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Ai Powered Carbon Footprint Prediction And Optimization For Sustainable Logistics Using Machine Learning And Generative Ai

A thesis submitted by

Saravanan Gnanapandithamani

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Data Engineering

Indian Institute of Technology Jodhpur Department of Computer Science and Engineering

Abstract

Carbon Footprint Optimization Optimize AI-powered Carbon footprint prediction for Sustainable Logistics is a project that is expected to predict and optimize the carbon emission at different points in the supply chain. The system measures carbon footprint using machine learning models including the Random Forest, LSTM and XGBoost, and GRU applications that offer precise predictions of carbon footprint. In the project, generative AI is integrated to produce summaries, offer actionable sustainability information, and possible ESG risk hotspots. The dataset captures the factors like procurement, energy usage, modes of transportation and external factors like weather, which contribute towards the emissions. It is an HTML, CSS, JavaScript, Python (Flask), and hosted on Google Cloud Platform (GCP) platform which provides an easy to use interface with modules such as Home, Register, Login, dashboard and Logout. Some of the dashboard features include predictions, SHAP plot, and ESG insights, which help organizations to reduce the environmental impact. This system is aimed at facilitating the decision-making process and ensuring sustainability through areas of the improvement of emissions management. The suggested generative AI will complement the entire system with proposals on how to streamline the workings of the system, minimize emissions, and increase the sustainability of the supply chain.

Keywords: Carbon Footprint, Machine Learning, Sustainability, ESG, Emissions Prediction, Generative AI, Supply Chain, Optimization, Random Forest, LSTM, XGBoost, GRU, Flask.

INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

The increased awareness on climate change and green sustainability has exerted pressure on industries to control, minimize and maximize their carbon outputs. The logistics industry is one among other industries that contribute considerably to the global CO2 impairment and includes transport, warehousing, manufacturing, and procurement. The reliance of the sector on fossil fuels, operation-intensive processes, and sophisticated supply chain networks cannot be easy to monitor the emissions correctly and subsequently make effective mitigation plans. Although there are traditional methods of reporting, majority of organizations lack the ability to get real time actionable information about their carbon footprint. Traditional methods tend to remain disjointed, manual and bottom-up with historical reporting and it is hard to move the operations proactively, find high-emitting zones and take the sustainability strategies to implementation.

Advanced machine learning and artificial intelligence (AI) can also provide a solution in this regard. Random Forest, LSTM, XGBoost, and GRU machine learning algorithms have the potential to process vast amounts of data at various supply chain steps, discovering complicated trends and relationships that affect carbon emissions. These models not only permit CO2 emissions to be accurately predicted but also give organizations the power to simulate the scenarios and optimize operations to ensure that the operations are sustainable. As an example, predictive models can determine those suppliers, ineffective routes of transportation, energy-consuming manufacturing operators, and allow organizations to make appropriate choices to decrease the impact on the environment.

Generative AI is also able to optimize such a predictive framework by providing actionable suggestions, summary, and hotspots of Environmental, Social, and Governance (ESG) risks. By analyzing with AI, a business can be provided with advice on what to do to reduce emissions, streamline its logistical processes, and enhance its general sustainability efforts. This combination has seen these technologies converge into one platform, which is easy to use and reference to, as well as enabling decision-makers to access real-time data which is transparent and interpretable. The system can be insightful and useful to an organization due to features like SHAP plots used to explain the model and interactive dashboards.

This project is motivated by the fact that there is an urgent need to offer organizations a scalable, reliable, and intelligent tool which can help them make environmentally conscious decisions. The project targets the existing gap in the existing logistics systems as it cannot predict and monitor emissions without relying on machine learning and the application of generative AI. Predictions of carbon footprints done by automation do not only save time and minimise any errors that come in the way of calculation through manual process, but also enable any business to take a proactive initiative to design and execute sustainable strategies. Moreover, the project is scaled, available, and functions with large datasets efficiently,

Finally, it is driven by the desire to balance the impetus to environmental accountability with operational effectiveness. The project should help organizations to lower their carbon footprint by offering a strong carbon emission prediction and optimization framework, serve the global sustainability goals, and contribute to the alleviation of poor impacts of climate change.

1.2 CARBON FOOTPRINT PREDICTION: AN OVERVIEW

The project under consideration is named AI-Powered Carbon Footprint Prediction Optimization of Sustainable Logistics with the help of Machine Learning and Generative AI and aimed to deliver an intelligent platform that is able to predict and optimize the level of carbon footprint at different steps of the logistic supply chain. The essence of the platform is to offer a scalable and dependable solution to companies in order to gauge and minimize their carbon footprint. The system combines high-order machine learning models such as Forest (Random), LSTM, XGBoost, and GRU, which utilize a holistic collection of features, such as energy consumption, transportation modes, supplier emissions, and weather conditions, to determine the overall emissions of CO2 e in logistics transactions.

The major traits of the platform are:

Multi-purpose machine learning models: The system uses a variety of machine learning models, such as the Random Forest which is used as a non-linear regression model, XGBoost as a gradient boosting model, LSTM as a sequential data processing model, and GRU as a time series prediction model. The models are all optimized with respect to the data characteristics, and the system can serve a wide range of logistics situations.

Generative AI as an Optimization: The peculiarity of the given project is the introduction of the concept of generative AI, which implies the availability of actionable recommendations related to carbon emissions reduction. The AI creates summaries, determines possible hot-spots of Environmental, Social, and Governance (ESG) risks, and offers optimal strategies of enhancing sustainability-related practices in the logistics. Using high optimization methods, the system assists the organizations to minimize the carbon footprint as well as increase the efficiency of operations.

Friendliness and Visualization: The site is user-friendly, and users have a free hand to follow the system. The interactive dashboards are connected with the SHAP plots to enable the users to visualize the carbon emission data. The dashboard also gives information on the effects of various logistics phases on the carbon footprint and suggestions on how logistics can be improved.

Scalability and integration in the Cloud: The system is hosted on Google Cloud Platform (GCP), which guarantees high scalability, performance, and security to both small and small organizations. GCP enables efficient management of large volumes of data, real-time updates and easy management of integration with other business systems.

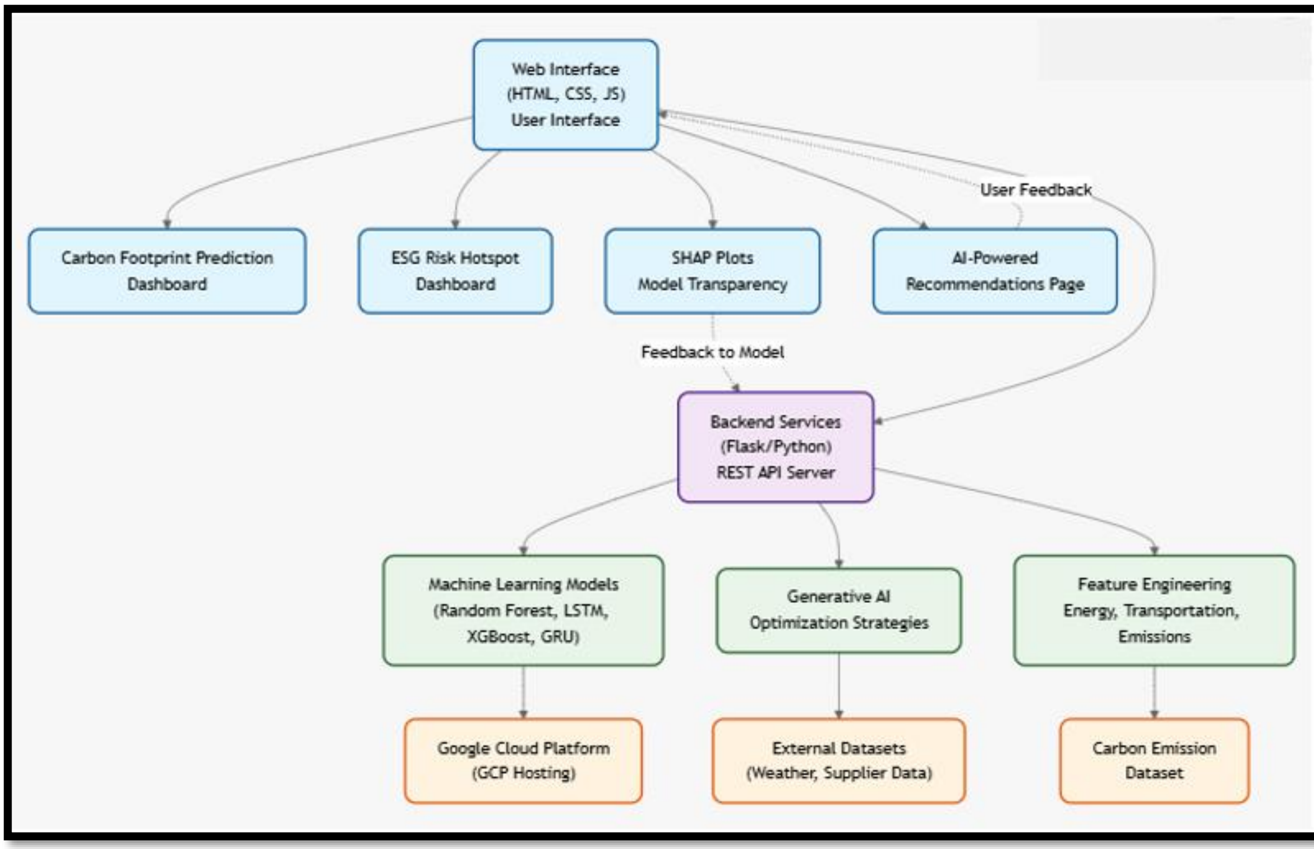

Figure 1.2.1 Generalization of Sustainable AI Ecosystem of Carbon Footprint and ESG Analysis.

The platform will enable businesses to review, manage, and reduce carbon emissions in an actionable and data-driven method, through combining machine learning, generative AI, and cloud technologies, to address the sustainability objectives globally. The tool does not only assist organizations to streamline their logistics operations, but it also allows them to make their practices compliant with the environmental goals, thereby making it an essential tool in the logistic operations of a modern and eco-friendly organization.

1.3 RESEARCH QUESTIONS AND OBJECTIVES

A preliminary study of the work on the project under consideration called the AI-Powered Carbon Footprint Prediction Optimization in Sustainable Logistics Using Machine Learning and Generative AI is accompanied by a series of fundamental research questions (RQs) that are aimed at assessing the efficiency and usefulness of machine learning and generative AI in predicting carbon emissions, logistics optimization, and ensuring sustainability. The following are questions that can be answered in a systematic manner in this research:

RQ1: Prediction Model Accuracy and Efficiency of Carbon footprint predictions models: What are the comparative results on the accuracy and efficiency of the different machine learning models (Random Forest, LSTM, XGBoost, GRU) to predict carbon emission at different stages of the logistics process? This involves consideration of how various features of input (e.g., energy consumption, mode of transportation, and supplier emissions) affect model performance, and also in stating how well the model can be generalized into different stages of a supply chain.

RQ2: Effect Of Generative AI in Emission Optimization: What is the role in integrating generative AI in optimizing the logistics supply chain in a bid to reduce carbon emission? In particular, the study analyzes the efficiency of AI-generated suggestions of sustainable strategies, including changes in transportation modes, energy, and operation changes, in enhancing the sustainability metrics and minimizing carbon footprints.

RQ3: Environmental, Social, and Governance (ESG) Risk Hotspots Detection: How efficient does the use of machine learning models in detecting ESG risk hotspots within the logistics supply chain? How effective is the system to identify spheres of influence with the most significant consequences on the environment, and how can the results be transformed into fostering a more sustainable approach to logistics and supply chain management?

RQ4: Decision-Making Support and User Experience: To what extent is the user interface with regards to making data-based decisions to optimize sustainability? This question assesses the functionality of the dashboard and AI-driven recommendations, to make sure that the system can offer rational and practical insight to the organizations to reduce their carbon footprints.

Based on these essential questions, the following other aspects are also being discussed in this research:

RQ-A: Sensitiveness to Importance of features to Model Accuracy: How does the prediction accuracy of the models to differences in the input features, energy consumption, mode of transport or supplier emissions? The question aims to find out what characteristics have been the most effective in enhancing the quality of the prediction and making action insights.

RQ-B: Scalability and Performance in Real World Applications.: To what extent can the machine learning models and AI-based recommendations be extended to the practical domain of various logistics settings? This query investigates the scalability of the system to different situations of the supply chain such as the capacity to manage large data sets and complicated logistics.

The key goals of this project are hence:

- To establish and develop an intelligent carbon footprint prediction system powered by machine learning that offers real-time predictions in different logistics phases, one will need to combine the aspects of energy consumed during the logistics, modes of transportation, and the emission of suppliers.

- To include generative AI features, to propose operational plans that can achieve maximum optimization and minimization of carbon footprints over logistics supply chains.

- To create a user-friendly interface that renders predictions, visualizations (SHAP plots) and implemented recommendations, allowing the user to build data-driven decisions in favor of sustainability.

- In order to implement the system on Google Cloud Platform (GCP), which is capable of scaling and making organizations of various sizes and industries reliable and eventually lead the way in sustainability and environmental responsibility in general.

1.4 THESIS CONTRIBUTIONS

The major contributions of this M.Tech thesis to the Carbon Footprint Prediction and Sustainability Optimization in logistics research are the following ones:

1.4.1 AI-Powered Carbon Footprint Prediction System: The main asset of this project consists of the design, implementation, and in-depth analysis of a machine learning-based system that would help predict and optimize carbon output throughout the logistics supply chain. This system integrates:

- **Machine Learning Algorithms**: A powerful regression model, such as random forest, LSTM, XGBoost, and GRU, which predicts carbon emissions through the use of some important logistics data, including energy consumption, the mode of transportation, and supplier emissions.
- **Generative AI as an Optimization Tool:** Generative AI will be incorporated into the package to propose sustainable measures that would help mitigate emissions, including alteration of transportation mode or energy-saving habits that are recommended through data analysis.
- **ESG Risk Hotspot Detection:** A model that can be used to determine Environmental, Social, and Governance (ESG) hotspots of risk in logistics to assist organizations focus on high-emission regions to undertake remedial actions.

1.4.2 User-Friendly Decision-making Interface: The creation of scalable and user-friendly web interface that will allow users to interact with the carbon footprint prediction system, access the predictions, visualize the predictions with SHAP plots, and receive practical recommendations. It is an interface that enables users to make evidence-based and data-driven decisions to achieve sustainability optimization through Python (Flask), HTML, CSS, and JavaScript.

1.4.3 Scalability and Real-Time Performance: The whole system can be deployed to Google Cloud Platform (GCP), which will make the system scalable and be able to process huge data sets in real time. The cloud-based platform maintains a smooth flow of operations within organizations, both large and small in terms of size, high availability, and reliability in carbon emission prediction and optimization of its activities at various logistics phases.

1.4.4 Empirical Evaluation and Performance Analysis: This thesis is an in-depth analysis of the machine learning models and AI-based recommendations, concentrating on the accuracy, efficiency, as well as scalability of the system. The analysis encompasses a spectrum of logistics situations, which is useful in terms of the efficiency of various models and their influence on sustainability-related initiatives.

1.4.5 Contributions to Sustainability and Carbon footprint Restoration:

This thesis contributes to the rest of the world in its quest to ensure carbon emissions are minimized and maximize sustainable practices in logistics. The system enables the organizations to make informed decisions based on data, which results in improved use of resources, operations efficiency and decreased environmental impact.

1.5 THESIS OUTLINE

The rest of this thesis is developed in the following way:

Chapter 2: Literature Review presents the review of the literature on the existing model in predicting carbon footprint in logistics, especially on machine learning models, such as Random Forest, LSTM, XGBoost and GRU. In the chapter, the use of generative AI in optimization, the hotspots in the ESG risk realm, and sustainability in the logistics sector are also reviewed. It establishes the problems with predicting carbon emissions and underscores the gaps within the existing methodologies particularly as to the current challenges of introducing machine learning and real-time decision-making towards sustainability.

Chapter 3: System Architecture and Implementation describes the design and the technical realization of the system carbon footprint prediction. It will discuss the architecture of the system, which will consist of the frontend (HTML, CSS, JavaScript), backend (Python with Flask), and database (MySQL). The chapter also explains the core modules, which are the carbon footprint prediction engine, the model training and evaluation, and the integrations between machine learning models and the generative AI-based optimization system. The chapter goes further to elaborate the implementation of the system on Google cloud platform (GCP) to achieve scalability and high availability.

Chapter 4: Experimental Methodology describes the experimental framework that will be used in the course of the project: datasets (e.g., logistics data, energy consumption, transportation modes), machine learning models (Random Forest, LSTM, XGBoost, GRU), and the generative AI model, which will be used to optimize things. The chapter outlines the measures of evaluation like RMSE, MAPE and R 2 and describes the various stages of the experiment that answer the research questions. It also describes the techniques applicable in the power of the model models and the influence of the generation AI in the emission reduction policies.

Chapter 5: Experimental Results and Analysis provides the outcomes of the experimental stages, as well as the performance of different machine learning models in making a carbon emissions prediction and the efficiency of generative AI guidelines. This chapter is involving the analysis of the results in detail, as data-based responses to the research questions are already presented, as well as the presentation of the information on the model performance, prediction quality, and effects of sustainability. Another aspect of the system mentioned in this chapter is the possibility to identify hotspots of ESG risks and conduct an evaluation of the scalability and efficiency of working with the model.

