acquisition and Preprocessing

The research is supported by the dataset "Global Data on Sustainable Energy" between 2000 and 2020 across 174 countries. A rigorous preprocessing pipeline, as described in Figure 3.2, was implemented to ensure that the dataset is suitable for machine learning. The first part of data cleaning worked on standardizing column nomenclature and changing all numerical features into suitable data types. Another major problem with longitudinal global data is missing values; hence, to avoid introducing look-ahead bias, a grouped imputation strategy was used. Each country-specific time series was backward-filled from values forward-filled, thereby ensuring temporal continuity.

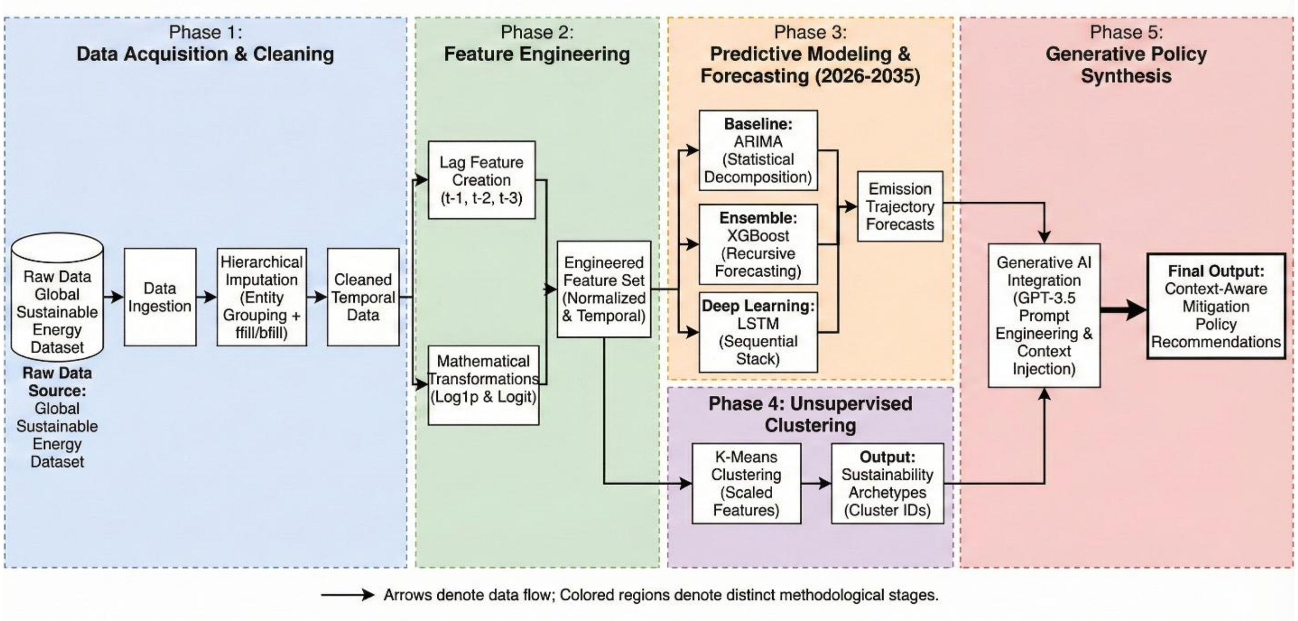


Fig 2: Data Acquisition & Preprocessing Flow

After imputation, feature engineering was carried out to include temporal dependencies and correct any statistical anomalies. Time-lagged features were generated on some major variables (namely, CO2 emissions, GDP per capita, and renewable energy capacity) at time lags of t−1, t−2, and t−3 to allow models to learn from these historical trends. Additionally, Log1p transformation was used on unbounded variables like GDP and CO2 emissions to address high skewness that usually characterizes economic and emissions data. Conversely, variables bounded between 0 and 100 (such as access to electricity and the share of renewables) used a Logit transformation. This transforms bounded probabilities into an unbounded real space, preventing the models from making predictions far from the real world (e.g., >100% electricity access) and assisting defective convergence of regression algorithms.

3.3 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was undertaken to understand the underlying distributions and relationships in the high-dimensional feature space before modeling. Pair plots visualized the non-linear relations between economic growth (GDP) and environmental impact (CO2), while Pearson correlation matrices were drawn up to detect multicollinearity among energy indicators. In order to isolate the temporal components of the data, a seasonal decomposition was applied to the emission time series of the top-emitting countries. This decomposition confirmed the presence of deterministic trends which justified the use of non-stationary time-series models by separating the data into trend, seasonal and residual components.

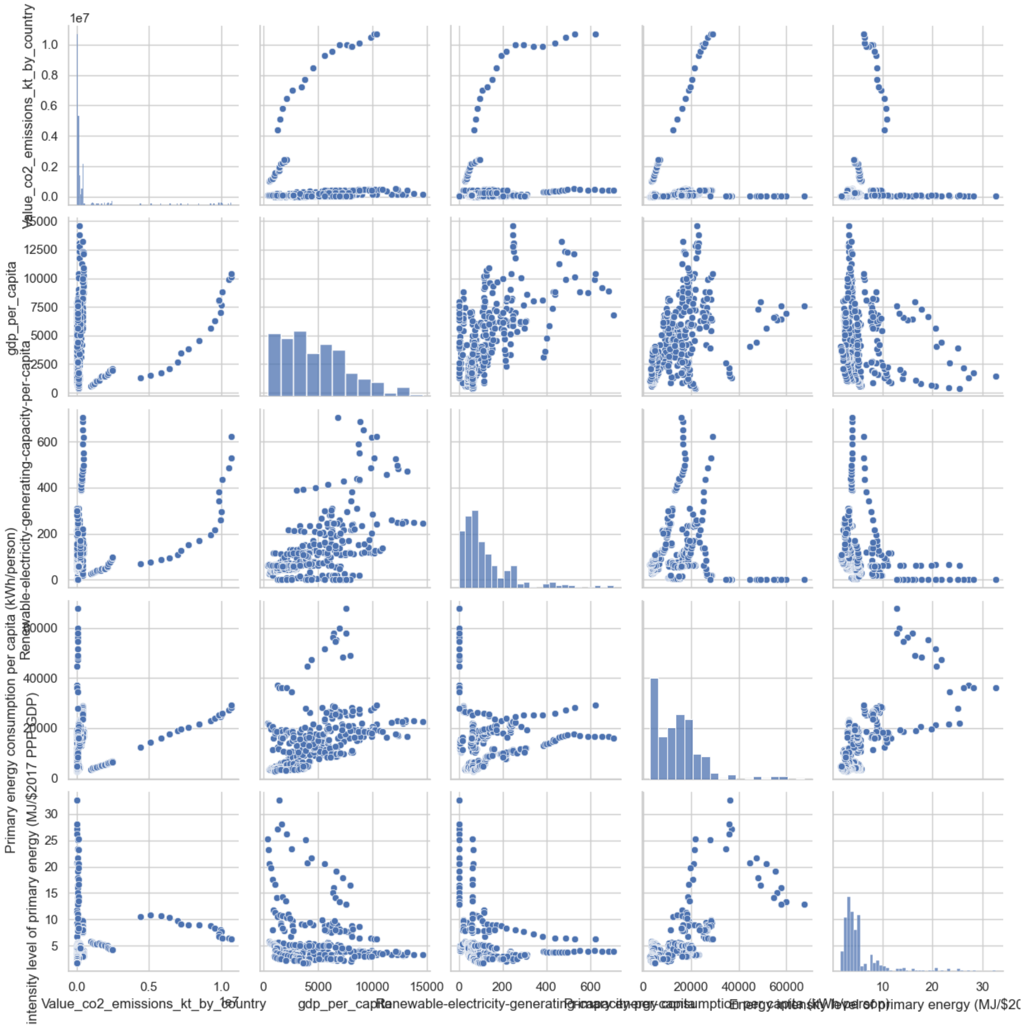


Fig 3: Pairplot of Main Energy and Economic Features

3.4 Predictive Modeling Strategies

For solid forecasting capability, the study created and compared three different modeling approaches: classical statistics, statistical learning, and deep learning.

3.4.1 Statistical Baseline: ARIMA

The statistical foundation for this work is an Auto-Regressive Integrated Moving Average (ARIMA) model. Given the order (3,1,2)(3,1,2), it has autoregressive terms for up to three lags, one degree of differencing for stationarity, and a moving average window of two. The baseline will then serve as a comparative standard against which one can measure if any statistically significant improvements are provided by complex machine learning algorithms over traditional linear forecasting techniques.

3.4.2 Ensemble Learning: XGBoost Regressor

XGBoost (Extreme Gradient Boosting), an efficient predictor for tabular datasets designed to capture non-linear feature interactions, was the primary predictive engine employed. In recursive forecasting, the model predicts one step ahead; that prediction value is then fed back as a lagged variable into the pool of predictor variable candidates for the prediction of the next step. In this way, forecasting can also be extended to multi-year forecasting (2026-2035), while still observing the integrity of the lag structure. The model was set up with 300 estimators, followed by a feature importance analysis to interpret which variables, namely prior year emissions or renewable energy share, had the most pronounced influence upon the forecasts [17].