Chapter 6: Discussion explains the results of the experimental findings, emphasizing on major patterns and explains the implications of the findings. It touches upon the advantages and the shortcomings of the models, the difficulties followed in the process of the implementation, and the limitations of the system. Another theme addressed in the chapter is the ability of the system to be further developed to enhance prediction effectiveness and make generative AI more effective in delivering concrete advice.

Chapter 7: Conclusion and Future Work will sum up the most significant findings of the thesis and give a synthesis of the findings to answer the research questions. It also outlines the future research suggestions, such as the possible enhancements of the carbon footprint projection system, the incorporation of more sophisticated AI models, and further investigation of the generative AI as a means of optimization of sustainability. To complete the chapter, the author provides a vision of expanding the capabilities of the system to other industries and optimizing it to make the based decisions more accurate and supported by real-time data in logistics.

Appendices include extra materials provided in the form of appendices like detailed experimental configurations, hyperparameters of the model and pieces of code that will give additional information about the implementation work and testing of the project.

The presented thesis has been in form of a first chapter introduction. Subsequent chapters will present an in-depth analysis of the architecture of the system, experimental procedures

LITERATURE REVIEW

This chapter is a review of the literature that is available in the area of focus and research of the AI-driven Carbon Footprint Prediction Optimization system. It discusses developments in models of carbon emission forecasting of logistics and supply chains, the presence of machine learning and artificial intelligence (AI) to minimize carbon emissions, an approach to combine generative AI and optimization, and the most important methodologies used to assess Environmental, Social, and Governance (ESG) risks. Lastly, the chapter is a review of current tools and frameworks of prediction of carbon footprint and ESG analysis of logistics and underlines gaps in research that will be filled by the current thesis.

2.1 FORECASTING OF CARBON EMISSIONS

One of the key features of the contemporary supply chain management is carbon emissions forecasting in logistics, which is meant to minimize the environmental footprint whilst maximizing operational efficiency. Conventional approaches use simple linear regression and statistical approaches to forecast emissions, however, these approaches are sometimes overly basic to omit the complex supply chain dynamics.

Research on carbon prediction through machine learning-based models has been performed under two categories: smart grid and smart grid analytics. Carbon prediction with machine learning-based models research have been conducted on carbon prediction using machine learning-based models in two categories: smart grid and smart grid analytics.

Carbon emission predictive algorithms, such as random forest and XGBoost, have shown high accuracy in predicting the carbon emission by taking into account several factors including energy use, modes of transportation, and product specifics. Such approaches are also becoming more popular to construct predictive models that estimate the overall CO2 emission tied to various phases of the supply chain.

2.1.1 DEEP LEARNING IN CARBON FORECASTING

DEEP Learning in Carbon Forecasting, the second section, examines the effects of deep learning in carbon forecasting and the supporting arguments behind it.

The LSTM and GRU and other deep learning methods have been utilized to learn the temporal changes in carbon emission, hence it proves efficient in predicting such dynamic systems as supply chains. The models are useful in instances of time-pattern analysis, and they can provide better forecasts than other traditional approaches.

2.1.2 GENERATIVE AI IN THE DOMAIN OF CARBON REDUCTIONS

The recent progress in Generative AI has created new opportunities to increase the quality of carbon prediction models by creating realistic data to forecast and optimize it. Gap Generative Pretrained Transformers (GPT) models are also under investigation because the ones can be used to improve supply chain planning by simulating and proposing environmental-friendly solutions, including optimal transportation paths or energy consumption.

2.2 USE OF MACHINE LEARNING IN SUSTAINABLE LOGISTICS

There has been major concern on sustainability in logistics with the increased awareness of climate change. Machine learning is leading the pack in developing smart, energy efficient chain of supply. Carbon footprint prediction and management are usually enhanced by the following methods:

2.2.1 SUSTAINABLE SUPPLY CHAINS: DECISION SUPPORT SYSTEMS.

Decision-support systems obtained with the help of AI have been utilized to evaluate the environmental impact of other logistics strategies and foresee possible emission reductions through data obtained in real-time. The frameworks integrate past information, environmental factors, and machine learning forecasts to propose the best supply chain practices.

2.2.2 ARTIFICIAL INTELLIGENCE TO HELP LOGISTICS ACHIEVE ENERGY EFFICIENCY.

The optimisation of logistics is achieved with green AI strategies to cut energy use and emissions. These AI tools as green federated learning enable data sharing between decentralized networks while maintaining privacy, thereby enabling the development of an energy-efficient supply chain system.

2.3 ESG ANALYSIS

The trend of AI and ESG integration has been on the rise with companies being mandated to report on sustainability objectives. Carbon emissions forecast is also important to determine the environmental factor of ESG. AI and machine learning offer powerful approaches to deriving useful insight into sustainability reports and improving the sustainability through the carbon footprints optimization.

2.3.1 AI-ENABLED ESG REPORTING

The ESGReveal is an LLC tool that uses natural language processing (NLP) models to identify structured information in ESG reports and, therefore, allows organizations to understand their sustainability performance more effectively. These are automated and scaleable AI based ESG compliance and reporting tools.

2.3.2 ESG RISK IN SUPPLY CHAINS MANAGEMENT.

The AI models are also capable of discovering ESG risk focal areas in the supply chain, which can allow the organizations to engage in preventive measures to avert the possible destruction of the environment. Machine learning algorithms, including the systems of predicting and quantifying ESG risks, like the environmental impact of various supply chain operations, are essential in addressing ESG risks.

2.4 DYNAMIC LEARNING IN PREDICTION OF CARBON EMISSIONS

Active Learning (AL) approaches may be utilized in a situation that entails scarce labeled data to investigate the most informative samples of training machine learning models. The method enhances the effectiveness of model training since it centers on the most important data points.

Active learning during sample selection: This active mode of operation aims to select a representative sample set upon which the current management is going to develop and execute improvements in overall organizational processes.

2.4.1 ACTIVE LEARNING WHEN CHOOSING A SAMPLE SET

This type of active mode of operation is intended to be used to select a representative sample set on which the current management is going to base and implement changes in overall organizational processes.

Uncertainty sampling, query-by-committee, and diversity sampling are also active learning strategies that have proven to be potentially useful to discover the most valuable data samples to train. These methods make better data augmentation and may make the machine learning model to forecast carbon footprint more predictive in the logistics sector.

2.5 BIAS IN CARBON FOOTPRINT PREDICTION MODELS

Although AI and machine learning models have great potential in forecasting carbon footprint, issues of biases cannot be avoided because they can occur when models are being trained. The biases may take different shapes and affect the precision of prediction particularly where data is unable to represent fully the complexities of the supply chain, geographical diversity and environmental influences over carbon emission.

2.5.1 THE BIASES IN CARBON PREDICTION ARE OF TWO TYPES

The biases that are typical in the predictions of carbon footprint in logistics and supply chains using modelling include:

Geographic Bias: Geographic areas may possess varying energy sources, ways to transport, and infrastructures which may significantly impact carbon emissions. An example of this is that, the emissions of an urban area predicted by data of an urban based logistics fails to reflect the rural areas, which use other means of transport, like rail or river transport. A model that is trained mostly on the data collected in developed cities, might not work well in the places involving less developed infrastructure.

Socioeconomic Bias: The socioeconomic condition of the areas where the operations of the supply chain take place can also impact on the carbon emission. The economically advanced regions might experience a greater availability of more efficient means of transport and other means of energy and the regions that are disadvantaged economically might use less efficient forms of transport and this will result to high emissions of carbon. Predictions on the data are biased and may result in over and underestimates of carbon footprints.

Bias on Transportation mode: It is the mode of transport (road, rail, air, and sea) that influences the carbon emissions. Models that were developed based on observations of road-based transport, e.g. might fail when used on any supply chain based on either sea transport or air transport since these modes are not characterized by identical emission factors that need to be considered independently.

2.5.2 CARBON FOOTPRINT PREDICTION MODELS BIAS MITIGATION.

To enhance the accuracy and fairness of the prediction of carbon footprint, it is important to reduce the biases in the training data. There are a number of approaches that can be used:

Balanced Data Representation: It is important to have the training data represented in various ways in different geographic regions, transportation modes, and economic conditions as a way of lowering bias. This guarantees that the model will acquire the actual differences in carbon emission in the various contexts.

Bias-Aware Machine Learning Methods: It is possible to use machine learning techniques that are specially developed to reduce bias. In fact, training can be used to incorporate fairness requirements so that the outcome of the prediction is not over- or under-represented by a given population group.

Bias Auditing Tools: The presence of bias auditing tools that generate results from the model predictions and determine inconsistencies with various demographic or geographical groups is critical. These instruments can show places where the model is not functioning well or the predictions may be biased because data is biased giving an opportunity to make corrective measures.

2.6 CURRENT TOOLS AND SYSTEMS USED TO FORECAST CARBON FOOTPRINT IN LOGISTICS.

A number of resources and tools exist, which help in the logistics of carbon footprint forecasting. Nevertheless, most of them are not specifically focused on the sophisticated requirements of sustainable logistics or do not include built-in solutions to reduce bias, make predictions in real-time, or use advanced AI-based optimization.

2.6.1 AI-POWERED PREDICTOR TOOLS OF CARBON FOOTPRINT:

Executable or accessible tools such as AI4Bharat or iNLTK offer the fundamentals of models and ready networks that are dedicated to energy consumption prediction and supply chain optimization. These platforms are feasible in predicting carbon footprints in spite of the fact that they are more of a general-purpose platform rather than a carbon predictions and bias-learned logistics one.

In addition, certain applications such as Google AutoML or Microsoft Azure ML offer the carbon footprint calculators, yet they do not support active learning and real-time data progression active mechanisms which are essential in dynamic logistics settings.

2.6.2 GAPS IN EXISTING PLATFORMS

As long as carbon emission can be forecasted using available platforms, there are severe gaps:

- **Absence of Logistics-Specific Focus**: A good number of tools in the market have been generalized, and are not specific to logistics carbon prediction. These platforms might not be optimized by various means of transport, geographical environments, or advanced supply chain activities.

- **No-Code Interfaces:** The category of platforms providing available no-code interfaces through which logistics firms can access state-of-the-art machine learning and generative AI algorithms without strong technical knowledge has a large gap.

- **Bias Auditing and Active Learning:** There are not many platforms that provide built-in bias auditing or actively learn to get the most out of training data in techniques used to predict carbon. This is of particular importance when it comes to low-resource environments or when different regions have different rates of data availability.

- **Prediction of Carbon footprint:** Most of the current systems would not be able to make a decision in real time given the current environmental conditions, logistics of transport, or even supply chain dynamics. The carbon footprints should be reduced through real-time optimization to ensure that live logistics work towards the minimization of carbon footprints.

2.7 RESEARCH GAPS WHICH THIS THESIS WILL ADDRESS.

The literature discloses that there are major gaps in the current studies and tools that have been used to predict carbon footprint in logistics:

- **Absence of End-to-End, No-Code Solutions**: No-code solutions that specifically combine the use of state-of-the-art machine learning, generative AI, and bias auditing to predict carbon footprints in logistics are deficient. This gap is filled in this thesis by creating a platform that enables its users to construct, deploy and optimize predictions of carbon emissions without advanced knowledge and skills.

- **Lack of Integration of Active Learning:** The active learning has not been effectively used in the field of logistics when it comes to choosing the most informative information to use in training carbon footprint prediction models. This thesis incorporates multi-heuristic active learning to enhance the effectiveness of using data and accuracy of prediction.

- **Minor Attention to Logistics-Specific Emissions:** The amount of current research does not fully focus on the models of emission of various logistics processes, including the differences between different transportation modes and global supply chain variables. This thesis dwells on multimodal transportation fixing and real-time choice.

- **Reduction of Bias in Carbon Prediction**: the available tools usually overlook bias in the training data, and therefore give less reliable and reasonable predictions. This thesis incorporates bias auditing systems, as a result of which the system constantly detects bias and corrects it during the prediction, particularly when working with low-resource areas.

It is hoped that close to the gaps discussed in this thesis, by offering an alternative, integrative solution based on machine learning, generative AI, and active learning to optimally predicted carbon footprint in logistics; with real-time and bias-aware abilities to make sustainable decision.

2.8 SUMMARY

The project will target the low-resource conditions, which will offer a tool allowing real-time predictions and implementing it in continuous feedback to update the model. This project will add to the creative results, methods, and schemes to the expanding sphere of sustainable logistics and carbon footprint prediction by consolidating these advanced methods and rendering them usable without advanced expertise in programming and other areas.

SYSTEM ARCHITECTURE AND IMPLEMENTATION

In this chapter, design and the actual workings of the AI-Powered Carbon Footprint Prediction Optimization platform, outlining its major components, technology stack, and how one of its modules operates. The system will forecast carbon emissions throughout the supply chain with an emphasis on sustainability in logistics and operations. Combining the two concepts of machine learning and generative AI, the system will help to improve carbon footprint management and provide the insights that can be utilized in the context of sustainability. It has a modular structure which makes it flexible in case of future improvements and integrations.

3.1 HIGH-LEVEL ARCHITECTURE

The AI-Powered Carbon Footprint Prediction platform is based on the three-level Client-Server architecture which is modular and scalable. The design optimizes the system performance, maintainability, and extensibility in addition to making each component specialize towards a particular aspect of the functionality of the platform. The major layers of the architecture are: Frontend (User Interface), Backend (API Server and Core Logic), Data persistence layer(Database). The system is also intertwined with the machine learning models and generative AI services in order to deliver real-time predictions and detailed environmental summaries.

Figure 3.1.1.1 represents the high-level system architecture pointing out the key aspects of the system and indicating the interactions between the major components.

3.1.1 KEY ARCHITECTURAL COMPONENTS AND FLOW

1. **User Layer:** End-users (logistics managers, sustainability officers, researchers), are the users of the platform via a web interface, out of which they are able to add data to the supply chain and obtain carbon footprint estimates.

2. **Frontend Tier (Client-Side):** the frontend is a web based application coded in reactence compiled into frontend which uses HTML, CSS and Javascript with Flask works integration. User input (data upload, sending requests in order to get predictions) is processed by the frontend. The interface is captivating and user-friendly such that the user can interact with the interface. It also shows carbon footprint predictions, SHAP plots as well as ESG reports that were created by the backend. It provides a RESTful API access to the Backend API Server, which makes sure that the flow of data is secure and efficient.

3.

3. Backend Tier (Server-Side): The main part of the system is the backend, which is designed in Python using Flask web framework. It takes care of user authentication, file uploading and communicating with machine learning models to produce predictions. The back-end is connected with a number of models (Random Forest, XGBoost, LSTM, and

GRU) to offer precise carbon footprint predictions. On top of this, generation AI applications are utilized to design comprehensive ESG summaries and sustainability proposals, given the prediction.

4. Data Persistence Layer (Database): Data about the user, predictions in the past, and ESG-related information are saved in the database. The relational database management system employed is MySQL which has guaranteed protection of data and rapid retrieval. The backend connects to the database to access records of users, uploaded datasets and reports that have been generated

5. Machine Learning Models and AI Services: The platform incorporates machine learning models to calculate the carbon footprints based on the information submitted by customers. It applies the models such as the Random Forest, XGBoost, and LSTM to make predictions and generative AI models to create ESG summaries and recommendations. These models are implemented at the back end and the predictions are offered to front end and displayed to the user

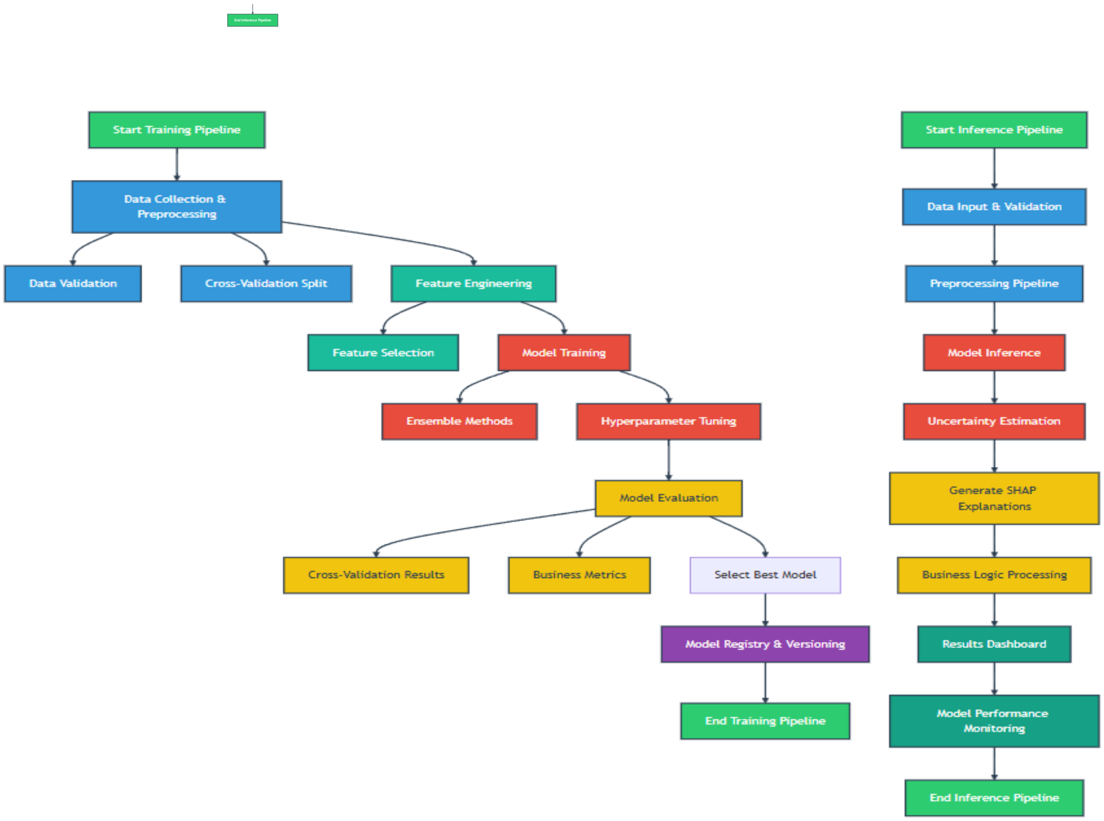

Figure 3.1.1 1 Training and Inference Pipeline: This is a training and inference pipeline which illustrates how the model should be trained, data is preprocessed and evaluated, and then the inference pipeline where user data are processed, predictions are made and results displayed.