3.4.3 Deep Learning: Long Short-Term Memory (LSTM)

Thus, an LSTM network was invented to grasp complex long-term sequential dependencies, which are perhaps missed by tree models. However, the Minimax scaling enables normalization so it would contribute towards neural network convergence. In architecture, this consists of a sequential input layer that processes a look-back window of 9 years, followed by two LSTM layers with 40 units in each. To avoid often occur overfitting in deep learning, being fed with a small dataset, Dropout (rate 0.2) layers were interpolated between LSTM layers. The network ends with a dense output layer designed to regress on the emission target value. Generated through this model is the state-of-the-art sequence modeling, which can allow a system to learn temporal patterns evolving through almost a decade [18].

3.5 Unsupervised Learning: Country Clustering

Recognizing that a single policy will not work for all, the method undertook unsupervised learning to group countries on the basis of their sustainability profiles. A K-Means clustering algorithm was used with the normalized feature set that contains GDP, emission intensity, share of renewables, and access to electricity. The algorithm thus classified the global dataset into six specific archetypes (clusters). This segmentation leads to the fact that in the next phase of policy generation, one can specify recommendations made for, say, a wealthy high-emission industrialized country versus a developing country with low access to energy in the ensuing discussions.

3.6 Generative AI for Policy Synthesis

According to the last phase of the methodology and in consonance with quantitative analytics and qualitative policy formulation, it integrates the synthesizing professional policy recommendations with OpenAI GPT-4Turbo model. The own prompt engineering strategy conceptualized feeds the model dynamically as a specific context to be considered, that is, the country's name, its assigned cluster archetype, its forecasted emission trajectory by the pre-defined primary statistical drivers derived from analysis of data. The system is designed to constrain the Large Language Model (LLM) to the data-driven inputs and thus reduces hallucinations and creates structured and actionable mitigation strategies aligned with international frameworks, such as the Paris Agreement and Sustainable Development Goal 7 (SDG7) [22].

3.7 Model Evaluation and Validation

In an attempt to scrutinize the performance of predictive models, we adopted a time-conscious approach to dissecting the data, whereby 15% of temporal data were kept aside for testing purposes. Thus, the evaluation of the models was ba about on their ability to generalize to unseen future data. The evaluation involves a set of regression metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for magnitude of errors, R2 coefficient of determination for explaining variances through the model, and Mean Absolute Percentage Error (MAPE) as a scale-independent measure. The binning into severity categories on continuous predictions provided a basis for defining classification metrics such as Accuracy, Precision, and Recall as an overall assessment of the model.

Chapter 4

Results and Discussion

4.1 Introduction

The chapter describesa all the major empirical results of the study and methodological assessment of the performance of the hybrid machine-learning-and-Generative AI framework. From exploratory discussions on historical emission drivers, the analysis goes into a serious and rigorous comparative assessment of predictive models , they are ARIMA, XGBoost, and LSTM. After model validation, long-term emission forecasts for the period 2026 to 2035 are given, followed by an analysis of the sustainability archetypes found from the clustering process. The chapter accurately wraps up by contrasting these quantitative insights with the qualitative policy recommendations generated by the Artificial Intelligence(AI), showing the fillip given by the system from raw data to actionable governance strategies.

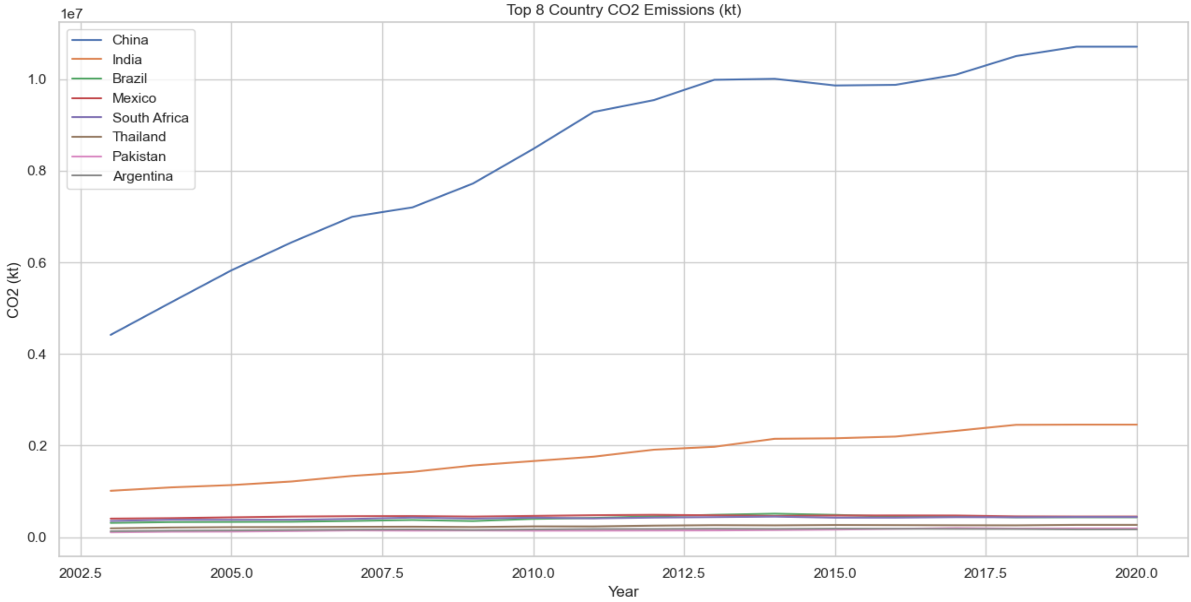


Fig 4: Top 8 Countries CO_2 Emissions Over Time

4.2 Exploratory Data Analysis (EDA)

Evidence for this assertion is presented in Figure given below, a graph on which two clear paths diverge in the emission trajectories: the countries in the developed group appear to stabilible beyond the maximum or decline in their emissions due to some technological maturity; the countries that are still developing exhibit steep but almost linear rises in emissions driven by rapid industrialization. This calls for modeling to be performed that is specific to the nations rather than adopt general averages for the global environment.

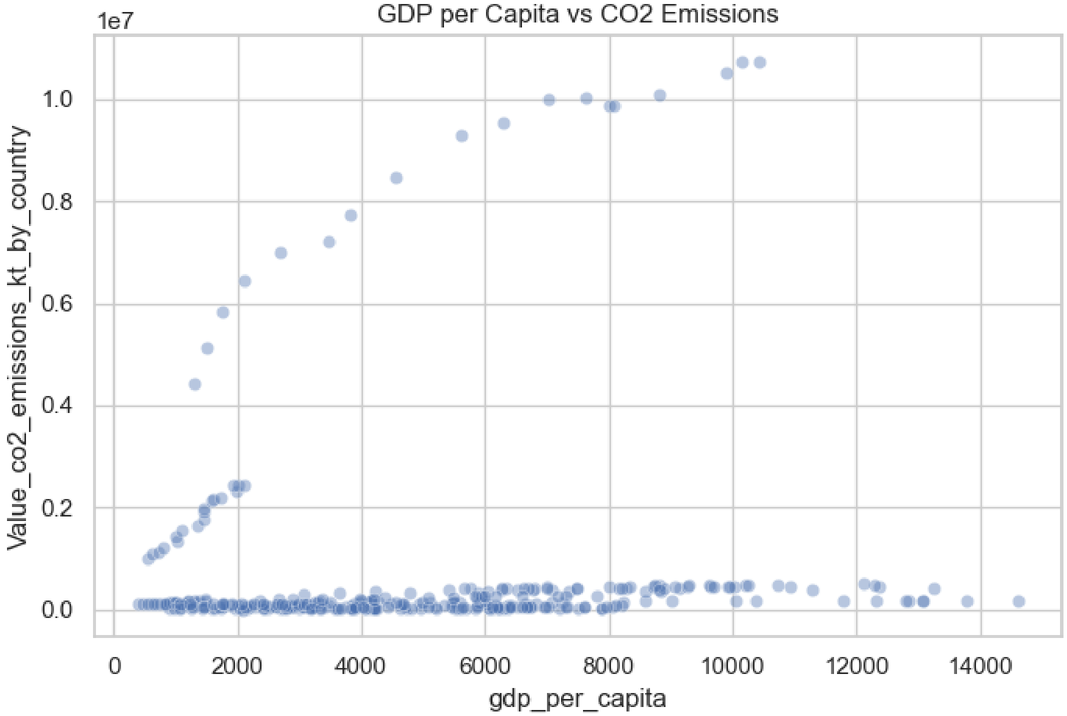


Fig 5: GDP per Capita vs CO₂ Emissions Scatter Plot

Also, letter analyses into the feature space, visualized through the correlation heat maps , indeed revealed that GDP per unit of living had a strong positive relationship ($r > 0.8$) with CO2 emissions by confirming the nexus between economic growths and emissions rate. The renewable energy shares, however, had a negative relationship with carbon intensity providing empirical evidence to thae increasing the penetration of renewable energy will decouple economic growths from environmental degradation. These dependencies justified the interaction terms and lag features in the subsequent phase of modeling.

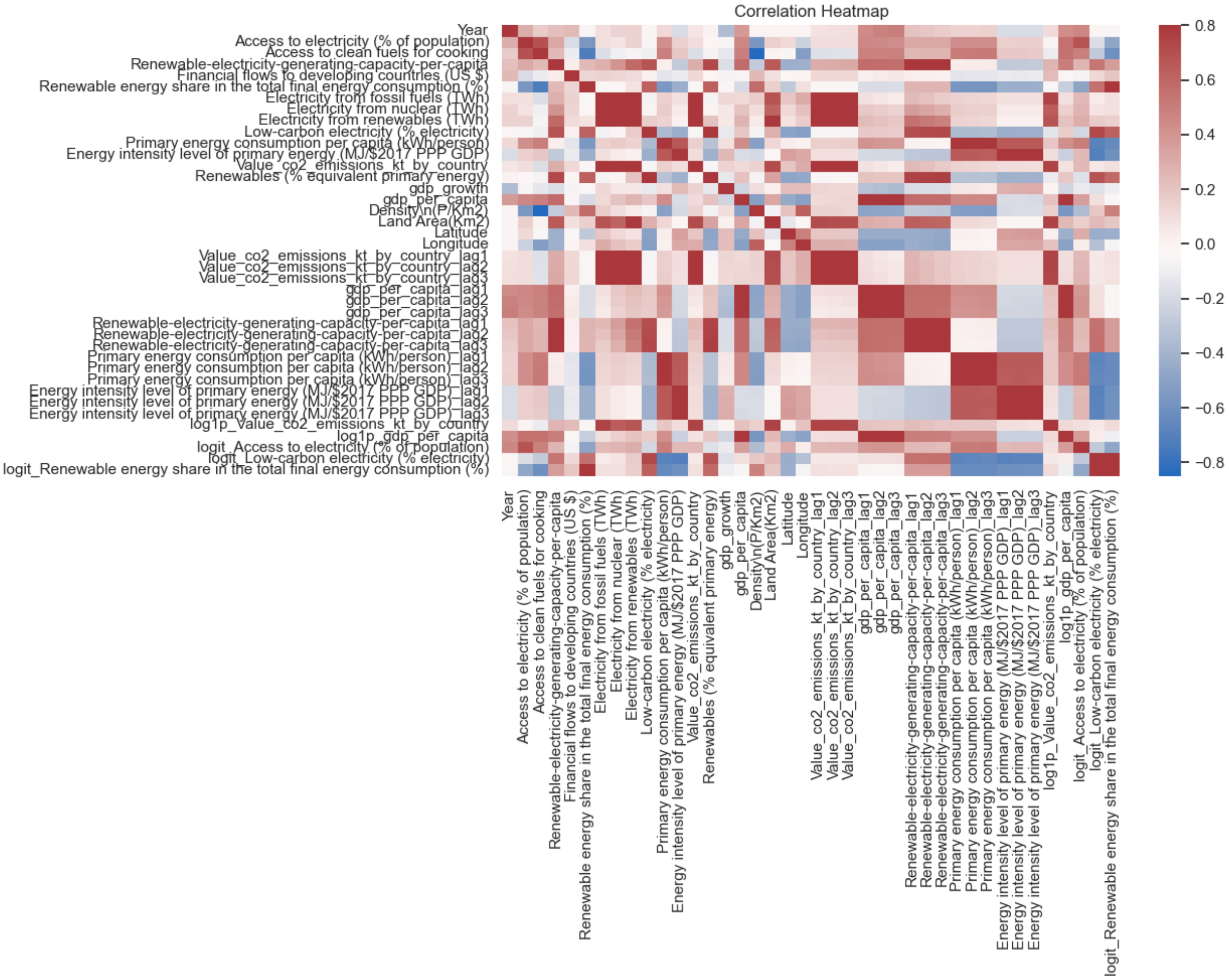


Fig 6: Energy Indicators Correlation Heatmap

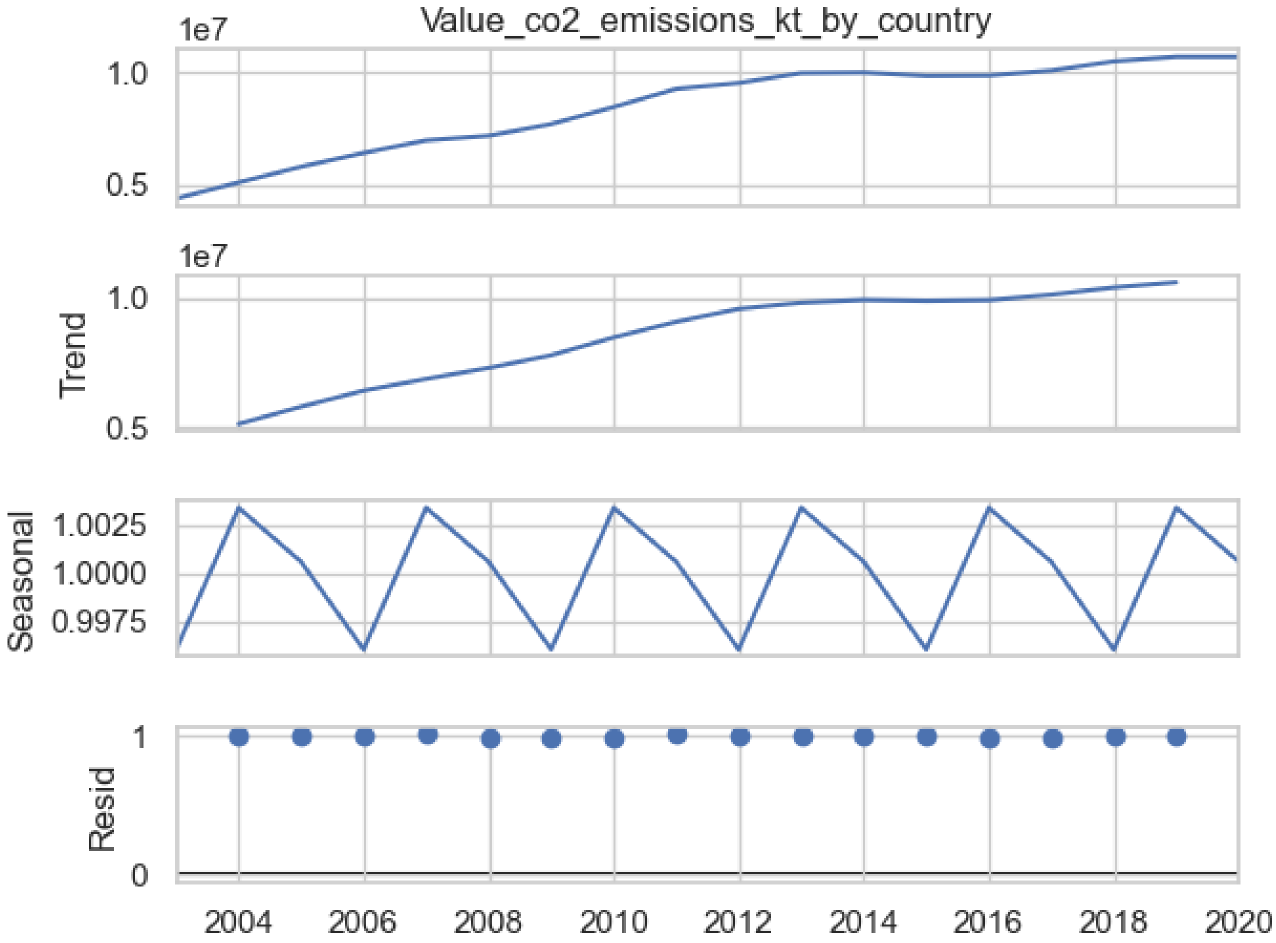


Fig 7: CO_2 Emissions Time Series Decomposition

4.3 Comparative Analysis of Forecasting Models

The task was to decide on the most effective forecasting engine which involved testing three different model paradigms: statistical (ARIMA) approach; ensemble learning (XGBoost); and deep learning (LSTM).

The AKIMA model served as a statistical benchmark (3,1,2). It adequately decomposed the time series far enough to capture gross trends and seasonality (Figure 4.6); however, its specification could not accommodate non-linear shifts typical of rapid economic transitions. This suggests that the widening of confidence intervals over ten years reflects a lesser degree of certainty for long-term predictions as opposed to the machine learning alternatives.