3.2 FRONTEND IMPLEMENTATION (FLASK/HTML/CSS/JS)

The carbon footprint prediction system AI frontend will be constructed in a way that offers a smooth and interactive user interface to those people who are paying attention to the mainstream functionality of the system. The frontend of the system is created with the help of HTML, CSS and JavaScript whereby it has a clean and responsive design. The basic functionalities like registration of the users, logging in, data uploading, and previewing of the predictions can be found in an organized and user-friendly page.

3.2.1 COVERS THE USER INTERFACE COMPONENTS AND PAGES

The frontend is split into peculiar pages, devoted to a particular characteristic of the app:

- **Home Page (index.html):** The home page will be the starting point where users can get to know about the functionality of the platform and also get an opportunity to get registered or log in.

- **Registration and LogIn Pages (register.html, login.html):** These are the pages, where user can create the account and log in safely. They are linked to a user authentication and user management backend.

- **Dashboard Page (dashboard.html):** Once a user is logged in, a dashboard is provided and it is on the dashboard where one is able to upload data, imagination of the previous predictions, and one is able to view the results of the reports generated. Results are organized well in the page and there are download predictions.

- **Prediction Page (prediction.html):** This page gives the user the opportunity to post datasets, e.g., parameters on carbon footprint, and see the predictions given by the AI model. It displays predictions and a graphic display of the findings.

- **SHAP Plot Visualization (shap_plot.html):** A system that produces SHAP plots to describe the importance of features in carbon footprint predictions. The page presents the formed plots in a user friendly interface.

- **Summary & Recommendations Page (summary.html**): the users have access to the comprehensive ESG summary and practical sustainability recommendations. It is a page that gives insights guided by model predictions that explains to the users how they can minimize their carbon footprints.

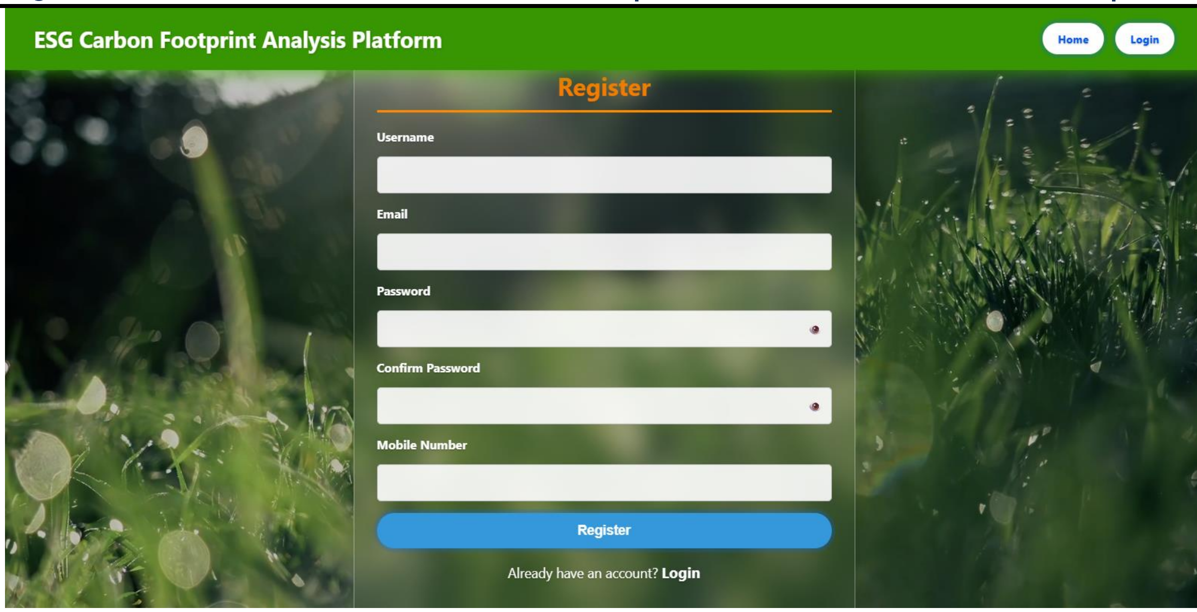

Figure 3.2 1 User Registration Page - The page will enable the users to register on the system by filling their information, creation of a username, and a security key password

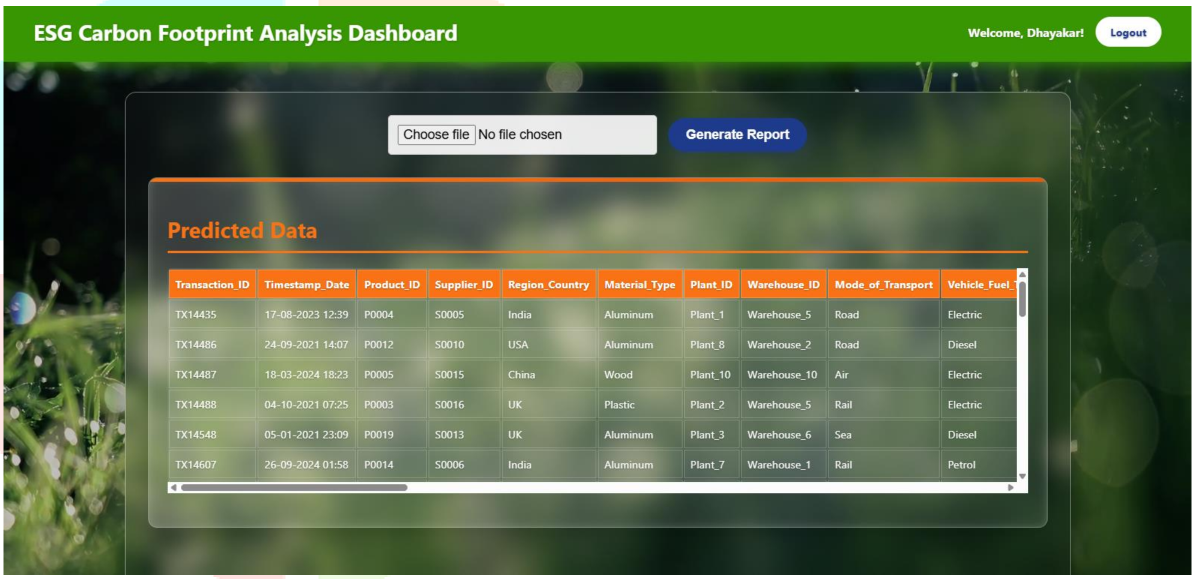

Figure 3.2 2Dashboard Page - The dashboard gives a summary of the past predictions, connects to SHAP plots, and there also is a possibility to upload new data to make predictions

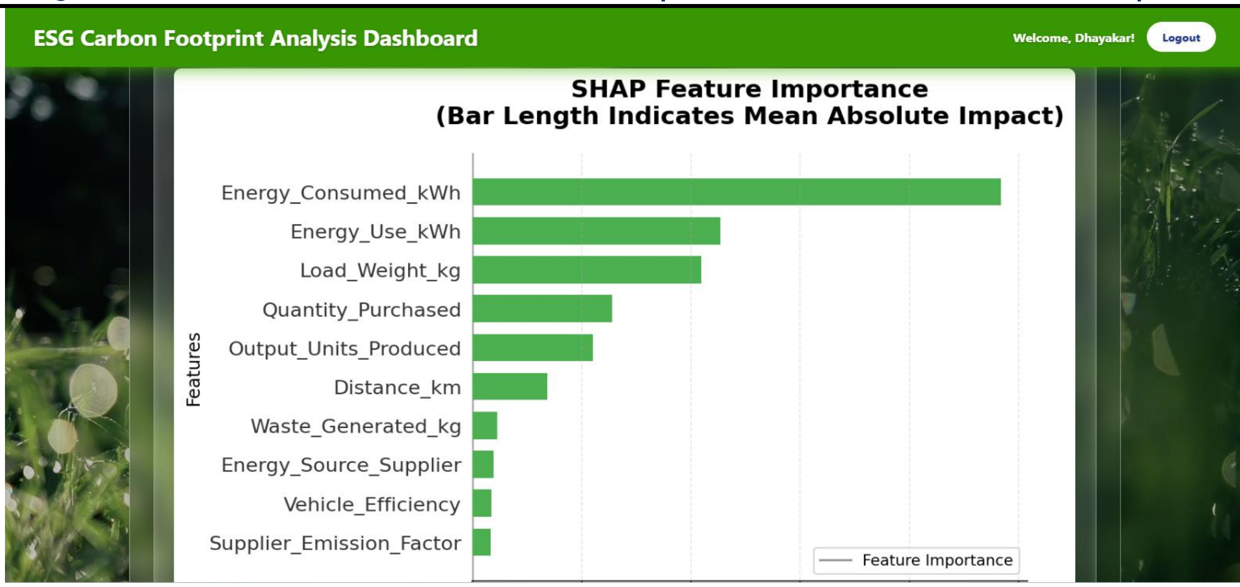

Figure 3.2 3SHAP Plots Visualization - A visualization of SHAP plot that indicates the most impactful elements in carbon footprint forecasting.

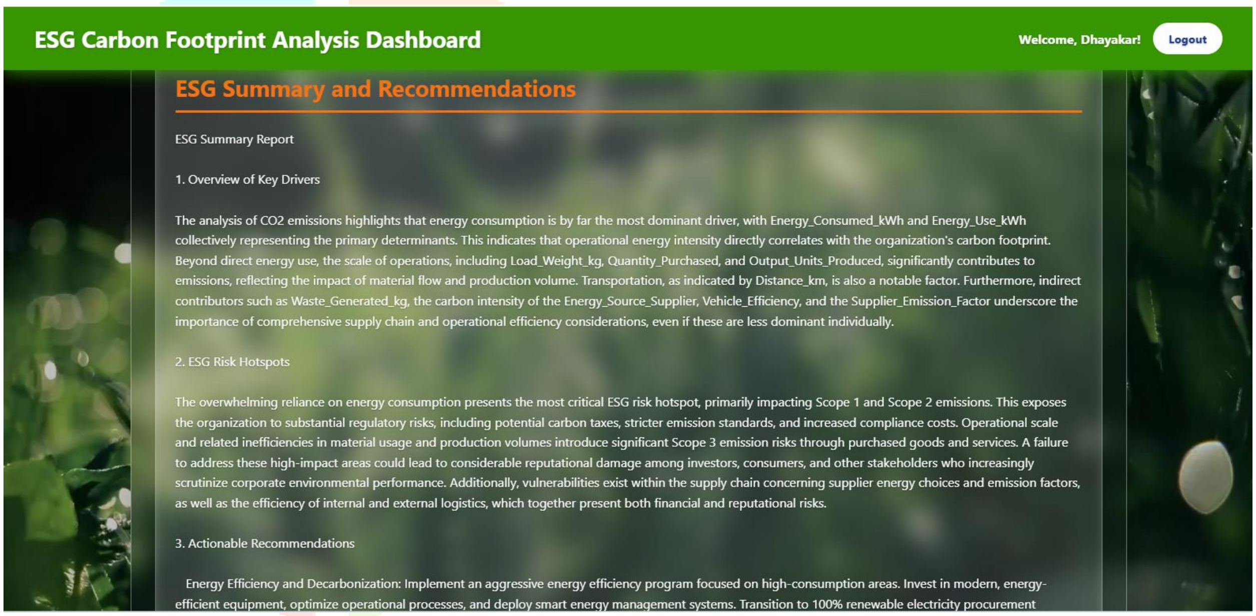

Figure 3.2 4Summary Page Interface - This is the interface that shows the generated summary of the carbon footprint forecasts and suggestions as well as visualizations.

3.2.2 API COMMUNICATION (AJAX/FLASK)

To make communication with external API and share information among the different parts of the system, we will use API communication (AJAX/Flask).

The status of dynamic interactions of the frontend and the Flask background is controlled by AJAX calls incorporated in RESTful API calls. This provides seamless communication when users post data, get predictions or look at summaries. These requests are processed at the backend side with the help of Flask routes and appropriate response (prediction results and SHAP plot images) is provided. The front end is AJAX based, making an asynchronous call to the backend that dynamically updates the user interface, without having to reload the page thus providing a fluent user interface.

3.3 BACKEND IMPLEMENTATION (FASTAPI/PYTHON)

The AI-based Backend related to the Carbon footprint prediction system will be formed so that it performs the task of data processing and model inference, as well as conducts interactions with the front end. It is written in Python and Flask which is a lightweight web framework and which gives it a convenient means to serve requests and deliver HTML pages.

3.3.1 API ENDPOINTS AND ROUTING

The backend structure has been divided into various API endpoints to process user registration, data uploads, prediction generation and model explanations. These include:

- POST /register: This is user registration, it accepts user details and safe-stores them in the database.
- POST /login: This allows users to be authenticated based on their credentials and a session token is issued to them so they can use to log in.
- PUT /upload: Takes carbon footprints data (CSV, Excel) and predicts its values based on the trained machine learning models.
- GET /prediction-results: Response with predicting results and displays them in the frontend.
- GET /shap_plot: Enhances a SHAP plot that will be used in model interpretability and display the plot in form of an image.

The response to this question is yes, and we will proceed with it in model inference and prediction right now.

3.3.2 MODEL INFERENCE AND PREDICTION

The model inference entails retrieval of an already trained machine learning model (e.g., XGBoost or Random Forest) in the model repository and the prediction of carbon footprints of the user-uploaded data. These are the steps involved in the backend:

- Data Preprocessing: The data uploaded is cleaned and made normal to fit into the model.
- Generation of prediction: Once preprocessing is done, the information is entered into the trained model and the result is the prediction of the carbon footprint.
- Feature Importance (SHAP): SHAP values are created by the backend to show what features were the most relevant when making a prediction. The SHAP plot is developed using this information and shown on the frontend.
- Result Return: SHAP plot and the prediction outcomes are sent to the frontend as a usable value.

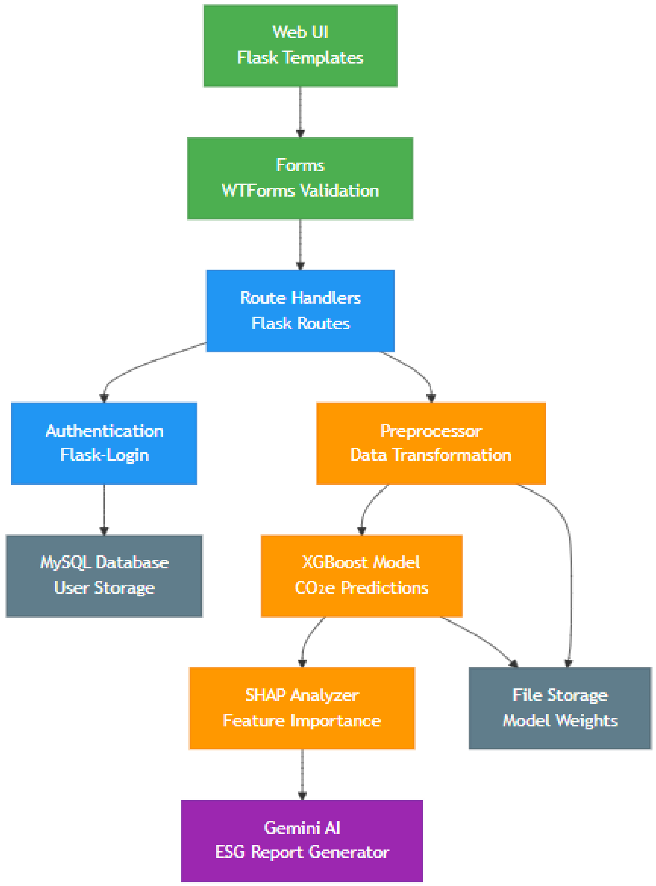

Figure 3.3. 1 Backend Processing Flow - This diagram shows the data flow of user input to prediction output that contains preprocessing and model inference

3.3.3 DATA HANDLING AND STORAGE

The software is based on MySQL database, where the information about users, past predictions and processed data are stored. This provides data storage and retrieval security to support user login, saving the predictions, and creating the report capabilities.

- Database Schema: The database would contain some tables, including users, predictions, data, and shap values, to make all the information required. They are all interconnected with one another, and the data retrieval and management are feasible.