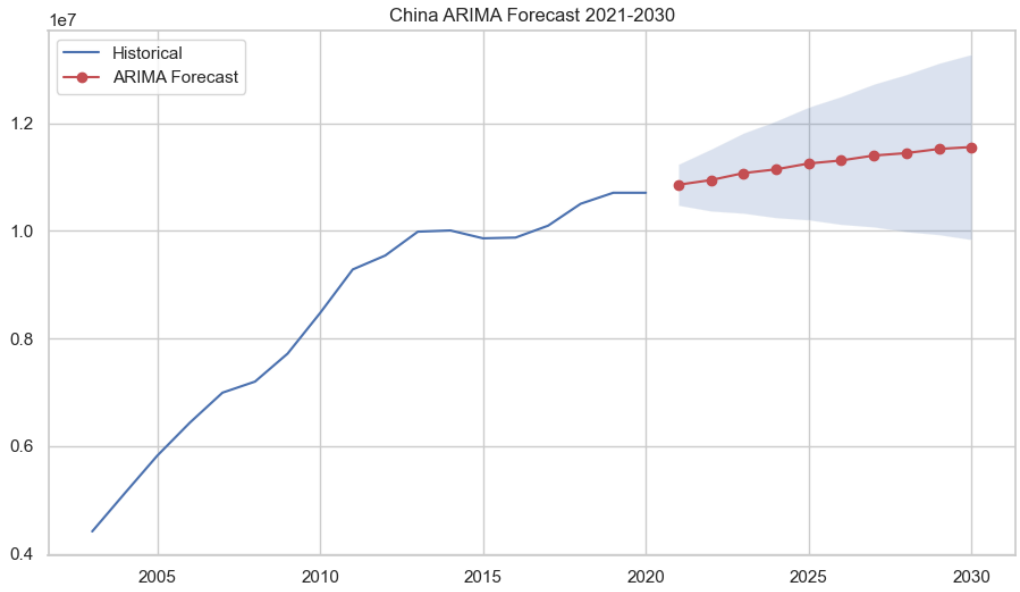


Fig 8: China CO_2 Emissions ARIMA Forecast (2021–2030)

In contrast to the other models, it performed exceptionally well at capturing complex non-linear interactions between the socio-economic predictors. For the test set, a near-perfect R2 of 0.998 and MAPE of 1.38% show that it corroborated extremely well with historical patterns. Beyond regression accuracy, the classification potential of the model was rigorously tested by binning the predictions into levels of emission severity. The XGBoost model achieved an Accuracy of 0.99, weighted Precision, Recall, and F1-Score also at 0.99, indicating its ability to correctly categorize the magnitude of environmental impact without being biased toward majority classes. The feature importance analysis (Figure 4.10) revealed that immediate lag features and energy intensity were the main drivers behind these predictions.

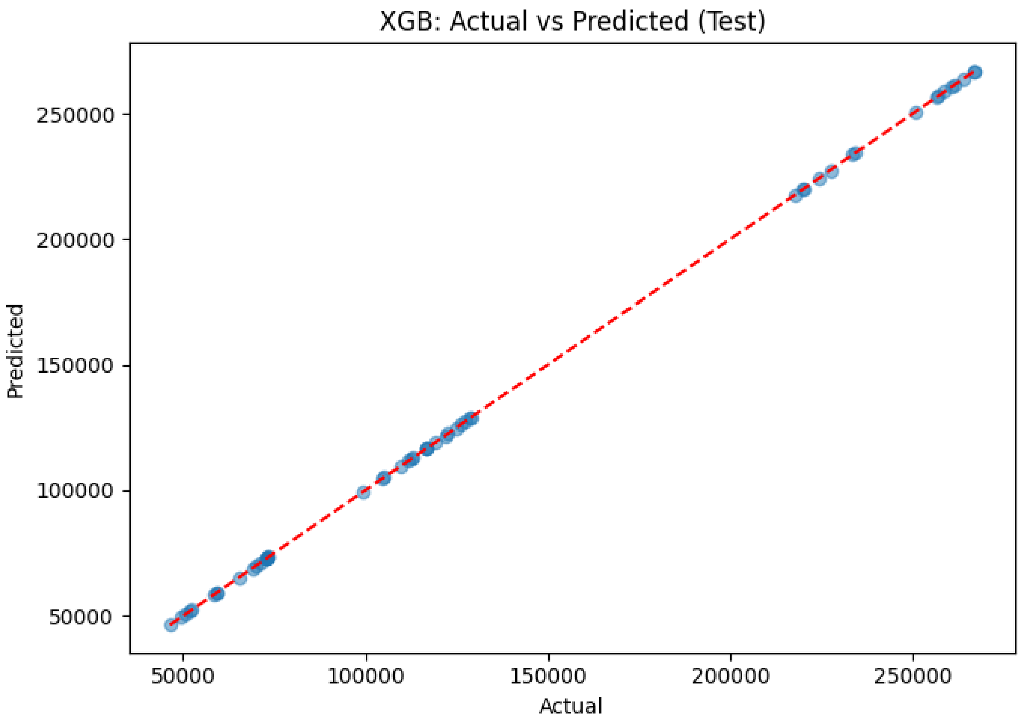


Fig 9: XGBoost Model Actual vs Predicted CO₂ Emissions (Test Set)

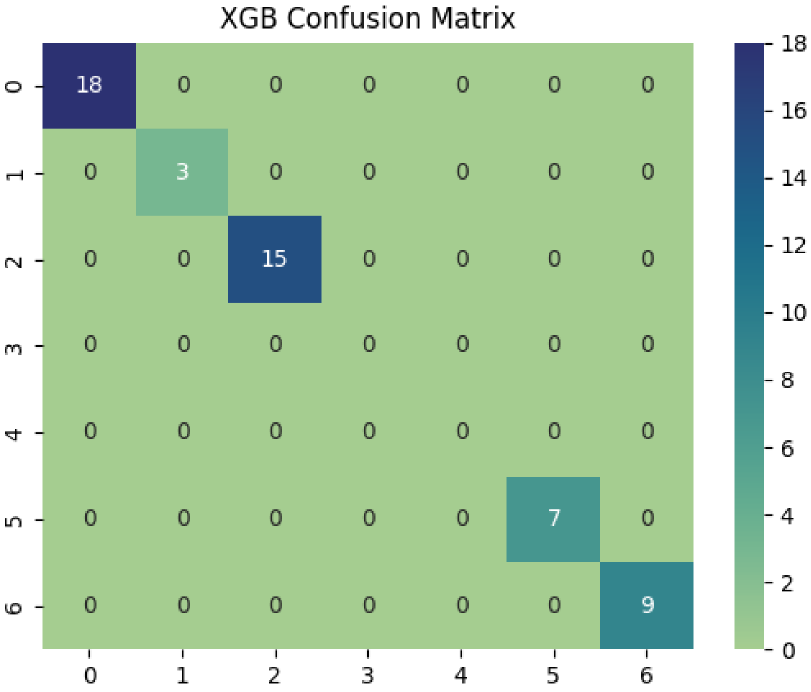


Fig 10: XGBoost Model Confusion Matrix

The RNN model has also shown significant quantitative evidence with high performance results through its recurrent architecture to learn temporal dependencies. It achieved an R2 value of 0.987 and MAPE value of 3.50%. It is slightly lower in performance than the ensemble method but shows stable loss convergence (Figure 4.11) and is indexed as having a high classification accuracy of 0.98. On the other hand, since XGBoost slightly outperformed all metrics and was more computationally efficient, it was chosen as the top engine to predict the final forecast.