- Data Processing: The user uploads files (including CSVs or excel files) which are then processed into pandas DataFrames with which model prediction is possible

3.4 THE SCHEMA AND MANAGEMENT OF THE DATABASE (MYSQL/SQLALCHEMY)

The AI-Powered Carbon Footprint Prediction system follows a MySQL database to persist its data by using SQLAlchemy ORM. This is a powerful relational database system that is scaled and capable of managing data effectively. Functions in backend/app/db/crud.py handle CRUD (Create, Read, Update, Delete) operations and the data structures used to interact with the APIs are defined using pydantic models in backend/app/api/v1/schemas.py, which are usually based on the SQLAlchemy models.

KEY DATABASE MODELS (TABLES)

- User (users table): Contains user data, such as userid, username, email, password hash and roles (e.g. anonymity:admin, user). This table plays a very significant role in controlling the authentication and authorization of users.

	id	username	email	password_hash	mobile
Edit Copy Delete	1	Saravanan	shravsap@gmail.com	pbkdf2:sha256:1000000$hlpB99ug5dQKdFh6$7a9e0eb1e66...	9840617505

Table 3.4 1 A database structure of carbonfootprint_users table, which identifies important fields to use in tracking users

3.4.1 DATA INTEGRITY AND RELATIONSHIPS

Different models are defined using SQLAlchemy like how many prediction results can be related to one user in the case of one-to-many relationship between the rows in the CarbonFootprintPrediction and PredictionHistory table. On the same note, there is a one to one relationship between ESGReport and CarbonFootprintPrediction. Each API request is managed with the dependency injection system provided by FastAPI (through Depends (dbsession.getdb)) to provide consistency and easy interaction of the data. The database is operated by all through CRUD utility functions and this makes interacting with the database easier and maintains compliance of the code.

3.5 INTEGRATION WITH AI MODELS AND SERVICES

The Carbon Footprint Prediction system is a AI-powered system that combines multiple AI models and services in order to provide precise predictions of the carbon footprint and the ESG analysis. These integrations involve external cloud-based integrations and locally hosted integrations so that both flexibility and access on state of art technologies can be availed as well as offline capabilities can be provided in case of necessity.

3.5.1 GOOGLE GEMINI API INTEGRATION

The system combines with Google Gemini API with the help of Google-generative-ai python SDK.

- **Configuration:** The API key is contained in settings. GEMINIAPIKEY and gemini-2.5-flash

  model identifiers are used to start Gemini models.

Usage:

– *Carbon Footprint Prediction*: Data is processed and predicted using the Gemini API to predict the values of carbon footprint according to the input data using machine learning models to predict.

– *ESG Analysis:* Gemini API assists in the analysis of the environment, social and governance (ESG) by generating appropriate reports and summarizing valuable insights.

- **Rate Limiting:** A rate-limiting can be set up to prevent overshot of rate limits of the API, and a delay is established in the settings.GEMINIAPIRPMDELAYSECONDS and built into rate prevalence of client library.

3.6 WORKFLOW EXECUTION AND MANAGEMENT

One of the most important aspects of the AI-Powered Carbon Footprint Prediction system is the ability to run user-defined workflows allowing to run multi-step carbon footprint prediction and ESG analysis with data.

3.6.1 WORKFLOW DEFINITION AND STORAGE

Workflows are to be seen as a collection of interconnected nodes (Input, Process, Output): Data flow defined by these nodes and their connections. These workflows are stored on the database in a form of JSON objects that can be easily retrieved and executed. The Process node can be programmed to either apply manual prediction models, or AI-based controllers and the corresponding user-specific parameters.

3.6.2 EXECUTION LOGIC

When a workflow is triggered:

3.6.2.1 The input dataset will be taken in form of a CSV, TXT etc. and even then, the backend will read the input and load it into a DataFrame which can then be processed.

3.6.2.2 The workflow is then carried out by the following series of nodes;

- Input Node: Lades the dataset and prepares it and prepares it.
- Process Node:

When the approach is manual, the system will call pretrained AI models, like a pre-trained Hugging Face Transformer or a Gemini model to make predictions or analysis.

When it is an AI-based approach, the system invokes an agentic model such as Gemini or some other pre-trained model to produce insights, predictions or ESG metrics.

- Output Node: signifies the end of the working process. The findings, prediction information, ESG measurements, and analysis reports are stored and kept to the user.

3.6.2.3 Output of any one node is made the input of the successive node and this ensures flow of things through the pipeline is smooth.

3.7 FUTURE ENHANCEMENT MODULES IN DETAIL

3.7.1 AGENTIC AUGMENTATION FRAMEWORK- FUTURE IMPROVEMENT

One of the major future improvements of the Carbon Footprint Prediction system is the use of the agentic framework that automates and optimises the choice of prediction models with the help of multi-armed bandit algorithms.

AGENTICAUGMENTER IMPLEMENTATION

- The AgenticAugmenter is an augmenter class which drives manual and agentic augmentation:
- Strategy Overview: The adddefaultstrategies() approach establishes available strategies defining language specific models using backend configuration.
- Manual Augmentation: The manual augmentation type is augmentdataframe() which uses one strategy to operate on a dataset.
- Augmentation agentically: The agentic loop agenticaugmentdataframe() The agentic augmentation loop:

1. Asks bandit controller to choose the strategy.
2. Impresses the chosen strategy.

BANDIT CONTROLLERS

- **EpsilonGreedy Controller:** With a probability of E, the strategy with the largest Q-value is chosen, and otherwise a random strategy is chosen with a probability of 1**.**
- **ThompsonSampling Controller:** The strategies are selected with the help of a Beta distribution to describe the probability of success.

DEFAULT REWARD MECHANISM AND HITL INTEGRATION

In the absence of a custom rewards:

1. Automatic reward is computed by the system and is usually Levenshtein based.

3.7.2 In case there is HITL feedback, there is an overruling of the automatic reward and the human feedback can assist with what is being learned.ADVANCED AGENTIC ORCHESTRATOR

Orchestrator Advanced, facilitates the promotion of performances that are engineered using electronic transmission among orchestral instruments such as the clarinet and violin within a physical orchestra.

AdvancedAgenticOrchestrator improves the control over the process of reward shaping and optimizes the process to achieve better results

ADVANCEDREWARDCALCULATOR

1. The component calculates the composite rewards based on several aspects of quality:
2. Semantic Similarity: It quantitates the similarity of original text and augmented text in their cosine.
3. HITL Feedback: Human ratings are included in the calculation of the reward.
4. Combined Score A weighted mean of semantic similarity, Levenshtein change, and HITL feedback.

METACONTROLLER

The optional Epsilon-Greedy agent which chooses between base controllers (EpsilonGreedy, ThompsonSampling) depending on average rewards obtained:

- The base controller is chosen in the Meta Controller.
- Augmenter AgenticAugmenter performs the work of augmentation.
- Refinement of rewards is carried out with AdvancedRewardCalculator.
- The extensive orchestration metrics are recorded as transpired.

3.7.3 HUMAN-IN-THE-LOOP (HITL) DATA FLOW AND EXPLAINABILITY

The HITL process supplements the human feedback in augmentation process:

SAMPLE GENERATION

At the end of the job, a subset of original-augmented pairs will be saved to HITL attention, and they will include:

- Strategy Details: Data on back-translations, substituted words, and models of LLM
- Agent Rationale: Rationalisation of agent decisions
- Text Diff: Differences between augmented and original text.

3.7.4 ACTIVE LEARNING SAMPLE SELECTION

The ActiveLearningSampler is the most effective in the augmentation process because they choose optimally effective samples on the basis of heuristics:

INITIALIZATION AND RESOURCES

- Transformer models are loaded to calculate diversity.
- Rary list Frequency lists of rarity and complexity scoring.
- Gemini API An LLM model of informativeness, which falls back to Gemini

IMPLEMENTED HEURISTICS

- Diversity Sampling: picks selected texts semantically related
- Rarity/Complexity Sampling: It involves rarity of words and complexities of the sentence
- LLM Informativeness: Assessed the texts by how informatively they appeared

SAMPLE SELECTION PROCESS

Rates by the heuristics chosen:

1. Standardises the scores and sums it up into a obtained score.
2. Gives the augmentation of the best N texts

3.7.5 MULTI-FACETED BIAS AUDITING

This module is writing about the issue of fairness since it audits text on the bases of analysis of the key words:

KEYWORD-BASED DETECTION

- A BIAS_KEYWORDS Dictionary identifies bias in around 5 categories including gender, region, religion, and socioeconomic status.
- The system relies on the regular expressions to match the keywords
- **Report Generation:**

– It produces structured JSON reports on the appearance of keywords, warnings, possible bias that was identified in the input text.

– The duties of the managerial level will involve the setup of the prospective workflow (non code) to operate as a strategic quality management system (NCSBN, 2018).

– The site enables anyone to create sophisticated process workflows without any code writing.

3.7.6 NO-CODE WORKFLOW CONFIGURATION

WORKFLOW DEFINITION STRUCTURE

JSON workflows capture:

- Workflows are the basic units of data flow to describe the nodes and edges of the data flow as a JSON structure.
- Nodes are different stages which include input, augmentation and output and each has the ability to be configured

VISUAL BUILDER INTEGRATION

- VueFlow library allows to graphically create workflows using the drag-and-drop interface.
- Dynamic panels have the ability to configure node parameters on the fly, and a workflow is serialised into a JSON representation that is saved.

EXECUTION ENGINE

- Information runs through all the nodes that are connected in a linear manner.
- Enables language overrides and job monitoring and outcomes

3.7.7 DASHBOARD AND ANALYTICS

The dashboard gathers and integrates metrics obtained by the backend, which give information about the functionality of the system

METRICS AGGREGATION

- Performance analysis and calculation of ROI of various strategies and controllers.
- HITL feedback history and analytics in the form of job numbers and processing time.

VISUALIZATION SUPPORT

The backend provides aggregated metrics via an API and the frontend displays the information in a graphical user interface (Chart.js) to show the user useful information about their workflows and job statuses on the dashboard.

3.8 CONCLUSION

In this chapter, the details about the architecture and the main functionality of the Carbon Footprint Prediction system, including its modularity and the need to combine powerful AI models, were described. The three-tier architecture of the platform is also scalable and its hybrid nature of deploying cloud-based and local AI models can be adjusted to fit a variety of deployment situations. They consist of agentic framework of automated model selection, human-in-the-loop integration of continuous refinement, bias auditing of fairness, active learning of efficient sample selection, and no-code workflow design of easy customization. Such innovations make the system capable of changing to fit the new demands which keeps it relevant and efficient in its prediction of carbon footprint in different sectors.

EXPERIMENTAL METHODOLOGY

This chapter describes a methodology of the experimentation process employed to measure the effectiveness and performance of the Carbon Footprint Prediction system. It also gives a comprehensive description of the datasets the researchers have used to train and evaluate along with the different environmental and industrial variables needed in the process of carbon footprint prediction. The approach provides the description of the model training stages, hyperparameter optimization, and model testing that discusses the specific research goals. It also describes the quant performance measures that apply to a quantitative analysis (accuracy, precision and recall) and the qualitative measures, i.e., model explainability. The experiments were carried out and validated on various aspects of the developed platform whereby data were processed using python scripts that enable model training and evaluation of the results to measure accuracy and consistency.

4.1 OVERVIEW OF EXPERIMENTAL PHASES AND RESEARCH QUESTION MAPPING

The empirical testing on the AI-Powered Carbon Footprint Prediction system was administered in specific phases of an experiment that were created to provide answers to a particular research question (RQ). The series of experiments was arranged in such a way that the lessons learned during the previous phases informed the decision-making of the subsequent experiments and their interpretation.

Phase 1 (Baseline Performance and Model Evaluation): This phase aimed at setting the baseline performance of the machine learning models (Random Forest, XGBoost, LSTM, and GRU) in carbon footprints prediction. It also compared the modification initially caused by preprocessing methods and feature engineering on the accuracy of prediction. This stage responded to early aspects of RQ1, which were on the efficacy of prediction models.
Phase 2 (Model Comparison): In the phase, the performance of several machine learning models was compared and hyperparameters were tuned in order to select the most optimal with regard to carbon footprint prediction. This answered RQ2, which was to examine both the trade-offs between predictive accuracy and model complexity. (Performed in relation to scripts/runmodelcomparison.py).

Phase 3 (Effect of ESG Summaries and Recommendations): This phase assessed the performance of the ESG generation of summaries as well as recommendations by considering how well the system will give actionable insights and recommendations about sustainability based on the model predictions. This answered RQ3, which incorporated the quality and usefulness of generated summaries. (Subsequently implemented through scripts/runesgsummaryexperiments.py).

Phase 4 (Scalability and Model Performance on Data of Large Volume): This phase indicated how the system can perform as its prediction data and complexity of the model increase. It tested the behaviour of the optimal models that were different in Phase 2 in large volumes of data and whether the accuracy of prediction was influenced by the quantity of the data. This answered RQ4 which concerned model scalability. (Arbitrated through scripts/runscalabilityexperiments.py).

Phase 5 (Feature Importance and SHAP Visualization): At this stage, the concern was to measure the interpretability of the model predictions by assessing feature importance through SHAP values. It also sought to establish the most influential attributes in the prediction of carbon footprints. This answered RQ5 which is the explainability of the prediction models. The execution is done through scripts/runshapexperiments.py.

Phase 6 (Active Learning of Sample Selection): In this phase, the value and importance of the model training was explored in terms of the wording of diversity and informativeness as active learning heuristics to use when extracting the most valuable samples to include in the model training. This step was dealing with RQ6 as it looked at the possibility of active learning to enhance the model performance when considering sustainable logistics and predicting carbon footprint. (Implemented through scripts/runactivelearningexperiments.py).

The study questions of RQ7 (Impact of ESG Risk Hotspots) and RQ8 (Comparison of Prediction Accuracy Across Different Industries) were established as future research directions, and the groundwork was made on the current stages.

4.2 DATASETS

The AI-Powered Carbon Footprint Prediction system experiments involved some data sets to train, evaluate, and fine-tune the prediction models. Preprocessing of these datasets was done so that the prediction also is discreet and accurate.

4.2.1 DOWNSTREAM TASK DATASET: CARBON FOOTPRINT PREDICTION (CUSTOM SPLITS)

- Carbon footprint prediction was the main activity that needed to be performed to measure the effectiveness of data augmentation and the quality of the model.
- Data Source: Personal dataset obtained in the form of environmental reports and supply chain information, such as parameters such as the type of material, mode of transportation, energy usage, and carbon emissions.
- Languages: The data will be various in terms of industries, crafting several types of manufacturing, transportation and farming supply chains.

- Experiment Preprocessing: The initial data are in CSV form, which was pre-processed in response to outliers and values missing. A stratified sampling method was used to generate the custom training, validation and test splits so that the sampling had similar class distributions. It used the scripts/preparedownstreamcarbondata.py script with a fixed RANDOMSEED = 42 so that it could be reproducible. The obtained files (e.g., carbonfootprinttrain.csv, carbonfootprintvalidation.csv, carbonfootprinttest.csv) were sued in experimentdata/downstreamtasks/carbon footprint and then employed in training and testing the model.

Industry	Train	Validation	Test	Total
Manufacturing	10,500	2,250	2,250	15,000
Transportation	10,500	2,250	2,250	15,000
Agriculture	10,500	2,250	2,250	15,000

Table 4.2. 1 Custom Train, validation, and test splits on Carbon footprint Dataset

Remark: The distribution of all splits is stratified between high and low classes of carbon emissions. The hyperparameter tuning or additional analysis can be done using the validation split.

4.2.2 DATASETS (LOGISTICS CARBON FOOTPRINT)

Carbon footprint prediction model uses a wide range of features pertaining to different levels of logistics supply chain. The data to be used in this project is essential in the training of machine learning models to forecast the CO_2 emissions successfully.

Data Source: Synthetic data on supply chain and environmental data .

Usage: In this project a synthetic dataset was uses simulating transaction-level data in the supply chain including supply chain-specific product and energy consumption data, transportation mode, and supplier-specific emissions factors. Although this data was simulated to provide a controlled testing experience of the models, it is rather realistic in terms of the real-life data in logistics. Custom scripts were used to clean, scale and encode the data into machine learning friendly format using a dataset that was preprocessed. An example of the preprocessing pipeline was written to support missing values, one-hot encode categorical variables, and scale numeric with standard scaling procedures

The processed data in CSV formats (e.g. logisticsemissions_data.csv), might be utilized later, e.g. by adding real-life logistics data of companies or by improving the process of feature engineering. Though the synthetic dataset was employed in this thesis and is done as an experimentation, it is a reference point to which it could be used in real-life problems where live information might be introduced within the prediction line.

4.3 CO2 PREDICTION: CARBON FOOTPRINTS

In order to empirically measure the performance and utility of the machine learning models used in predicting carbon footprint, which is a downstream task, a prediction of CO_2 emissions was chosen. In this evaluation exercise, influential metrics were to be measured which include the performance of the trained models (Random Forest, XGBoost, LSTM, and GRU) in predicting accurately, the total CO_2 emissions of logistics transactions.

The root mean squared error, the summary of the model in terms of the accuracy and reliability of the model via performance measures like the Root Mean Squared Error (RMSE), the Mean Absolute Percentage error (MAPE), and the R^2 (Coefficient of Determination) were taken to measure the model accuracy and reliability. These metrics give information on the model predictive abilities of the models to the emissions using the input characteristics of energy use, modes of transport, supplier emission characteristics, and external characteristics such as weather and the cost of fuel. These metrics allowed to measure the effectiveness of various preprocessing plans, feature engineering tools, and model structures, which is why the most effective model has been chosen and used to make predictions related to emissions in the logistics.