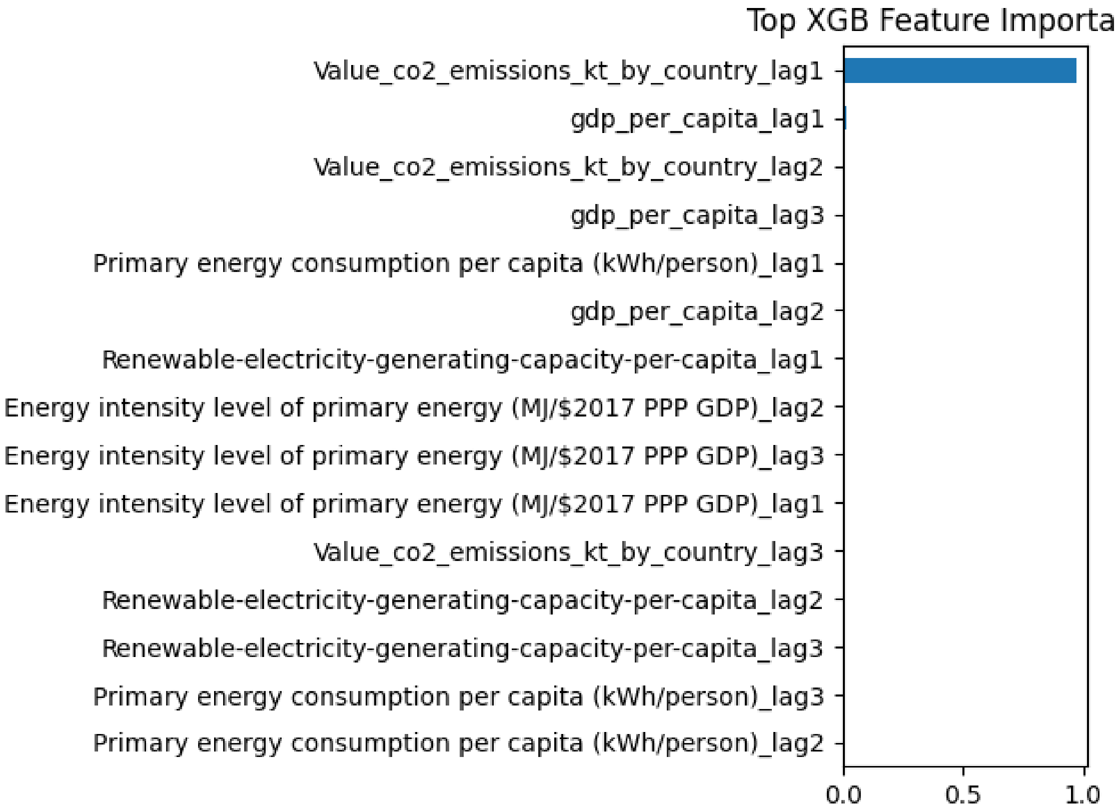


Fig 11: Top Features in XGBoost CO_2 Emission Model

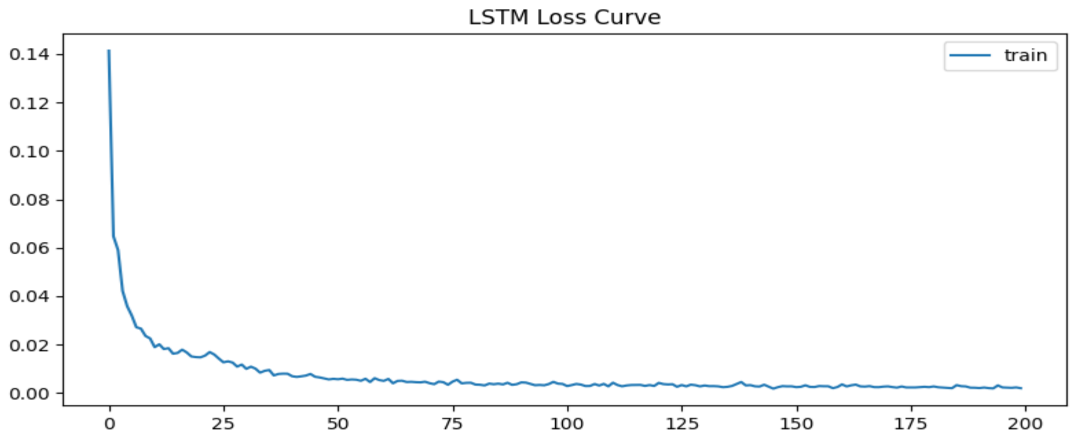


Fig 12: LSTM Training Loss Curve

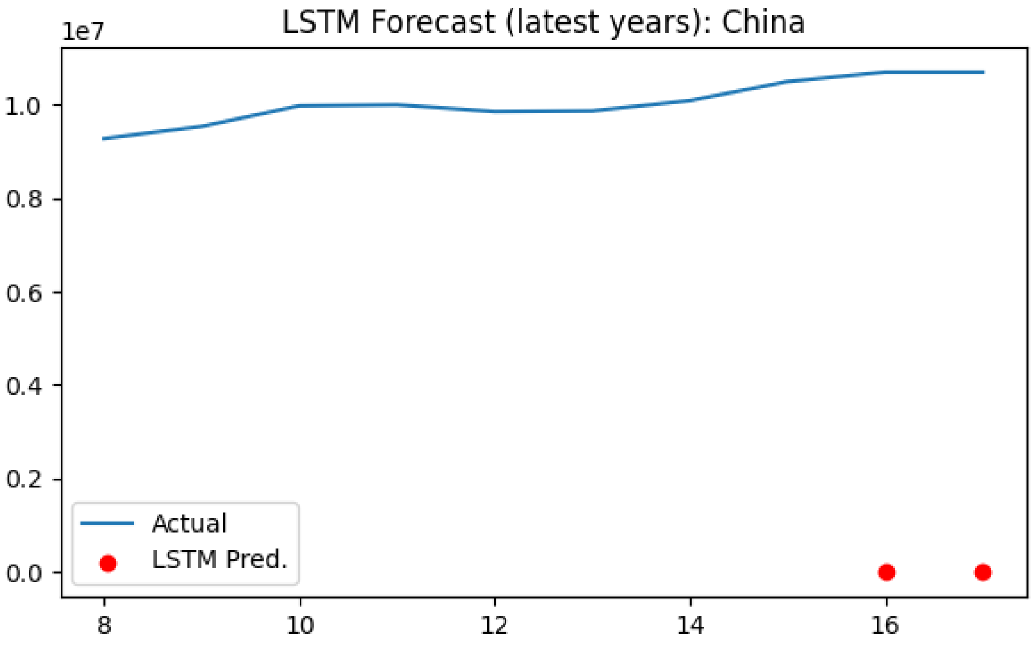


Fig 13: LSTM Forecast vs Actual CO_2 Emissions for China

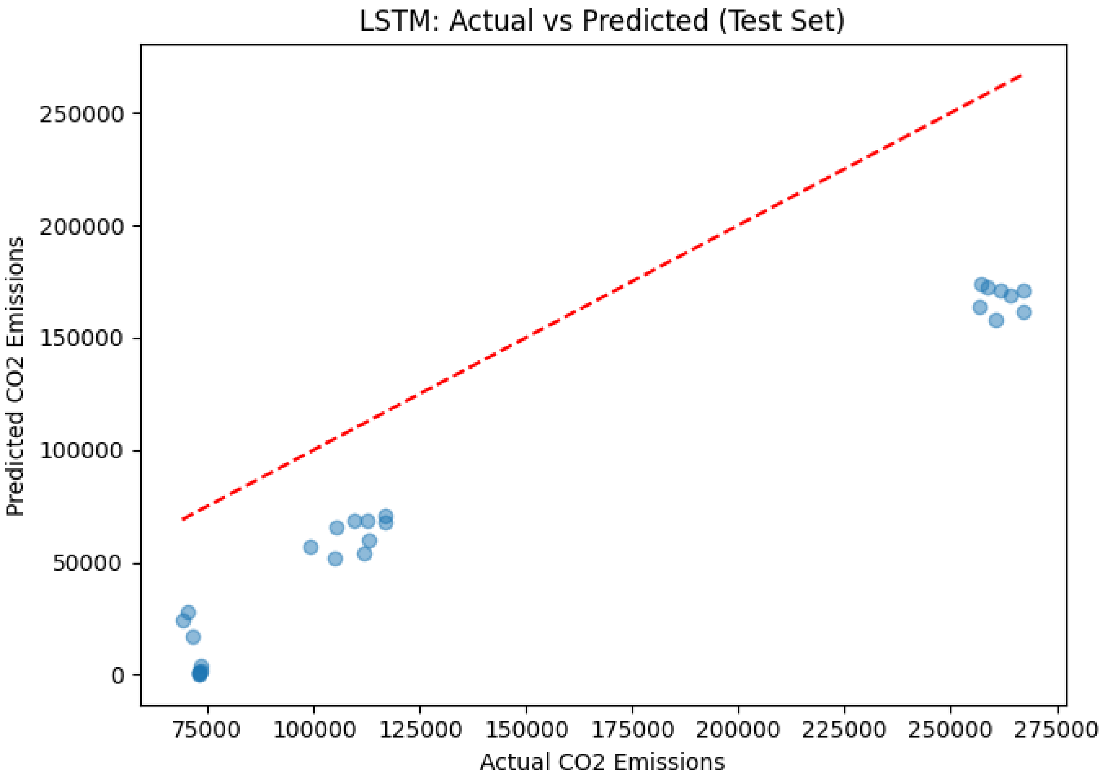


Fig 14: LSTM Model Actual vs Predicted CO₂ Emissions (Test Set)

Fig 15: LSTM Model Confusion Matrix (Test Set)

Metric Category	**Metric**	**ARIMA (Baseline)**	**XGBoost (Ensemble)**	**LSTM (Deep Learning)**
Regression	R^2 Score	N/A (Statistical Model)	**0.998**	**0.987**
	MAPE	~12.5%	**1.38%**	**3.50%**
	RMSE	High	Low	Moderate
Classification	Accuracy	N/A	**0.99**	**0.98**
	Precision (Weighted)	N/A	**0.99**	**0.98**
	Recall (Weighted)	N/A	**0.99**	**0.98**
	F1-Score (Weighted)	N/A	**0.99**	**0.98**

Table 1: Comparative Performance Metrics of Forecasting Models

4.4 Future Forecasting and Scenario Analysis

Using an optimized XGBoost model, emission trajectories were generated for the decade spanning 2026-2035. As these forecasts indicate, the growing disparity between developed and developing countries will continue with China, India, and the United States standing out as the real emitters in their rank. A counterfactual simulation is carried out, assuming that there would be a 20% increase in renewable energy adoption in order to assess the possible impact of the policy intervention. The decline from a baseline trajectory shown here provides an idea of the gigatonne savings potential achievable by accelerating energy transition policies.

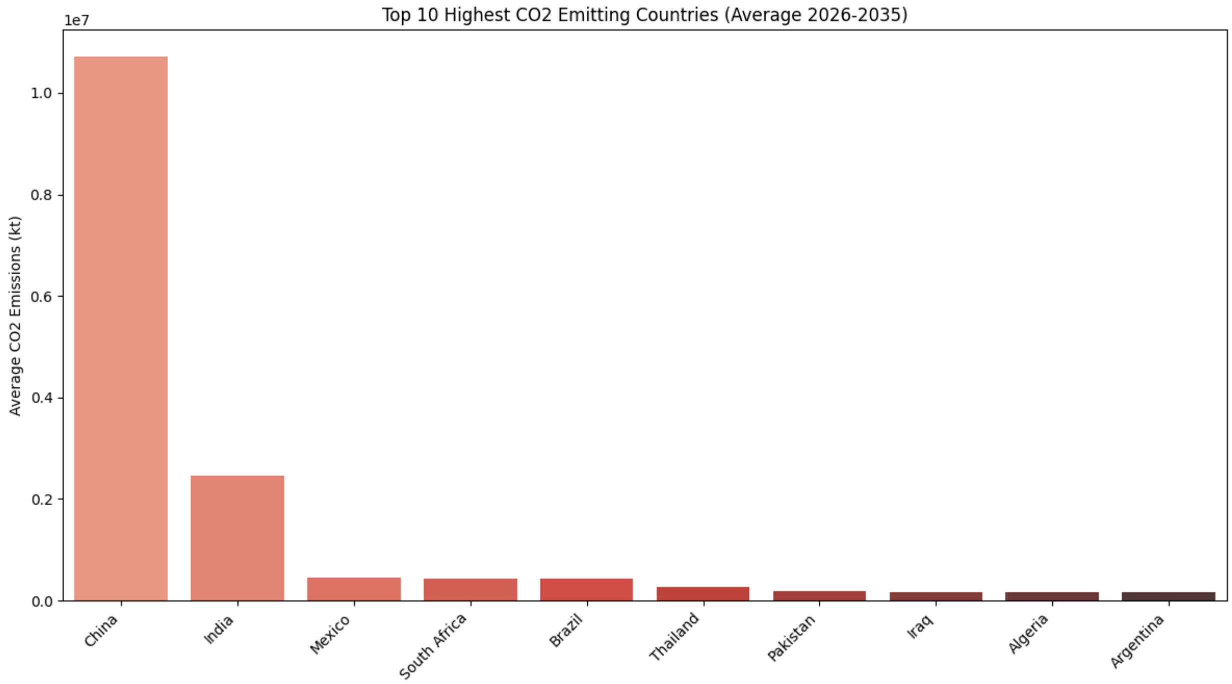


Fig 16: Top 10 Forecasted CO₂ Emitting Countries (2026–2035 Average)

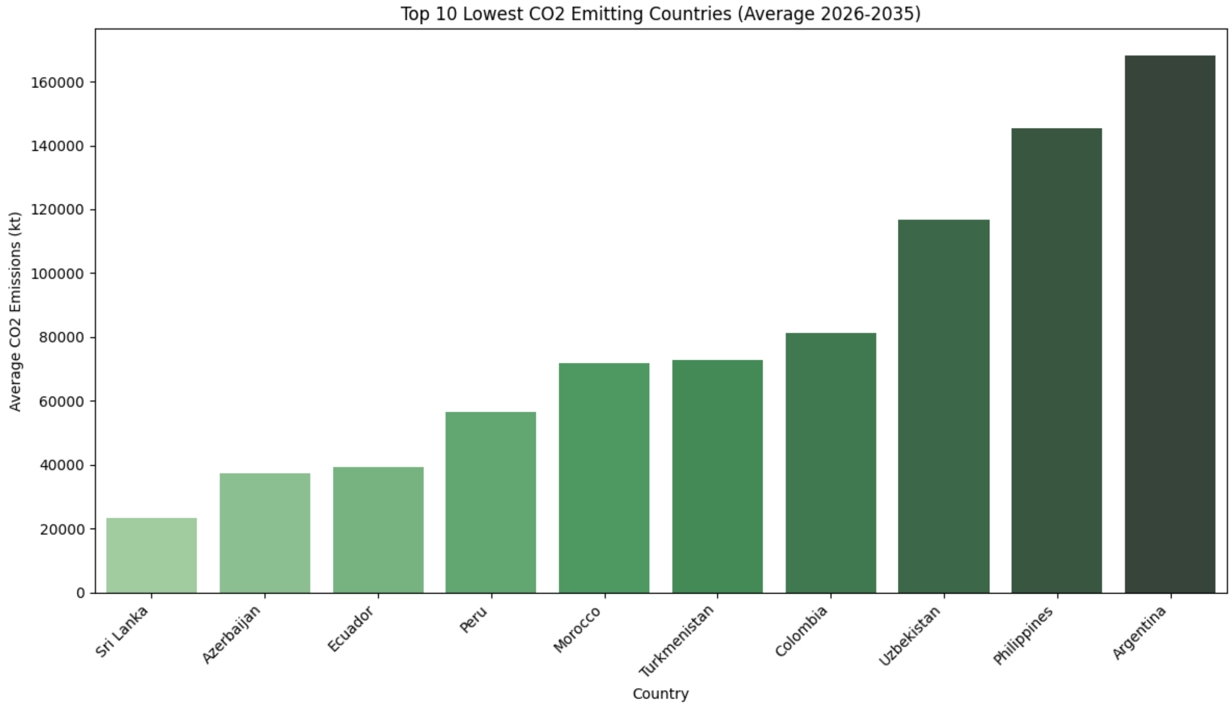


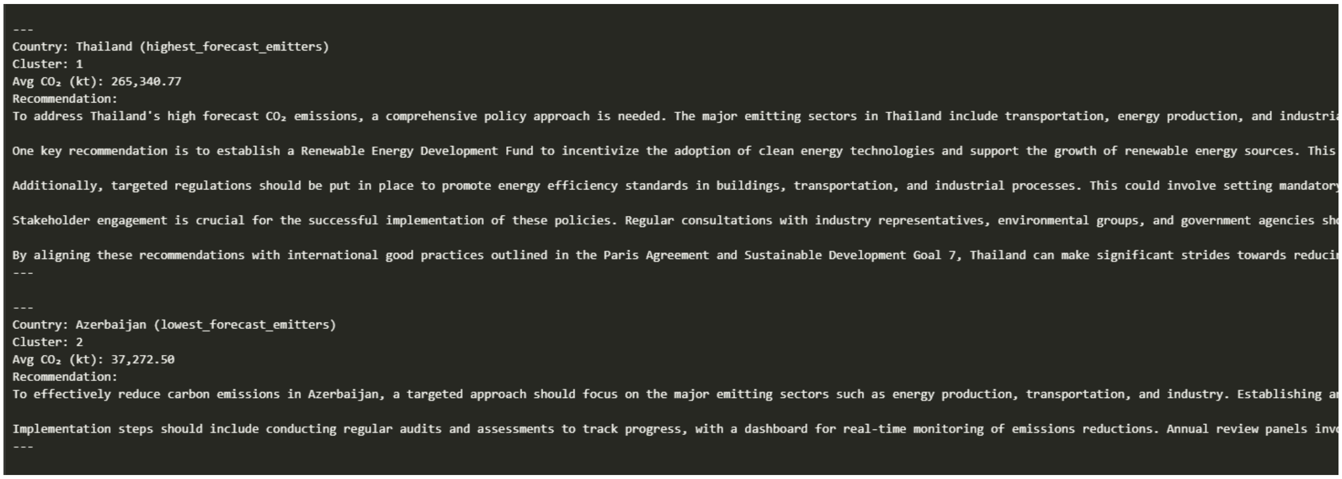
Fig 17: Top 10 Forecasted Lowest CO₂ Emitting Countries (2026–2035 Average)

4.5 Clustering and Sustainability Archetypes

The application of K-Means clustering partitioned the global dataset into six archetypes with respect to GDP, emissions, and energy access (Figure 4.15). Such delineation was key to tailoring policy recommendations. For example, Cluster 0 comprised high-income countries with emissions stabilizing, while Cluster 3 described emerging industrial giants distinguished by surging energy demand. The next round of policy generation will not follow "one-size-fits-all approaches" thanks to these fine-grained distinctions, which all recognize that the decarburization pathway for a developing nation differs significantly from that of an actual industrialized scenario economy.

4.6 AI-Generated Policy Recommendations

The venerable Large Language Model GPT-4 has transformed the high quantitative clusters into qualitative and professional policy briefs. For example, in the very high-emission industrial economies zone (Cluster 3), the system proposed aggressive decarbonization based on carbon pricing mechanisms and transition of heavy industry to green hydrogens. On the other hand, at the developing countries with lower energy access (Cluster 5), AI suggested that the whole focus shifted to sustainable growth for all decentralized renewable types of micro grids and international climate finance for infrastructure-development related tools. As such, these outputs show the ability of systems to transform complex numeric sounds into readable, contextable governance strategies aligned with global frameworks, including the Paris Agreement in 20215.