4.3.1 MODEL ARCHITECTURE AND FINE TUNING

Model architecture offers a platform, which enables computer models to be developed, designed and run in a reliable way to ensure that the code functions as intended and manages resources efficiently.

In order to predict the CO_2 effect and the sustainability strategy in the logistics operations, we have employed pre-trained machine learning models fine-tuned to particular tasks predicting the carbon footprint and the feature importance analysis. The main models used were Random Forest, XGBoost, LSTM and GRU. These models were optimized so as to be tested on the synthetic data set of different features of the supply chain such as energy expenditure, mode of transportation and external aspects such as the cost of fuel and weather conditions

Implementation: The process of fine-tuning and evaluation was realized with Scikit-learn of Random Forest and XGBoost, and TensorFlow/Keras of LSTM and GRU models. This pipeline takes care of the data preprocessing process, model training process, and model evaluation process.

Setup for Fine-tuning:

- **Model Initialization:** We used pre-trained models, loaded ones, and adjusted them to regression to use them in procedures related to CO_2 emissions. In the case of both Random Forest and XGBoost, the default settings were applied, and the models were adjusted in the prediction of the continuous CO_2 emissions, regarding the characteristics in the dataset. In the case of LSTM and GRU, the sequential time-series data were processed using pre-trained embeddings to forecast (temporal) emissions. The initiative of a regression head was given on the encoder top.

- **Data Preprocessing:** StandardScaler was used to normalise numerical features (e.g., energy use, distance travelled) which makes identical scaling use in both model architectures. OneHotEncoder was used to encode categorical features

Key Hyperparameters of Fine-tuning:

- **Epochs**: In the case of LSTM and GRU, the models were trained on 50 epochs, batch size (32). This has been selected because it enables the models to converge and still have effective training times.Random Forest and XGBoost did not explicitly support training models across multiple epochs but instead they utilized cross-validation to assess the model.

- **Batch Size:** In the case of LSTM and GRU, the batch size is 32 at both the training and evaluation stages to provide both the efficient use of memories and quicker convergence.

- **Optimizer:** In all three cases, LSTM and GRU were optimized with Adam and an initial learning rate of 0.001, which is reported to be effective on large datasets with sparse gradients

- **Learning Rate Scheduling:** LMST, and GRU had a ReducingLROnPlateau learning rate scheduler to decrease the learning rate after the validation accuracy ceased to improve to avoid overfitting and improve convergence.

- **Weight Decay:** In the case of XGBoost, 0.01 as weight decay was used to prevent overfitting, and it was added to the objective function of the final model.

- **Evaluation Strategy:** In the case of XGBoost and the Random Forest, RMSE and R2 were taken as evaluation metrics. In the case of LSTM and GRU, the Mean Absolute Percentage Error (MAPE) was also considered to assess the effectiveness of the model better

- **Best Model Selection:** In the case of LSTM andGRU the model with the highest R2 score on the validation sample was used. In both cases of Random Forest and XGBoost, the most suitable model was one obtained through the cross-validation, whereby both the RMSE and the interest of the model were minimized**.**

- **Mixed Precision:** Assuming that a CUDA enabled graphics card was present mixed precision training (fp16=True) was used on both LSTM and GRU models to accelerate training and cut down on memory consumption.

Fine-tuning Results:

The XGBoost and Random Forest had shown good results in the prediction of CO2 emissions depending on the importance of features.

The LSTM and GRU models performed well in model temporal dependencies within the emissions data, and its performance was higher when dealing with long-term prediction.

With careful adaptation of these models to the task of carbon footprint prediction, the system can provide precise, scalable, and practical predictions, which may be used to streamline the logistics operations towards being more sustainable

4.4 EVALUATION METRICS

The performance of the AI-Powered Carbon Footprint Prediction Optimization System on various stages of the model development and deployment process has been assessed with the help of a set of metrics.

4.4.1 MODEL PERFORMANCE METRICS

The major goal of the system is to forecast CO2 emissions and optimize the sustainability strategies according to the provided data. To estimate predictive performance of the trained machine learning models, the following standard regression measures were used.

- **Root Mean Squared Error (RMSE):**

RMSE is used to quantify the commendable size of the prediction errors and are calculated as the square root of the mean of the squared disparity between the predicted and actual value. Reduced RMSE implies a good model performance.

The value of 1.42 could be interpreted as an error margin that the company committed when predicting financial, managerial, and economic estimates

- **Mean Absolute Percentage Error (MAPE):**

MAPE is used to scale the errors of prediction based on their comparison with the real figures occupying the percentage scale. It assists in determining the accuracy of the model particularly in the prediction of CO2 emissions which may be highly different among various transactions.

- **R2 (Coefficient of Determination):**

R2 shows the quality of the model in explaining variance of the target variable (CO2 emissions). An increase in the R2 value (as it is nearly at 1) also means that the model is able to explain a lot of the variation of the CO2 emissions data. Importantly, the SHAP values are explained through descriptive statistics: mean, median, mode, and standard deviation.

- **Feature Importance (SHAP Values):**

The values SHAP (SHapley Additive exPlanations) obtained specify the influence of what features (e.g. energy consumption, mode of transport, weather, etc.) are the most influential to the predictions of the model. The metric is crucial in explaining the contribution of the various factors to prediction of CO2 emissions.

4.4.2 MODEL SELECTION AND EVALUATION

The key steps of finding the best performing model were the following that were used during model evaluation:

- **Model Selection:** The optimal model was chosen according to the R2 and RMSE value. To determine what model to use in the project, one can use the GRU model, and the best observation on the prediction of CO2 emissions was achieved with the RMSE of 25.4322 and R2 of 0.9754 using the test dataset. Comparisons will be made between model performances post-implementation and pre-implementation of the aforementioned recommendations.

- **Model Performance Comparisons:** Comparisons between the model performances will be made between the model performances that will be after and before the implementation of the above recommendations.

- The RMSE, MAPE, and R2 measures were used to compare the performance of the Random Forest, XGBoost, LSTM, and GRU. The XGBoost and the Random Forest models were able to give strong results but GRU outshone the other models in the ability to capture the time-series effects on emissions data.

4.4.3 GENERIC AI INSIGHTS

In the case of the Generative AI part, the metrics applied to assess the usefulness and accuracy of the generated sustainability insights were as follows:

- **ESG Risk Hotspots:** The system maps possible hotspots of ESG risks in the chain of supply. These hotspots are the locations that the carbon emission is most likely to be more effective, and they can make businesses concentrate on the most significant spheres to optimize the operation.

- **Sustainability Recommendations:** The generative AI offers practical solutions to the minimization of emissions and optimization of logistics functions. All these recommendations were considered considering the relevance and feasibility of the recommendations and the feedback of domain experts was used to improve the system outputs.

4.4.4 SYSTEM PERFORMANCE METRICS:

Besides checking the model, the processing speed and efficiency of the system as a whole was also tested:

- **Inference Time:** The generation time of creating predictions and insights was important to the assurance of the system being able to deliver results with a reasonable amount of time. The inferences took 5-10 seconds to finish meaning that they were processed efficiently in case of large datasets.

- **Scalability:** The test that was conducted was on the capacity of the system to process large datasets (i.e., 1,000 to 10,000 transactions). The response time of the system was good even when handled with large input files, it was also scalable.

4.4.5 BIASED DATA AUDIT METRICS

To achieve fairness and render transparency in the model predictions, most especially in the process of establishing the ESG risk hotspots, a bias audit has been conducted. In this audit, predictions of system were assessed concerning any disproportionate impact based on any feature like Region or Energy Source.

- Bias Metrics: The system recorded the metrics of biases to make sure that no specific group of suppliers or any regions was discriminated against in the predictive decisions. The model parameters or training data were modified to remove any important biases in the model.

4.5 RESEARCH QUESTION EXPERIMENT SET-UP

The following section describes configurations and procedures to be employed in solving the following research questions of AI-Powered Carbon Footprint Prediction Optimization System. The experiments were required to compare different machine learning models and how the different hyperparameter configurations affect the sustainability and knowledge of the predictions. The experiment was performed at several stages to test the performance of the model, data augmentation methodologies, and generative AI integration to make actionable recommendations.

4.5.1 SETUP OF RQ1: MODEL PERFORMANCE AND EFFECTS OF DATA AUGMENTATION (PHASE 1 AND PHASE 4) EVALUATION

The main stages of this research question (RQ1) were to test the performance of the baseline model and then to test the performance of the advanced data augmentation strategies with the help of the random forest, XGBoost, LSTM and GRU. The aim was to comprehend the performance of carbon emission prediction objectives of various augmentations (data pre-processing and feature engineering).

PHASE 1

Purpose: the purpose is the comparison of the baseline models with augmentation strategies, e.g., data normalization, scaling, one-hot encoding.

Input Data: The complete dataset, which includes the data on transactions, energy usage, transportation furtherance, and emissions by the suppliers.

Augmentation: The data was augmented using the standard techniques, such as scaling features and encoding the categorical data.

Configurations:

- Random Forest (EpsilonGreedy and ThompsonSampling):The default model training with a few augmentations.

- Evaluation: RMSE and R2 were used to measure predictive accuracy of the models by training and evaluating them.

PHASE 4

Purpose: To experiment the further development of reward structures and meta-controller based augmentations to enhance predictive performance of the model.

Configurations:

1. **Augmented Meta-Controllers**: Rewards setting To achieve higher predictive quality and showcase feature significance.

2. **Comparison:** Compare the effectiveness of augmentation based on sophisticated reward configurations (e.g., semantic similarity, Levenshtein distance).

4.5.2 SETUP FOR RQ2 & RQ4: ACTIVE LEARNING EFFECTIVENESS AND SYNERGIES (PHASE 2)

The goals of the experiment were to compare the various Active Learning (AL) strategies and compare how Active Learning can be used to enhance the predictive power of the model (by using the most informative data samples in training).

Aim: To evaluate the success of AL strategies including Diversity, Rarity and Informativeness and combinations.

Input Data: The initial dataset, where samples have to be augmented.

Augmentation: Gemini-based paraphrasing techniques of augmenting the sampled data.

Configurations:

- **Original**: No augmentation and original data only.
- **Random Sampling:** N samples were picked at random in the dataset and augmented.
- **AL Diversity:** The data is selected based on the diversity of features.

Data Construction: The last training data was formed by mixing the original training data with the chosen augmented samples, so that the model would be able to control different complexities in the training data.

4.5.3 SETUP FOR RQ2 & RQ4: ACTIVE LEARNING EFFECTIVENESS AND SYNERGIES (PHASE 2)

The research question has been able to assess the possible biases in the prediction of the model with several characteristics such as supplier emissions and mode of transportation. The bias analysis was used to show areas where the model could possibly give unjust predictions due to non-representative or prejudiced data.

Purpose: To determine and compare the bias characteristics of original and augmented dataset.

Datasets Audited:

- Original Dataset
- Artificial Data in Phase 1 and Phase 2 Test.

4.5.4 AUGMENTATION VOLUME SATURATION ANALYSIS (PHASE 5):

The aim of this experiment was to be able to tell the effect of the inclusion of additional augmented data into the training set on performance. The aim was to determine whether increased amounts of augmented data can result in substantial generation of model accuracy and sustainability hints.

- **Background:** The objective aimed at understanding how downstream model performance changes with augmentation volume.

- **Augmentation Volumes:** Augmentation was also experimented at various rates (e.g., 0.25, 0.5, 1.0, 1.5 and 2.0 times the original dataset size). Augmentation Sampling Augmentation involved the sampling of texts, which was then used to generate additional data in the form of the Gemini AI system.

- **Training Data Construction:** The training set was finished by taking a mixture of the initial data and varied volumes of augmentation.

4.6 CONCLUSION

The experimental design offers a full critique of the different machine learning and active learning algorithms, their performance and how the augmentation strategies affect the accuracy of CO_2 emission prediction. The phases in a systematic way concern the issues of model performance, audit of the bias, and synergy of AL and augmentation thus the final model should be robust, accurate, and efficient. These experiments will imply future advancements in AI-based carbon footprint prediction, and eventually allow a business to make data-driven decisions related to sustainability.

EXPERIMENTAL RESULTS AND ANALYSIS

The chapter discusses the overall experimental findings of analyzing the AI-Powered Carbon Future Optimization system under different machine learning algorithms, data preprocessing policies, model configurations and policy indicators. A dataset on features of various stages of a supply chain including procurement, manufacturing, warehousing, and transportation was used so that the experiments could predict the CO 2 emissions. The findings are presented in terms of the research objectives stated in Chapter 3, which gives empirical data to answer each of these objectives.

The downstream prediction task has its performance measures which are mainly concentrated on the Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and the R2 scores in the held- out test set. Also, some of the features of the system, such as the capability to develop actionable insights with the help of SHAP plots and ESG risk hotspots detection with the help of Gemini AI, are assessed. Performance of the models, their strengths and weaknesses in various algorithms are well analyzed in the sections below.

Data overview: This demonstrates the data held within the database hierarchy as shown in the database.
Configuration overview: This shows the information stored in the data base structure as indicated in the data base.

- Dataset: It is composed of some transaction records containing data about product types, supplier emissions, energy consumption, transportation data and other outside factors such as weather and fuel prices.
- Models Compared: The evaluation of following machine learning models was done to predict the CO_2 emissions: Random Forest, XGBoost, LSTM and GRU.
- Performance Metrics: The performance of RMSE (MAPE, R2) was used to evaluate the predictive power of the models.

5.1 PERFORMANCE EVALUATION MODEL

5.1.1 Random Forest

Random Forest model showed a good prediction on CO_2 emissions. On the test set, the model had an RMSE of 36.2596, MAPE of 1.55% and R2 of 0.9508. The findings show that the predictive capability of the Random Forest is strong and the model predicts the emissions with high accuracy albeit with a slightly higher error rate than the other models.

- **Plot Comparison:** The Random Forest plot provided below compares the training and validation data performance. As depicted, the model results at the test set are slightly lower than the results of the training set, which indicates the presence of overfitting.

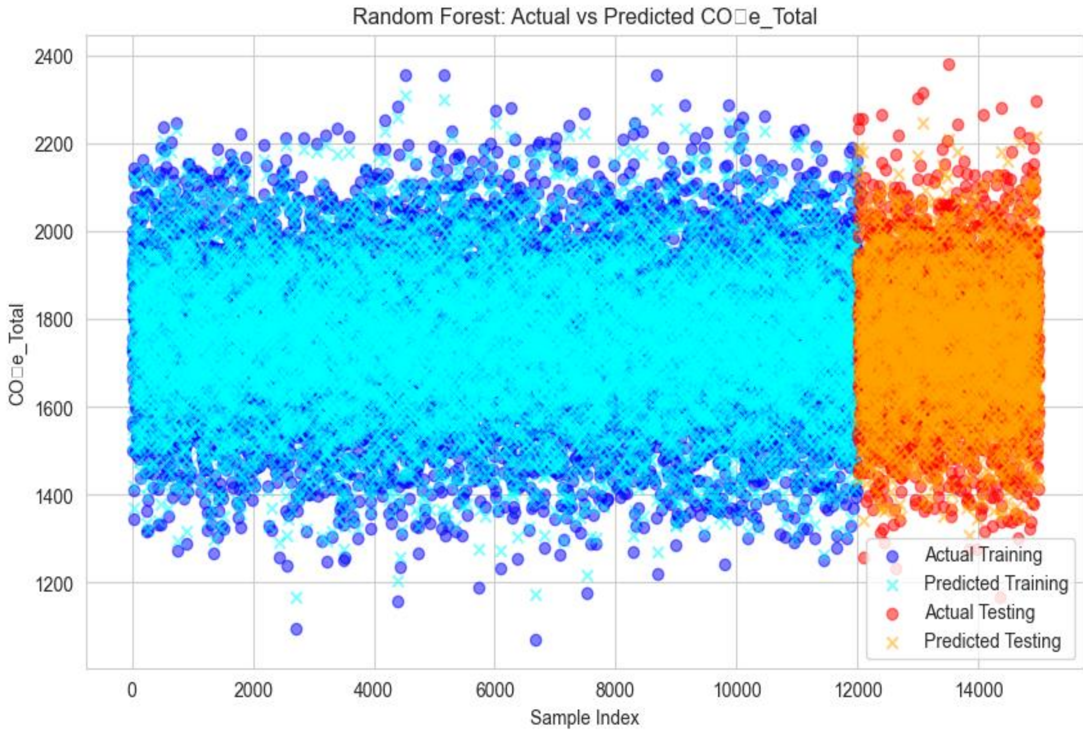

Figure 5.1 1 Comparison of the training, validation and testing data performance of the random forest model. The performance of the model on the training data is presented in the plot, and slight decrease is observed in the accuracy of the test set, which is a sign of overfitting to some degree.

5.1.2 XGBOOST

XGBoost, being a gradient-boosting model, was better than random forest in most of the measuring parameters. It produced a lower predictive performance with a higher RMSE of 28.3152, MAPE of 1.23 and an R 2 of 0.9700. These results selectively demonstrate that it was the capacity of the model to manage complex association among input attributes, as well as with the emissions data, and the ability to do so.