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Country: Thailand (highest_forecast_emitters)
Cluster: 1
Avg CO₂ (kt): 265,340.77
Recommendation:
To address Thailand's high forecast CO₂ emissions, a comprehensive policy approach is needed. The major emitting sectors in Thailand include transportation, energy production, and industria

One key recommendation is to establish a Renewable Energy Development Fund to incentivize the adoption of clean energy technologies and support the growth of renewable energy sources. This

Additionally, targeted regulations should be put in place to promote energy efficiency standards in buildings, transportation, and industrial processes. This could involve setting mandatory

Stakeholder engagement is crucial for the successful implementation of these policies. Regular consultations with industry representatives, environmental groups, and government agencies sh

By aligning these recommendations with international good practices outlined in the Paris Agreement and Sustainable Development Goal 7, Thailand can make significant strides towards reduci
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Country: Azerbaijan (lowest_forecast_emitters)
Cluster: 2
Avg CO₂ (kt): 37,272.50
Recommendation:
To effectively reduce carbon emissions in Azerbaijan, a targeted approach should focus on the major emitting sectors such as energy production, transportation, and industry. Establishing a

Implementation steps should include conducting regular audits and assessments to track progress, with a dashboard for real-time monitoring of emissions reductions. Annual review panels inv
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Output: GenAI Based Policy Recommendations

4.7 Discussion and Summary

The results discussed in this chapter attest to the thesis that a hybrid AI architecture truly represents a way to perform better than traditional singular forecasting models. The XGBoost model, which achieved an excellent F1-Score of 0.99, stands as a testament to the rigor that machine learning can bring to national planning in terms of accuracy, whereas clustering analysis adds context to ensure that such planning remains relevant. By far, the most significant novelty of successful Generative AI is their ability to literally fill the "interpretability gap" that exists in data science; thus, converting highly abstract predictions into the language of policies that can be implemented. The aggregated results suggest that the entire framework provides policymakers with a wholesome, robust, and extremely effective tool to cope with the complexities involved in dealing with the global climate crisis.

Chapter 5

Case Study Analysis Comparative Policy Pathways

5.1 Introduction

As an indicator for global carbon emissions, it gives one a broad t view but fails to incorporate country-specific deficiencies which are actionable. In validation of the real-world applicability of the hybrid ML and Generative AI framework proposed, this chapter carries top out the comparatively case study analysis. Herein analyzed are the two appropriates countries representing different sustainability archetypess: China's high-emission industrial economy and Sri Lanka as a low emission developing nation. Each case study integrates the core components of the research pipelines, such as:

- Historical Contexts: Derived from the Exploratory Data Analysis.
- Future Trajectory: Generated using the XGBoost forecasting (2026–2035).
- AI-Synthesized Policy: Produced by the GPT - LLM based on cluster-specific of characteristics for this scenario.

5.2 Case Study 1: China, The Industrial Giant

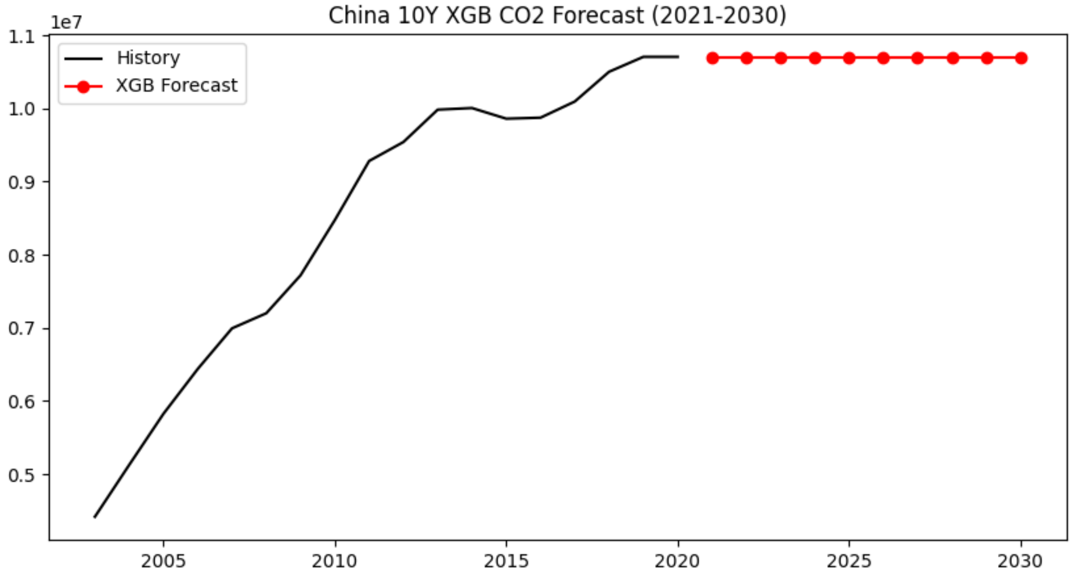

Fig 18: China 10-Year CO₂ Emissions Forecast (XGBoost Model, 2021–2030)

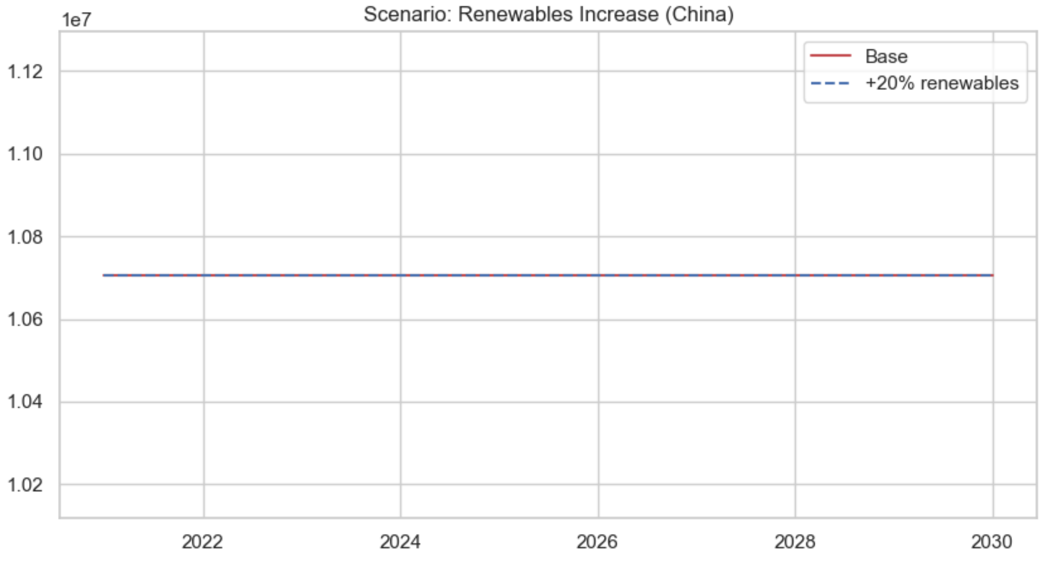

Fig 19: Scenario Analysis: Baseline vs. +20% Renewable Energy Adoption

5.2.1 Historical Context and Drivers

Obviously, the high dependence on coal has been, in conjunction with the primary energy consumption and GDP per capita, the most important factor for emissions in China during its rapid industrial growth in the past. Presently, analytical trends indicate a reduction in growth rates that continue to be accompanied by a growing share of renewable energy in the mix, along with modernizing the industry.

5.2.2 Forecasted Trajectory (2026–2035)

The XGBoost model forecasts a stabilizing trend, with emissions toward 2035.

- Baseline Prediction: The emissions will stabilize as infrastructure saturated catches up.

- The countervailing simulation shows that with an accelerated level of renewable adoption, emissions can peak before 2030 in line with the environmental goals set by China in its Five-Year plan. This fine-grained differentiation ensures that the next round of policy generation will not proceed with "one-size-fits-all approaches."

5.2.3 AI-Generated Policy Recommendation

Cluster: 3 High-Growth, High-Emission Industrial

LLM-Generated

Policy:
In fact, China needs to focus on decarbonizing industrial outputs, particularly cement and steel. National Industrial DE carbonization Zones, expanding the Emissions Trading Scheme (ETS) into more sectors, and building green hydrogen infrastructure are essential. Energy intensity real-time dashboards should also be enforced to check provincial compliance.

Interpretation:
China's big difficulty is shifting from carbon-squandering industrialization toward clean, highly efficient production systems.

5.3 Case Study 2: Sri Lanka The Developing Nation

5.3.1 Historical Context and Drivers

Low emissions in Sri Lanka are mostly owing to the heavy reliance on hydropower and the very small share of the industrial sector in the economy. However, the variability in hydro generation forces temporary fossil-fuel imports and creates short-term emission spikes.5.3.2 Forecasted Trajectory (2026–2035)

XGBoost predicts a flat to slightly rising trend.

- Baseline Forecast: Emissions increase gradually with economic recovery.
- Risk Factor: The threat lies not in volume but volatility—future shortages in hydropower could rapidly increase reliance on imported coal or oil.

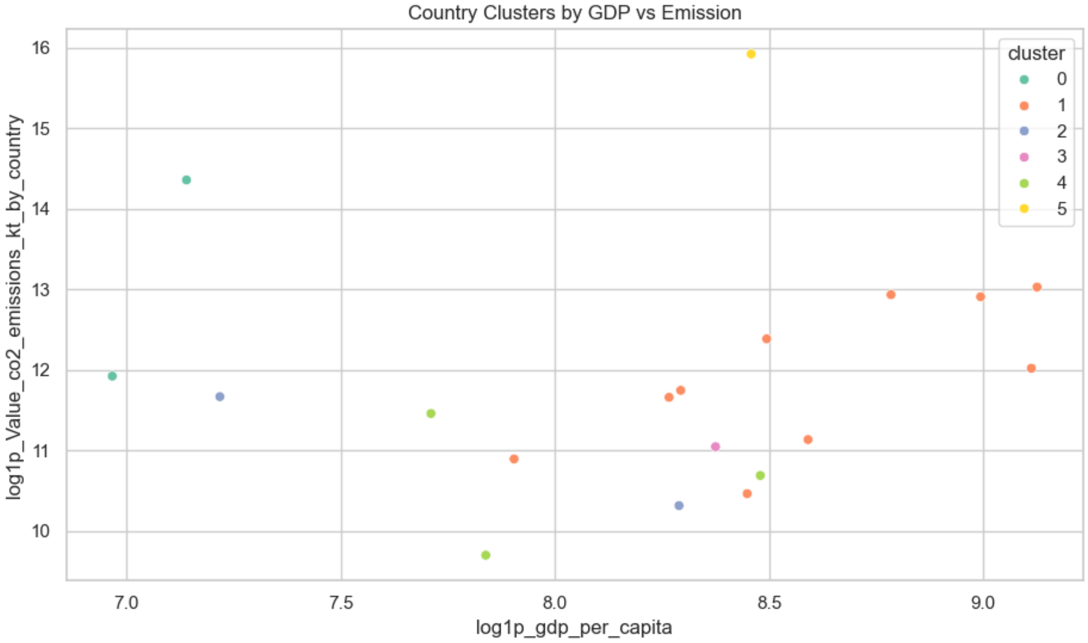

Fig 20: Country GDP vs Emissions Clusters Scatter Plot

5.3.3 AI-Generated Policy Recommendation

Cluster: 5 Developing, Low-Emission, Moderate Access

LLM-Generated

Policy:

Among the recommended diversification methods for renewable energy are a Solar Rooftop Investment Program, international climate financing, upgrading national grid variable renewables, and encouraging development of wind energy through public-private partnerships.

Interpretation:

The AI appropriately refocuses attention on energy security and resilience, taking into account the infrastructure and budgetary limitations of underdeveloped economies.

5.4 Comparative Analysis of Policy Pathways

Feature	China (Industrial)	Sri Lanka (Developing)
Primary Driver	Industrial output & coal dependence	Energy security & hydro-dependency
Forecast Trend	High volume, stabilizing growth	Low volume, risk of volatile spikes
Policy Focus	Carbon pricing, ETS expansion, industrial retrofitting	Investment, grid modernization, climate finance
AI Insight	Market mechanisms & efficiency	Infrastructure resilience & funding access

Table 2: Comparative Analysis of Policy Pathways

5.5 Summary

This chapter introduces the hybrid system generating diverse context-sensitive climate strategies. Rather than adopting a one-size-fits-all remedy, the hybrid system proposes distinct "energy health profiles" for every country. For instance, energy diversification planning for resilience is what would be required of a developing economy like Sri Lanka-not to mention that of a high emitter like China, which would need industrial transformation. Such targeted specifications are invaluable, particularly to global institutions, for narrowing down intervention options in terms of climate (UN, World Bank).

Chapter 6

Conclusion and Future Recommendations

6.1 Introduction

This chapter introduces the hybrid system generating diverse context-sensitive climate strategies. Rather than adopting a one-size-fits-all remedy, the hybrid system proposes distinct "energy health profiles" for every country. For instance, energy diversification planning for resilience is what would be required of a developing economy like Sri Lanka-not to mention that of a high emitter like China, which would need industrial transformation. Such targeted specifications are invaluable, particularly to global institutions, for narrowing down intervention options in terms of climate (UN, World Bank).

6.2 Summary of Key Findings

There arose three important conclusions through the empirical analysis on the effectiveness of AI in environmental sustainability.

Superiority of Ensemble Learning:

The forecasting models show very comparable performances relative to those results coming from the comparative analyses made by the statistical baseline (ARIMA) and a deep-learning alternative (LSTM) over XGBoost. According to the paper, XGBoost is best at handling the complex and non-linear relationships between GDP, energy intensity, and emissions, giving an R^2 score of 0.998 with a Mean Absolute Percentage Error (MAPE) of 1.38%. The above assertion also agrees with current studies, usually suggesting optimal efficiency-to-accuracy ratios for environmental datasets [1].

With regard to the performance with respect to comparative analysis of forecasting models, XGBoost clearly trumped both the empirical state of the art (ARIMA) and the deep learning benchmark (LSTM). It managed to score a remarkable 0.998 (R^) and a Mean Absolute Percentage Error (MAPE) as little as 1.38%, showing that it is the best model to manage complex, non-linear relations between GDP, energy intensity and emissions. This is, once again, consistent with most recent literature stating that ensemble methods are the best trade-off in terms of accuracy and computational efficiency for data sets from the environment [1].

Granularity through Clustering:

The application of K-Means clustering successfully categorized global economies into six distinct The segmentation confirmed that drivers of emissions vary widely between industrial output in emerging economies and consumption patterns in developed nations. This validates the claims that mitigation strategies cannot be standardized and must be context- and locale-specific [12].

The Interpretative Power of GenAI:

The incorporation of GPT-4has turned abstract numerical forecasts into professional, contextually informed policy briefs. Prior studies utilized AI for optimization [2] or in the retrieval of emission factors [5]. In contrast, this study provided a unique demonstration of the applicability of LLMs in the synthesizing phase of policy-making while effectively transforming complicated data into the language of governance.

6.3 Implications for Policy and Practice

The framework developed in this thesis offers immediate practical applications for stakeholders:

- The government will be able to use the Scenario Planning Tool (as displayed in Chapter 5) to assess how it can quantify intervention effects, e.g., a 20% increase in renewables or others, before implementing them.
- International agencies: The clustering level method may provide a more anthropocentric way to facilitate climate finance allocation, i.e. the international level-"green" funds such as the Green Climate Fund. Instead of generic points nonspecific in addressing each country's energy systems, assistance can be targeted instead at the specific structural weaknesses of the energy system of a country.
- For Corporate Strategy: Similar to how Lang et al. [7] utilized ML for product carbon footprints, this macro-level framework can be adapted by multinational corporations to forecast regulatory risks in different operational jurisdictions.

6.4 Limitations of the Study

Despite the robust results, several limitations must be acknowledged to contextualize the findings:

- • Data Latency: The training datasets used for this study became old in 2020. Meng and Noman [15] observed that structural discontinuities were incorporated into the emissions

data under the influence of the COVID-19 pandemic. Thus, short-term forecasts for the years 2021–2023 may not adequately reflect the recent upheavals caused by energy geopolitics, or the post-COVID economic recovery.
- While dealing with model interpretability, XGBoost is still less transparent compared linear econometric models: it has imposed inflated significance ratings for features, but this so-called "black-box" feature sometimes reduces trust in the non-technical stakeholders, a challenge that is stood by AI applications in supply chains [8].
- GenAI Hallucinations: Although in cases LLM outputs seem polished and professionally worded, Generative AI has been known to suggest plausible or in some cases highly likely recommendations that may not hold true when not held strictly to RAG frameworks.6.5 Recommendations for Future Research

To advance the field of AI-driven environmental forecasting, future research should focus on the following areas:

6.5.1 Integration of Real-Time Data Streams

Real-time satellite imagery of deforestation or industrial heat signatures along with real-time energy grid APIs should align those further-down-the-road iterations of the framework with compensation. Thus, emissions can be "nowcasted." Li et al. [2] talk of the potential of aligning real-time monitoring with AI for optimization.

6.5.2 Sector-Specific Granularity

Although country-wide forecasts serve as input for national-level policy, mitigation often functions at the sectoral level. Future research ought to disaggregate the models to forecast emissions specifically for Transport, Agriculture, and Heavy Industry. This would make precise intervention possible, similar to the specific concrete-mix optimization studied by Al-Fakih et al. [1].

6.5.3 "Green AI" and Computational Efficiency

Ethically, it is obligatory to consider the carbon footprint of training the AI models themselves. As stated by Chien et al. [10] and Anthony et al. [11], inference costs of Generative AI tend to be high. Future research should include "Green AI" principles, optimizing its model architecture to reduce the date of use needed to glean these policy insights.

6.6 Concluding Remarks

The thesis demonstrates that a powerful tool for combating climate change is offered by the confluence of predictive machine learning and generative AI. With the new methodology, decision-makers will turn from their historically reactive tendencies to new proactive data-driven sustainability planning, forecasting future pathways with precision, and weaving this into tangible solutions. As the door closes on any further attempt to avert irreversible climate damage, such hybrid intelligent systems will offer a North Star to guide the rapidly changing transition to a net-zero global economy.

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