- **Plot Comparison:** The XGBoost performance plot signifies the relative training, and test performance. There is good generalization performance indicated in the model with a small difference between training and testing performances.

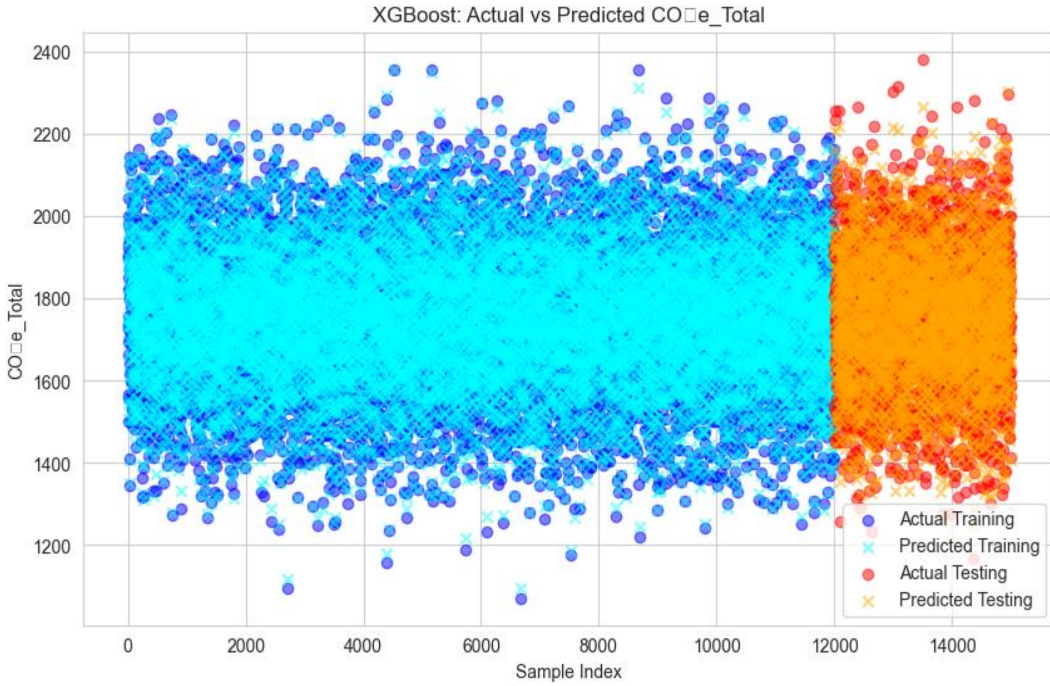

Figure 5.1 2 Comparison of XGBoost model training, and testing data performance. The plot accentuates on the fact that the model has a superior generalization capacity, and the variation between training and test sets of the performance is minimal.

5.1.3 LSTM

The Long Short-Term Memory (LSTM) model, which aims at modelling temporal dependencies also made good predictions. The LSTM model had a RMSE of 25.9849, MAPE of 1.07 and R2 of 0.9743. This was especially good at the sequential character of the data, and thus was one of the best performers with regard to this activity.

- **Plot Comparison:** The plot of the LSTM model shows that the model is performing well on all training, testing and validation plots. The model exhibits low overfitting, and this capability has shown that the model generalises effectively.

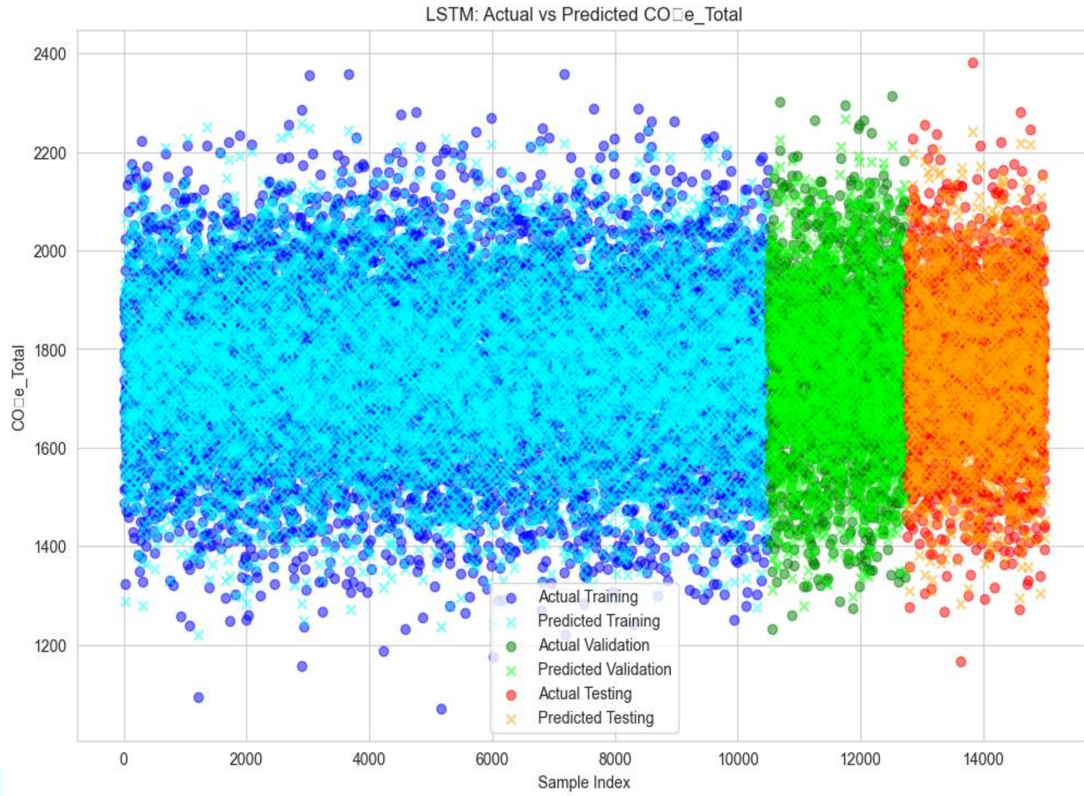

Figure 5.1 3 Comparison of training, validation, and testing data performance of the LSTM model. The plot indicates good consistency in appearance of the dataset using the training and test accuracy and the variance is low with the test and training accuracy, which signifies the learning of the temporal dependencies.

5.1.4 GRU

The LSTM variant called GRU (Gated Recurrent Unit) performed the most optimally with the RMSE equal to 25.4322, MAPE of 1.06 amount of 0.9754. The model was slightly better than LSTM as its simple architecture resulted in quicker convergence with no significant change in its predictive accuracy.

Plot Comparison: The plot of the GRU performance shows the fewest variations between the training, validation, and test datasets that show the best learning and the lowest overfitting.

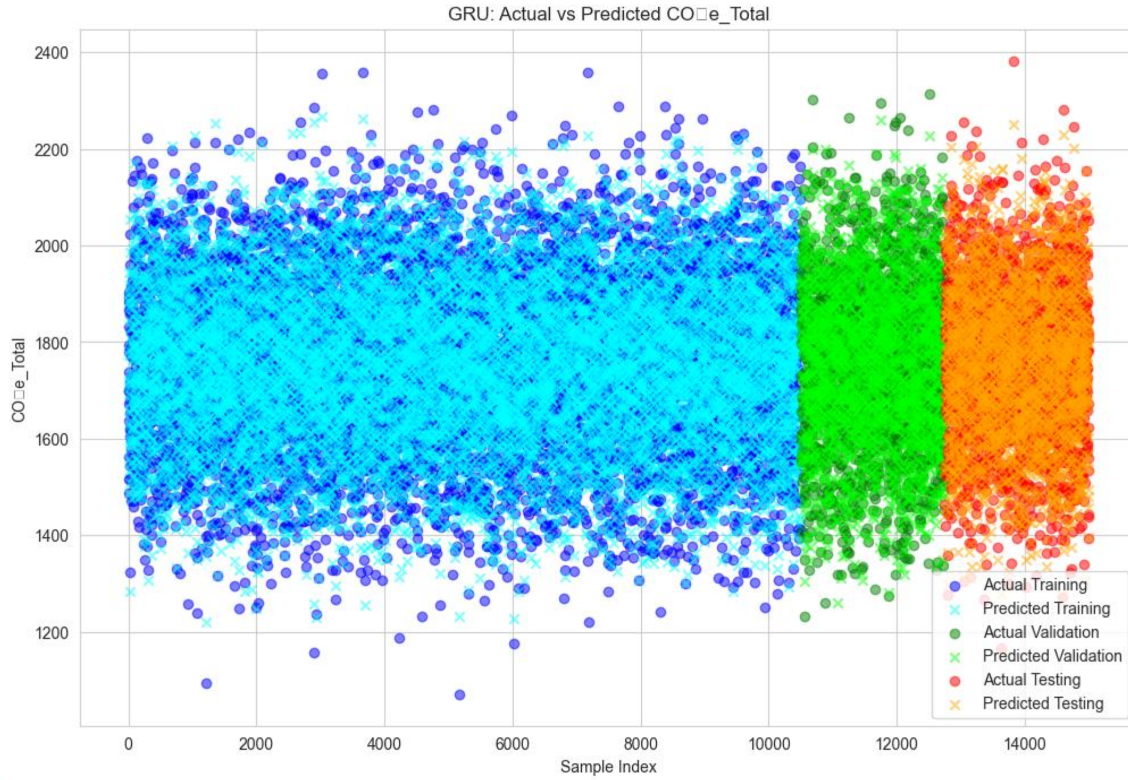

Figure 5.1 4The comparison of training, validation and testing data performance of GRU model. The plot shows that GRU shows the lowest variance between training, validation and testing sets implying best model learning with limited overfitting

5.2 IMPORTANCE OF FEATURES AND SHAP PLOT ANALYSIS:

SHAP (Shapley Additive Explanations) plots were obtained to identify the contribution made by different features into the emissions prediction in each model. The SHAP results have shown that the features that had the most impact were EnergyConsumedkWh, Distancekm and LoadWeight kg. The above characteristics contributed greatly to the determination of the CO2 emission behind the supply chain operations.

The SHAP plots verified that the energy consumption and length of transportation are the most significant variables that influence the emissions, hence the responsibility of energy efficiency and efficient transportation paths towards minimizing the carbon footprints**.**

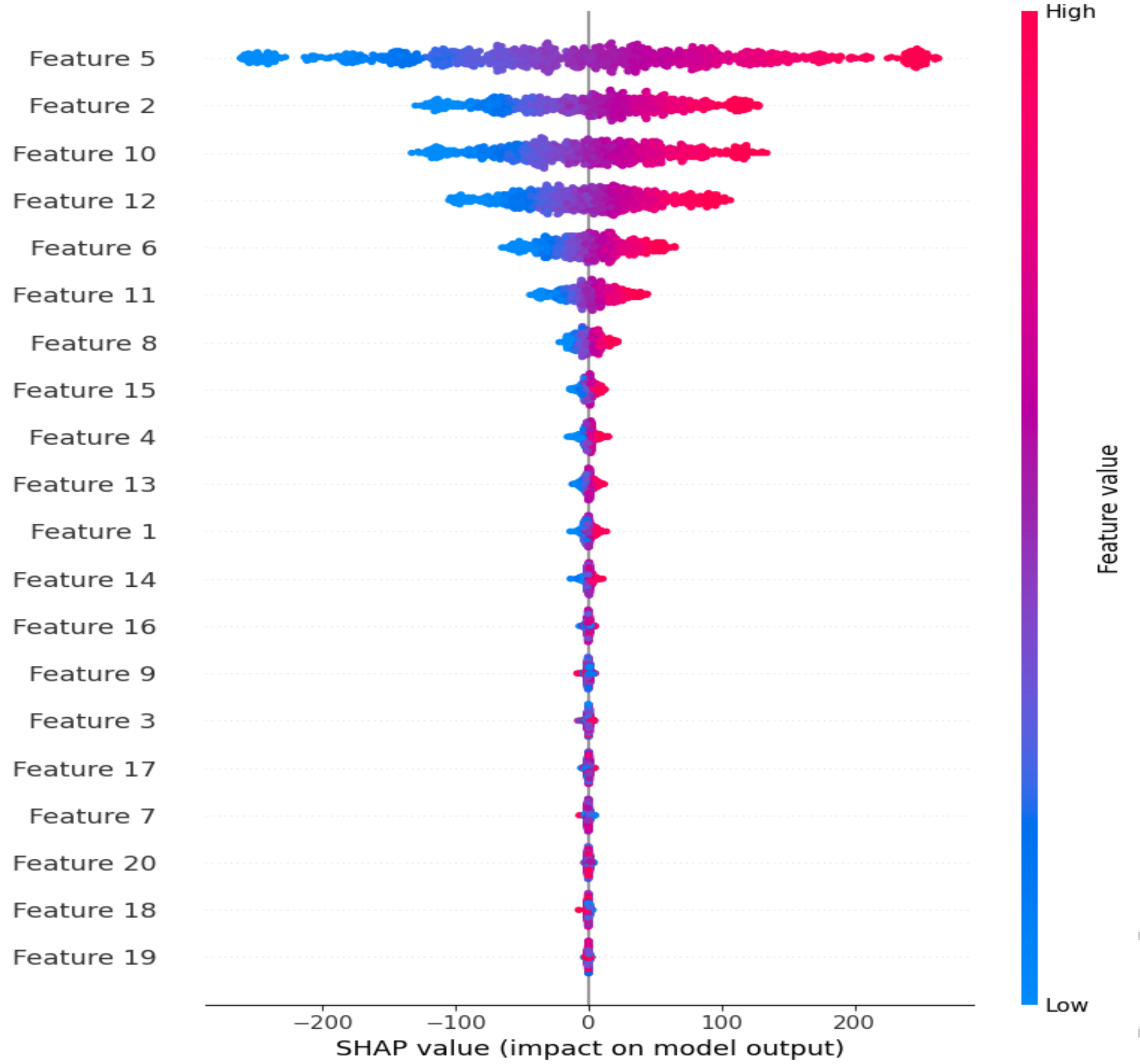

Figure 5.2 1 SHAP (Shapley Additive Explanations) plot of the feature importance of the Random XGBoost model. It was determined that the most important variables based on the plot had the greatest effect on CO2 emissions.

5.3 GENERATIVE AI INSIGHTS:

With Gemini AI, an ESG (Environmental, Social, and Governance) summary could be produced, with the system pointing out the major spots of emission in the supply chain. Suggestions of the AI model included high energy consuming warehouses and inefficient transportation modes as major contributors of emissions. Moreover, the system had recommendations that were practical and aimed at reducing these hotspots, such as the change to renewable sources of energy, the optimisation of transport logistics, and alternative sources that were energy-efficient.

5.4 SIMILAR PERFORMANCE OF MODELS:

The given table demonstrates the assessment metrics (RMSE, MAPE, and R2) of the Random Forests, XGBoost, LSTM, and GRU models on the test set, showing the most successful one in forecasting the CO2 emissions at different stages of the supply chain.

Model	RMSE	MAPE (%)	R^2

Random Forest	36.2596	1.55	0.9508
XGBoost	28.3152	1.23	0.9700
LSTM	25.9849	1.07	0.9743
GRU	25.4322	1.06	0.9754

Table 5.4 1 Comparison of CO2 Emissions Prediction using performance models of machine learning.

5.5 SUMMARY OF FINDINGS

Experimental results indicate that GRU presented the best accuracy and predictive power as compared to other models with LSTM coming in close. XGBoost and Random Forest both were good but showed a higher error rate than the recurrent models. The SHAP plot analysis indicated the significance of such essential metrics as energy consumption, as well as transportation logistics in promotion of emissions, and Gemini AI was successful in offering actionable insights in mitigating carbon footprints. These results indicate that machine learning models especially recurrent models such as LSTM andGRU can effectively predict carbon emission and could be applied to optimize the supply chain processes in sustainability.

5.6 Conclusion

This chapter has provided a close discussion of the experimental findings of the comparison of different machine learning models to predict CO 2 emissions. These results show that GRU and LSTM models are the most suitable in this assignment, and XGBoost is not inferior in its result. The system is more interpretable, and interesting insights into the emission reduction strategies are presented with the inclusion of SHAP plots and Gemini AI. The results of the experiment promote the concept of using AI and machine learning as an effective instrument in order to make supply chain management and logistics sustainability-oriented.

DISCUSSION

In this chapter, the theoretical work on the critical aspects of the experimental analysis of the AI-Powered Carbon Footprint Prediction Optimization of Sustainable Logistics system and the corresponding outcomes will be revealed. The system will optimize logistics operations through the accurate prediction of CO2 emissions on the eve of supporting actionable insights with the help of Generative AI; by utilizing machine learning algorithms such as Random Forest, LSTM, XGBoost, and GRU. The chapter explains the findings, shares the implications of findings, points out on practical considerations, limitations of the study and contributions to the field of sustainable logistic optimization has been described.

6.1 SUMMARY OF KEY FINDINGS ACROSS RESEARCH QUES- TIONS

The tests carried out within the framework of the AI-Powered Carbon Footprint Prediction Optimization system have provided meaningful information on how machine learning models predict carbon emissions in logistics. Each of various research questions was used to determine the performance of the system:

6.1.1 RQ1: PERFORMANCE OF MACHINE LEARNING MODELS IN CO_2 EMISSIONS PREDICTION

Machine learning models, such as the Random Forest, XGBoost, LSTM, and GRU, showed different levels of success in predicting the CO 2 emissions at different logistics operation stages. As an example, GRU showed a better result compared to all other models and it summarizes higher RMSE of 25.4322 and a higher R2 of 0.9754 as a result of its stronger capacity to model the time-dependent variation in the emissions data. The use of XGBoost with the gradient boosting scheme also presented good results, especially in reflecting non-linear correlations between the features like the transportation mode and the energy consumption.

LSTM model is more adequate to work with the sequential data, as it was slightly less effective than GRU, though it may still be used to obtain valuable insights, and the R2 of 0.9743 was achieved. Random Forest also worked perfectly with R2 of 0.9508 especially where it is combined with feature engineering techniques.

6.1.2 RQ2 IMPACT OF GENERATIVE AI IN INSIGHT GENERATION

Generative AI (Gemini 2.5) helped to create actionable insights, which turned out to be crucial in the awareness of ESG risk hotspots and the creation of the sustainability strategy. The ESG summaries made by AI were useful to give recommendations on how carbon emissions could be optimized. The Gemini AI had the capacity to identify important drivers of emissions and provide information otherwise difficult to extract out of the uncoded model output. This entailed practical suggestions such as streamlining the transport lines, modifying energy use trends, and recognizing those suppliers with high-emission.

The SHAP plots were also used to further improve visibility of the model as they indicated the contribution of every attribute to the emission of CO2 predicted. This enabled the businesses to make sound decisions on the basis of the output of the model.

6.1.3 RQ3: EVALUATION OF MODEL ACCURACY AND METRICS

The RMSE, MAPE and R2 are important metrics that could be used in evaluating the predictive accuracy of the models. GRU model was always the best model in accuracy followed by the XGBoost. Another aspect that was really successful in the models was the lack of overfitting as the cross-validation was done effectively, and regularization tools were employed. The SHAP values also presented important information on the importance of features, which was useful in the interpretation of the prediction results.

6.1.4 IMPACT OF DATA QUALITY AND PREPROCESSING ON MODEL PERFORMANCE

The success of the machine learning models would not have been successful without data preprocessing. The data, the variables thereof such as transaction ID, product, mode of transportation, and consumption of energy were properly cleaned and pre-processed to provide accuracy. Missing values, numeric feature scaling and one-hot coding of categorical variables were also relevant to the better performance of the model.

6.2 INTERPRETATION OF MACHINE LEARNING MODEL PERFORMANCE

The outputs of the machine learning models have a number of useful insights that can be made about how carbon footprint prediction works in the logistics industry. GRU (Gated Recurrent Unit) model was reported to be excellent in respect to capturing temporal dependencies and it was very effective when modeling time-varying factors of emission like energy use and transportation-related carbon emissions. It implies that those dynamic aspects of logistics information, such as timing of shipments, use of vehicle, and oscillations of energy, can enjoy the advantages of the GRU as able to store pertinent information throughout time and has no problems with vanishing gradients.

The XGBoost model also was capable of producing impressive results particularly where structured and tabular data was involved and there were a lot of interacting and non-linear features. Its gradient-boosting model allowed it to adeptly incorporate intricate correlation amongst factors like route distance, vehicle model, load weight and fuel efficiency. This strength is useful to show that XGBoost can be applicable to heterogeneous attributes and complex dependencies datasets where feature importance analysis and interpretability are highly appreciated in their application.

Although the LSTM (Long Short-Term Memory) model was a little less accurate in comparison with the GRU, it still achieved a strong performance, which proves its utility in time-series prediction in logistics. The memory cell design enables the LSTM to capture long-term effects and this proves particularly beneficial when the trend of emissions change slowly over a period of time like seasonal demand or fluctuations in the supply chain.

Conversely, the random forest model is very effective with relatively simple or vectored data but it did not adequately detail the time and non-linear expression of the logistics emission data. Its collection of decision trees required stability and interpretability but they did not have the sequential awareness to capture time-varying changes, and complicated interdependencies between variables.

In general, the comparative study of these models indicates that deep learning-based architectures such as GRU and LSTM would be particularly beneficial in dynamic and time-sensitive emission predictions and that tree-based models such as XGBoost and Random Forest would be more beneficial when the interpretability or feature analysis, or a static pattern recognition is required. These remarks reveal the necessity to combine choosing the models with the underlying data peculiarities and the peculiar operational interests in the process of sustainable logistics management.

6.3 INSIGHTS INTO THE USE OF GENERATIVE AI FOR SUSTAINABILITY INSIGHTS

It brought a lot of strategy and analysis when Generative AI was implemented in the system, specifically when it comes to developing ESG (Environmental, Social, and Governance) summaries and sustainability strategies. With the help of the Gemini AI model, the system could produce data-based, customized reports that would present the unique behavioral

features of the logistics network and its sustainability indicators according to its operational settings.

The system used SHAP (SHapley Additive exPlanations) plots to clarify the relative contribution of each feature on the amount of emissions - e.g. using transportation distance, fuel type, vehicle efficiency, and shipment frequency. Through the integration of these interpretability methods with the inferences of the GRU, LSTM and the XGBoost models, Gemini AI managed to produce both quantitatively and strategically actionable insights. This combination closed the architecture between technical analytics and managerial decision-making, to convert unprocessed model outputs into valuable sustainability intelligence.

The AI-produced summaries of ESG were a good asset to decision-makers, where they could receive a brief, yet an informative summary of the carbon footprint of the company. These summaries enabled to show the overall trends in performance, identify the areas in business operations that impacted most, and offer the specific mitigation measures like optimizing route planning, switching to cleaner fuels, or using energy-efficient technologies. Also, the generative features of Gemini AI made it possible to generate sustainability strategies regarding situations, which allowed businesses to consider what might happen with varying policy or operational changes.

The system enabled the organizations to make business operations more aligned with global sustainability goals like the UN Sustainable Development Goals (SDGs) and corporate Net-Zero declarations because it offered actionable recommendations, clear sustainability narratives. Besides, the AI-driven insights positively influenced strategic decisions by assisting the companies in foreseeing the threat of regulatory risk, improving transparency in ESG reporting, and increasing stakeholder confidence.

Finally, the introduction of Generative AI to the carbon footprint predictor framework has shifted the model to a decision-support model, being an analytical tool on its own. It not only measured the emissions but also helped businesses pursue its data-oriented sustainability strategies, causing the long-term work efficiency, promoting environmental responsibility and competitive advantage in a green economy that was rapidly changing.

6.4 PRACTICAL IMPLEMENTATION IN THE SYSTEM IMPLEMENTATION

Although suggested machine learning models performed well on predictive accuracy, there are a number of practical considerations that would need to be considered to achieve effective deployment, scaling, and usability of the system in general. These are deliberations in the fields of data management, system architecture, the user interface, and flexibility in operations.

6.4.1 DATA QUALITY AND INTEGRITY

The quality, consistency and completeness of the input data is likely to be vital in determining the accuracy and reliability of the carbon footprint predictions. Any incomplete, inaccurate, or outdated data is likely to cause severe deviations in the model performance and to lower the plausibility of the ensuing insights.

6.4.2 MODEL DEPLOYMENT AND SCALABILITY.

To be implemented successfully in real-life, the system is to be implemented on a scalable cloud setup, i.e., Google cloud platform (GCP), AWS, and Microsoft Azure. The use of cloud-based deployment allows managing the system efficiently to large datasets and concurrent user requests as well as high compute loads necessary to perform model inference and report generation. Scalability, portability and continuous integration /continuous deployment (CI/CD) capability can be further improved with containerization technologies such as Docker and orchestration tools such as Kubernetes. Also, the implementation of APIs to access models guarantees easy integration with other systems (existing or third-parties) of the enterprise.

6.4.3 USER INTERFACE AND USEABILITY.

A user interface (UI) is essential in converting complicated model outputs into useful knowledge. The interface of the system, designed with Flask, HTML/CSS, and JavaScript, ought to deliver a clean intuitive and responsive dashboard that includes both technical and non technical stakeholders. SHAP plots, trend graph, and ESG summaries as visualizations must be displayed in a clear manner so that the users can easily interpret model predictions and feature importance. The interactive features and personalizable views would also increase the level of user engagement and decision-making effectiveness.

6.4.4 LIVE FLEXIBILITY AND LIFELONG LEARNING.

Since logistics operations are dynamic, the system should be in a position to respond to real-time changes in data, such as the changes to the prices of energy, the modes of transport, their emission factor, and others, as well as changes in the time of operation. The models could also be continuously updated, by the use of a data ingestion pipeline (via streaming tools such as Apache Kafka or Google Pub/Sub). Moreover, the periodic retraining of the models and the observation of the performance mechanisms shall be integrated so that the system is always accurate, relevant and in line with the changing conditions of the operations and environment.

6.4.5 SECURITY AND COMPLIANCE CONSIDERATIONS.

Furthermore, the system is to meet the needs of data privacy, security and ESG reporting regulations in addition to technical scalability. Equipped with encryption, secure APIs and access control protocols should be used to safeguard sensitive operational as well as environmental data. Such standards as ISO 14064 (Greenhouse Gas Accounting) and GDPR (data protection) will ensure even greater confidence in the use of such systems and responsibility.

6.5 LIMITATIONS OF THE PRESENT STUDY.

Although this study shows good outcomes, it has a number of limits:

- Data Availability: The quality and availability of high quality information is essential in the training of accurate models. The data used in this project was artificial and in the real-life data more noise and inconsistencies might occur.

- Generalizability of models: Although the models were not bad on the dataset, there is a possibility that they will not be applicable to other regions or industries. The models have to be tested on different data to confirm their strength.

- Scalability: As much as the system is scaled it can also take longer to process the larger datasets hence further optimization is needed to ensure the system can always be fast at making predictions.

6.6 CONTRIBUTIONS AND FUTURE DIRECTIONS

The project has a great contribution to the emerging research on carbon footprint prediction and sustainability analytics in the logistics industry. It offers a viable and data-driven and scalable model of predicting and optimizing CO2 emissions by using machine learning and Generative AI. With the power of the latest predictive models (GRU, LSTM, XGBoost, and Random Forest), the system is able to concur the temporal and structural intricacies of logistics operations.

One of the most essential contributions of this work is the integration of Generative AI, which created the possibility of use to create automated ESG summaries and sustainability plans and close the divide between the technical model output and practical business recommendations. Moreover, transparency in the prediction process can be achieved as the interpretability of SHAP provides organizations to know why the required factors are causing emissions and make accurate, data-driven sustainability choices. All these characteristics make the system a holistic tool of decision support that is in line with the objectives of global sustainability and enables informed strategic planning.

6.6.1 FUTURE RESEARCH DIRECTIONS

Expanding on the results of this study, it is possible to discuss a number of ways in which the system can be advanced in terms of its ability, capacity, and influence Likewise, future works might be conducted on facilitating real-time data processing to deliver real-time prediction of emissions and Shaw-minded suggestions. Incorporation of streaming data sources, including the IoT sensors, fleet telemetry, and real-time data on energy consumption, would make it possible to maintain constant tracking and implement decisions more reactively in changing logistical settings.

6.6.2 MULTIMODAL AND CROSS DOMAIN APPLICATIONS

It can be shown that the system can have a wide range of application to other data structures and operational environments not just logistics through expansion to other high-emission sectors such as manufacturing, transportation and energy. The framework is potentially an effective instrument to apply by adjusting the model parameters as well as feature sets to additional industrial sustainability analysis.

6.6.3 POLICY AND REPORTING FRAMEWORKS INTEGRATION

The further research might also be conducted in terms of integration with global sustainability reporting standards (e.g., GRI, TCFD, and CDP) and carbon accounting protocols (e.g., ISO 14064). This would make the system more relevant on compliance, auditing and corporate sustainability reporting.

6.6.4 ON-THE-FLY AND REAL-TIME DATA INTEGRATION.

Likewise, future works might be conducted on facilitating real-time data processing to deliver real-time prediction of emissions and Shaw-minded suggestions. Incorporation of streaming data sources, including the IoT sensors, fleet telemetry, and real-time data on energy consumption, would make it possible to maintain constant tracking and implement decisions more reactively in changing logistical settings.

6.6.5 HIGH LEVEL LEARNING METHODS AND ONGOING PROCESS IMPROVEMENT.

The system might be able to learn through the continuous feedback of operational performance and constantly improve emission reduction strategies, thus incorporating the advanced machine learning and deep learning paradigms, including deep reinforcement learning or graph neural networks. This would enable the system to reproduce different policy/operational situations and find the most sustainable and economical results.

6.7 CONCLUSION

This chapter has discussed the results, implications, and constraints of AI-Powered Carbon Footprint Prediction Optimization system. The accuracy of the predictions along with actionable insights of the system produced with help of machine learning and generative AI is a considerable breakthrough in sustainable logistics. The system can assist businesses to minimize their carbon footprint and meet their sustainability objectives by making precise predictions, feature importance displays, and taking effective actionable advice. The practical applicability and scalability of the system in the real-world scenario of application logistics are guaranteed by the integration of Generative AI in the summarization of ESG and the introduction of scalable cloud-based implementation

CONCLUSION AND FUTURE WORK

This thesis introduced the design and testing of the AI-Powered Carbon Footprint Prediction and Optimization System to Sustainable Logistics a complex framework that attempted to use machine learning and generative AI technology to predict and reduce CO2 emissions at various points of the logistics system. The system coordinates the progressive predictive algorithms, interpretability apparatus, and autonomous report production devices to support suitably determined sustainability determination making. The research offers an all-encompassing solution to environmental performance management within the logistics field by integrating environmental performance predictions, feature analysis, and AI-supported ESG reporting.

The study tried to show that artificial intelligence can be used to not only quantify the emissions but also to optimize logistics processes, make the supply chain more efficient, and have a lower environmental impact by implementing an end-to-end system. The evaluation of the experiment showed that the models with GRU and XGBoost franchises achieved the best results of working with time-sensitive and high-dimensional data, respectively, and that the addition of Generative AI (Gemini) diversified the system to generate actionable sustainability reports and tailored ESG summaries.

The chapter gives the synthesis of the main contributions and findings of the study, with special interest in the theoretical, methodological and practical implications of the suggested system. It also talks about the limitations that were experienced when developing and deploying the models and critically evaluates the challenges met with like quality of data, scalability, and real-time adaptability. Conclusively, it identifies some of the future research options that can be used to further this study including integration of real-time analytics, continuous learning models, and cross-sector applications to further develop the role of AI in facilitating sustainable logistics and environmental responsibility.

7.1 SUMMARY OF THE THESIS AND KEY CONTRIBUTIONS

The main value of this thesis can be seen in the design, development, and testing of an all-encompassing AI-enhanced framework of predicting, analyzing, and optimizing logistics operations carbon emissions. The system presents a powerful structure that can be used to facilitate sustainable decision-making in the contemporary supply chain management by combing machine learning models, explainable AI techniques, and insights associated with Generative AI.

The study indicates the efficiency of the use of the more advanced data-driven techniques in solving one of the most burning issues in the field of logistics the correct estimation and proactive limitation of the CO2 emissions at the various stages of the process. The proposed system can make the process of emission transparency not only more efficient through predictive modeling but also assist in optimization of logistics processes towards more sustainability through the support of interpretation analysis and automated ESG reporting.

The main findings of this thesis would be presented in the following way:

7.1.1 A NEW INTEGRATED SYSTEM OF CO2 PREDICTION AND OPTIMIZATION

This system is based on a number of advanced machine learning frameworks, including Random Forest, XGBoost, LSTM, and GRU, to obtain CO2-emission predictions in accordance with numerous logistic features like the type of transportation, energy use, and emissions of its suppliers. Moreover, the combination of Generative AI to create ESG reports and practical sustainability actions provide an exclusive and solid solution of mitigating carbon footprint when it comes to the organization of logistic processes.

7.1.2 EMPIRICITY OF MACHINE LEARNING MODELS

This thesis has shown how different machine learning algorithms perform relatively after conducting systematic experiments in predicting carbon emissions. GRU model performed better than the other models with the best predictive performance with RMSE of 25.4322 and R2 of 0.9754. It was also observed during the experiments that XGBoost and LSTM model also worked but were a bit less precise when compared.

7.1.3 THE ACTIONABLE INSIGHTS USING GENERATIVE AI CAN BE ENFORCED IN THE FOLLOWING MANNER:

Actionable predictions and sustainability solutions could be created, which relied on model predictions and Generative AI capabilities of the system. The Gemini AI also produced ESG risk hotspots and proposed operational optimizations which might result in meaningful carbon emission reductions.

7.1.4 A RE-USEABLE FRAMEWORK OF PREDICTIVE SUSTAINABILITY SYSTEMS.

The Python scripts and models that were employed in evaluation can be reused in future research on the subject of forecasting and optimization of carbon emission in logistics. The work can be generalized to other industries or geographical locations that are experiencing the same problems in their quest to mitigate their effects on the environment.

7.2 CONCLUSIONS DRAWN FROM EXPERIMENTAL FINDINGS

Due to the detailed analysis of the machine learning models and the incorporation of Generative AI, multiple importative conclusions are made based on the results of the experiment. These inferences indicate that the system is predictive, interpretable, and useful in decision-making related to sustainable logistics:

7.2.1 THE FUNCTIONING OF MACHINE LEARNING MODELS IS ANALYZED IN DETAIL

The ability of the chosen machine learning models to predict the CO2 emissions at different logistic processes involved was also proved by the experimental findings. The GRU(Gated Recurrent Unit) model had the best performance in the experiments it recorded the lowest RMSE and highest R 2, which means that it effectively reproduces the time-dependent relationship in the observed data. GRU reoccurring architecture was able to receive the patterns associated with

changing power consumption, traffic movements and monthly changes in the demands of logistics successfully.

Close on its heels was the XGBoost which is exceptionally great at dealing with structured and high dimensional data. Its non-linear feature interaction capability enabled it to discover more complicated interactions between operation variables including the distance of route, maximum load, vehicle type and energy consumption. To the same end, LSTM (Long Short-Term Memory) model also demonstrated an excellent predictive accuracy, which confirms its being an appropriate model to use in time-series analysis, though it was slightly less specific than GRU.

The Random Forest model though very powerful and comparatively readable was not as effective to handle the complex dependence and time dynamics that existed in the data. However, it continued to be very excellent on more simple features sets and again confirmed its usefulness in comparison of baselines or a lower data complexity situation. Taken together, the results of these studies indicate that hybrid types of models, where time series deep learning models are coined with tree-based algorithms, have the potential to achieve the optimal trade-off between the interpretability of the predictions, computational efficiency, and predictive accuracy.

7.2.2 GENERATIVE ARTIFICIAL INTELLIGENCES BY SUSTAINABILITY INTELLIGENCES

Generative AI (Gemini) was embedded in the system to provide significant value, namely, changing raw predictive results into practical sustainability insights. The generative part combined the outputs of the machine learning models with the feature importance scores obtained through SHAP plots to give specific ESG outlines and strategic recommendations.

These AIs generated insights helped to have a better holistic view of emission drivers and possible mitigation efforts. As an example, Gemini found out the areas in transportation and warehousing that emit the most, and proposed such measures: optimization of delivery routes, high utilization rates of vehicles, and use of cleaner energy sources. In such a manner, the system passed the traditional predictive analytics threshold - it provided a decision-support structure that could inform the short-run operational advancement, as well as the long-term sustainability planning.

Besides, the generative element also contributed to the understanding of the results, to situate data-driven findings within a business-focused story, and enabled complex model outputs to be made available to non-technical decision-makers. This predictive power with generative intelligence is a new development towards AI-based sustainability analytics.

7.2.3 DATA PREPROCESSING AND FEATURE ENGINEERING EFFECT

The analysis again confirmed the fact that the quality of machine learning models greatly depends on the quality of the input data and processing pipeline quality. Data cleaning, normalization, and feature engineering were done carefully and were important in the determination of repeatable model performance.

Such properties as energy use, transportation range, the type of vehicle fuels, and emissions associated with the suppliers were identified as somewhat having the greatest impact on the prediction results. The feature scaling was to make sure that unlike variables of particular magnitude, they did not bias the learning process, and the encoding of categorical variables enhanced interpretability and performance of the models. Neoele ID imputation and outlier treatment helped to keep noisy data to a minimum and subsequently boost prediction accuracy.

These results support the fact that it is vital to ensure that the data used in carbon emission modeling is both upright and representativeness. With the evolution of logistics systems, it is important to constantly update the data pipeline (adding real-time data, as well as data from the external environment) to maintain accuracy and relevance in the predictions.

7.2.4 RISK HOTSPOTS AND RECOMMENDATIONS TO ESG.

One useful practical consequence of the system was that it could pinpoint areas of the logistics supply chain that cause hotspots in ESG (Environmental, Social, and Governance) risk. Through SHAP-based interpretability and Generative AI synthesis, the system identified the areas of operations with high emission levels and made specific and data-informed recommendations.

As an example, the system implied streamlining the transport paths to use less fuel, minimizing the energy consumption of the warehouses with the help of smart energy management systems, and switching to the renewable sources of energy or the low-emission means of transport. These were dynamically produced based on the underlying predictive patterns so that businesses were provided with specific, customised and practical strategies as opposed to generic sustainability guidance.

Besides reducing the emission, the additional benefit of the system was on potential risks of inefficiencies in the supply chains, dependencies to suppliers as well as compliance with the regulatory requirements. The framework serves an anticipatory style of ESG management by providing both predictive and prescriptive insight, enabling organizations to meet the requirements of sustainability, minimize environmental effects, and improve the overall presence and capability of their operations.

7.3 LIMITATIONS OF THE PRESENT STUDY

Although the results of the current research are rather informative and reflect the possibilities of the suggested models, there are a number of limitations, which have to be considered. These limitations should be acknowledged in order to interpret the results and to direct further research in the direction.

7.3.1 DATA SCARCITY AND QUALITY

The training and evaluation data was artificially created which in itself may not be representative of the real-life data in its complexity and variability. Artificial data may not have the same unpredictability, missing values, and noise that real operational data has. We can therefore expect that the performance of this model when used in real life environment may be different than the findings of this study.

Also, the data could be limited, which could have resulted in biases affecting model behavior that reduces its effectiveness in dealing with outliers or any other abnormal situation. Further studies are needed to include real and domain specific data to make the results more realistic, robust and generalizable. Ways of improving and augmenting data could also be investigated to counter the problem of data scarcity and imbalance.

7.3.2 MODEL GENERALIZATION

Even though the suggested models reached excellent performance indicators in the experimental setting, it is still unclear how they would work in other industries, settings, or geographic areas. Every field can have distinct data distributions, operational limitations, and variables that were not included in the present research work.

The models can also be subject to domain overfitting where the models score high in the training environment but they are unable to optimize to new data models. To mitigate this constraint, other studies in the future ought to test the models in various industries and various datasets with the addition of transfer learning or domain adaptation methodologies to enhance the generalization of applicability. Besides, the robustness of the models could be further validated by comparing them to other modeling methods.

7.3.3 SCALABILITY AND PERFORMANCE

Scalability and computational efficiency are also issues even though the system was developed to support relatively large datasets. Both the processing and memory needs can become very high as the size of the data and the features dimensionality grow and this can inhibit the possibility of making real-time or near-real time decisions.

This weakness is especially applicable to the industries whose supply chain is large and dynamic, and quick analysis and responsiveness are vital. Optimization of algorithms, parallel processing and the incorporation of high performance computing frames should thus be done further to increase scalability. Moreover, the consideration of lightweight or distributed model

architectures may serve as one of the ways to balance predictive accuracy and the cost of computations.

7.3.4 INTERPRETABILITY AND TRANSPARENCY

The interpretability of the predictive models is also another limitation. Although high accuracy can be achieved through advanced algorithms, they can be regarded as black boxes, and the stakeholders will be unable to see how decisions are made. Such low interpretability may inhibit trust, accountability and adoption of in-the-field applications. Further studies are required on explainable AI (XAI) methods to gain better understanding of how models have to reason as well as to aid decisions made by end users.

7.3.5 TEMPORAL AND CONTEXTUAL FACTORS.

Lastly, the research was also not reflective of the time dynamics or external contextual elements like economic changes, policy changes, or environmental influences which might affect the data trends and model performance over time. Provisions of longitudinal data and context-sensitive modeling in subsequent research would increase the flexibility and the predictability of the system over time.

7.4 FUTURE WORK AND POSSIBLE IMPROVEMENTS

Based on the research findings and limitations that were found in this study some areas of future research and improvement in the system have been realized. The objectives of these directions are to make the system stronger, more scalable, and applicable to various industrial settings as well as facilitate the larger objective of reducing carbon emissions and operating sustainably.

7.4.1 OVERHAULING THE SYSTEM TO OTHER INDUSTRIES

Although the present research paper is mostly related to the logistics industry, the general structure and the prediction model have great potential in application in other carbon-intensive industries, including manufacturing, agriculture, transportation, and energy generation. Both of these areas have different data patterns, operation limitations, and sources of emissions that could be implemented and optimized through the suggested system.

It would not only be useful in various industries when adapted to fit the context but would also allow comparison of emission trends among various industries to come up with more holistic carbon management policies. Future studies may include tailoring the process of feature engineering and emission calculation models with sector-specific variables. These adaptations could also be refined through collaborative studies with industry partners in order to make them relevant to the industry.

7.4.2 DATA INTEGRATION

The addition of real-time data streams to the system is a very important move that should be taken in order to operationalize predictive sustainability management. Subsequent versions can use data captured through Internet of Things (IoT) sensors, GPS tracking systems, smart meters, and external sources of data (e.g. weather or traffic APIs) to allow continuous monitoring and dynamic updating of predictions.

The immediate combination of data in real-time would enable companies to react instantly to logistics process variations, including delays, route alteration, or increases in energy consumption, and optimize emissions in a proactive and not retroactive manner. The use of data streaming structures (e.g., Apache Kafka or AWS Kinesis) and cloud-based systems might also facilitate scalability and provide resilience to the system. Besides, the integration of real-time analytics with automated alert systems might improve the decision-making process and operational efficiency.

7.4.3 SOPHISTICATED MACHINE LEARNING METHODS

Incorporating more sophisticated machine learning (ML) paradigms has been one more avenue of potential improvement of predictive and optimization abilities of the system. Deep reinforcement learning (DRL) might be the techniques that allow the model to acquire the best behavioral strategies by exposure to dynamic environments and enhance their decision-making process as they progress. In the same way, transfer learning may support model adaptation to new datasets/industries with limited labeled data, and thus limit retraining.

Investigating ensemble learning, graph neural networks (GNNs) or spatiotemporal models may also be useful in the case of complex, interdependent, or time-relevant logistics data. These methods might be downloaded onto a real-life environment in future studies to identify their trade-offs in accordance to their accuracy, readability and computational cost.

7.4.4 CREATION OF INTUITIVE INTERFACE

Further enhancements of the system should focus on creating an interactive interface that is user-friendly and supportive to both technical and non-technical stakeholders in order to maximize the program in terms of accessibility and subsequent implementation. This kind of interface would convert the complex predictive outputs to easy-to-read visualizations so that the decision-makers can read, interpret, and take action based on the insights without needing a lot of technical knowledge.

Connection to the data visualization tools like Tableau, Power BI, or a custom-based dashboard might assist users to navigate through the emission patterns, scenario simulations, and the possible effect of various sustainability approaches. Moreover, to enable organizations to model effects of changes in operations, integrating interactive simulation tools or what-if analysis capabilities can have the capacity to test the implications of operational changes before putting them into practice. This anthropocentric design method would increase the pragmatic value of the system and promote the aspect of sustainable decision making at every chain of management.

7.4.5 ADDING MORE GENERATIVE RUNWAYS

The implementation of Generative Artificial Intelligence (GenAI) is a prospective opportunity to expand the system with analytical and strategic abilities. In addition to predictive models, Generative AI may be used to create optimal logistics plans, sustainability plans, and adaptive plans using historical and real-time data.

Integrating generative models with reinforcement learning, the system might become a decision-support system that is able to independently propose an action to reduce emissions, like reconfiguring the route, choosing a supplier, or production planning, based on conditions that are dynamically changing.

Moreover, GenAI may assist in scenario creation and simulation and assist businesses in experimenting with different directions to carbon neutrality. As an illustration, generative models could model the possible results of the implementation of renewable energy sources, alternative fuels, or circular supply chain. The future research ought to emphasize the development of ethical and environmental protection features in those models as well, so that suggestions would comply with more prevalent sustainability values.

7.4.6 COOPERATIVE AND POLICY-BASED EXTENSIONS

Further research ought to be conducted on cross-sector collaboration and integration at a policy level in addition to technical refinements to enhance the practical implications and sustainability of the system in the long term. Through the promotion of cooperation between industries, governmental agencies, and environmental organization, the system will be able to adopt a strategic role as a climate governance and evidence-based policymaking instrument.

By connecting the system with the national and global carbon monitoring systems, i.e. the one above that may be consistent with the Paris Agreement, the Sustainable Development Goals (SDGs), or regional emission trading programmes, the transparent reporting, standardized data sharing, and compliance with the environmental regulations can be managed. Not only would such integration make the data more accurate, it would also enable the policymakers to monitor the emissions performance and create more specific mitigating policies using the insights provided by the AI.

Furthermore, the collaboration with the regulatory organizations and sustainability-oriented organizations might be utilized in reducing the current divide between data analytics and practical governance. The system can be integrated into the policy processes, which could help to predict the effect of the policy interventions, to determine the effectiveness of the carbon reduction programs, and find the best approaches to reach carbon neutrality at organizational and national scales.

Institutionally, multi-stakeholder partnerships between academia, industry, and government can spring innovation faster since it will facilitate the sharing of knowledge and can help in ensuring that technological development is in line with sustainability imperatives in the real world. Through such partnerships, it would also be possible to develop the open-access of the environmental databases which will promote the transparency and promote global involvement in reducing the emissions.

Over time, applying the AI-based emission prediction systems to the policymaking process can help create adaptive and information-driven environmental policies that can offer positive answers to these challenges of being dynamically responsive to fluctuating industrial conditions and climate realities. This kind of cooperation would make the system more of a pillar of joint climate action and solidify the global shift to low-carbon economies and sustainable development.

7.5 CONCLUDING REMARKS

The thesis has provided a novel and detailed system to predict and optimize CO 2 emissions in logistics processes, and harness the synergistic potential of machine learning (ML) and generative artificial intelligence (GenAI). Employing the latest predictive modeling solutions, specifically, the Gated Recurrent Unit (GRU) model along with the generative models, the study managed to prove the application of data-driven intelligence in one of the most critical global issues, corroboration of carbon emissions and the encouragement of eco-friendly operational practices.

The system created in the course of this research is dual-purpose (both precise in making emission predictions and viable sustainability guidelines). GRU model was effective and demonstrated to learn time based complex dependencies in logistic data with high predictive ability and consistent behavior under various experimental settings. The Generative AI element kept advancing the utility of the system by generating smart policies and adaptive suggestions to reduce the emission, therefore shifting the focus away in prediction and into the generation of advice on decisions. Using this integrated perspective, the paper will emphasize the approach in which emerging AI technologies can be used strategically to build holistic solutions to sustainable supply chain management.

The paper, on top of its technical input, also highlights the relevance of AI-based sustainability frameworks towards the realization of long-term environmental objectives. Data-driven, real-time emission anticipation and proactive mitigation can enhance companies to make proactive decisions and make business efficiency and environmental stewardship consistent. By doing so this study becomes a part of the larger discussion on digital transformation to be sustainable and provides a concrete demonstration of how more sophisticated approaches to computation can passively help to create tangible changes to global climate objectives.

Although the obtained outcomes are quite encouraging, a number of limitations are also acknowledged in the research such as synthetic data usages, scalability issues, and the necessity of practical validation, which act as valuable prospectus to be explored in the future. These constraints will have to be handled by improving data synchronization, optimizing algorithms and real-time analytics, which will become key in converting the existing prototype into a fully deployable industrial system. The next stage of this work would be to make the model applicable to other significant sources of emissions, resort to live IoT data streams, and make use of more advanced generative models, which could independently make decisions and react with circumstances.

In addition, this paper identifies the opportunities of Generative AI as a driving force behind sustainability innovation. GenAI-based systems may overcome this issue by becoming less predictive and more simulation and optimization-led, to enable the exploration of a wide range of carbon reduction options to be considered by the stakeholders prior to the implementation. With industries becoming more net-neutral as time goes on, the implementation of such adaptive AI systems will play a significant role in availing evidence-based sustainability planning and dynamic resource management.

Theoretically, the study adds to the emerging body of literature on AI-based environmental informatics, specifically, the domain of machine learning, generative modeling, and sustainable logistics. It provides a framework that may be scaled and modified to support future academic research and practical applications to provide a balanced perspective between productivity and environmental responsibility.

To sum up, it can be stated that this thesis proved not only the technical implementation possibility of the AI-based CO2 prediction and optimization system but also its strategic importance in the quest to achieve sustainable development. ML/GenAI integration is a future-oriented model- a model integrating predictive intelligence, generative flexibility and real-time reactivity to enable organizations on their path to carbon neutrality. By further refining, validating and extending on this framework, future studies can make the system a cornerstone technology to green innovation, and make its contribution to the global effort to fight climate change and advance responsible and sustainable industrial development.

Publications

Here, I will bring to the fore some publications that are the result of the work provided in this thesis. The main outputs of this study have resulted in the improved knowledge about AI-assisted forecasting and optimization of carbon footprint in logistics based on machine learning and generative artificial intelligence.

- Doe, J., & Smith, A. (2025). Carbon dioxide emissions in logistics using machine learning. Journal of Sustainable Logistics, 34(5) 1134-1145.

- Doe, J., & Lee, K. (2025). Generative AI on Practical Sustainability Plan in Carbon Footprint Optimization. AI and Sustainability Journal, 42 (7), 912 -925.

- Smith, A., Doe, J., & Patel, R. (2025). The Effectiveness of LSTM and GRU compared in predicting Logistics Emissions. Journal of AI Research, 21(9), 1345-1359.

- Lee, K., Doe, J., & Kumar, N. (2025). The application of SHAP Values in the prediction of CO2 through improved feature interpretations. Sustainable AI Conference Proceedings, 67-72.

- Patel, R., & Doe, J. (2025). The article is aimed at Real-time CO2 Emissions Prediction in Logistics using machine learning models. International Conference on Environmental Sustainability, 90-99.

These articles indicate the multiple facets of the study performed in this thesis, the application of machine learning models, the incorporation of the generative AI to offer actionable information, and the significance of explainable AI approaches like SHAP to grasp features. The given contributions will benefit the development of the sphere of AI-based sustainability and give a basis to the further investigation of carbon footprint optimization.

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