The Environmental Impact and Risk Assessment of CO2 Emissions

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01-136221-033

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Bachelor of Science in Artificial Intelligence

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Dec, 2025

Certificate

We accept the work contained in the report titled "The Environmental Impact and Risk Assessment of CO2 Emissions", written by Mr. Babar Ali as a confirmation to the required standard for the partial fulfillment of the degree of Bachelor of Science in Artificial Intelligence.

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Abstract

Pollution carbon dioxide also known as climate change is a menace to the global environment, and the transport sector plays a leading role in the growth of a developing country such as Pakistan. The conventional statistical approaches usually cannot fulfill the non linear interactions between environmental outcomes and socio economic drivers, which are complex. In this project, the forecasting system is developed based on data, which uses hybrid ensemble architecture. The model, using a weighted average ensemble strategy to train Feed Forward Neural Networks (FFNN), Adaptive Neuro Fuzzy Inference Systems (ANFIS), and Long Short Term Memory (LSTM) networks, to model past data (1970–2022), demonstrates high predictive performance ($R^2 = 0.961$, RMSE = 3.67 Mt CO_2). The system in its implemented form is a modular web platform that allows policy makers to visualize their trends, as well as conducting comparative analysis of scenarios between a business as usual and an intervention approach giving a decision support tool that is sustainable in terms of transport planning.

Keywords: CO_2 Emissions, Transport Sector, Ensemble Learning, LSTM, ANFIS, FFNN, Environmental Policy, Pakistan.

Acknowledgement

We would like to express our sincere gratitude to our supervisor, Dr. Kabeer Ahmed Bhatti, for invaluable guidance and support. We also thank the faculty and staff of the Department of Artificial Intelligence for the infrastructure and learning environment. Finally, we are grateful to our families and friends for their constant encouragement.

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Acronyms and Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
CO_2	Carbon Dioxide
GHG	Greenhouse Gas
FFNN	Feed-Forward Neural Network
ANFIS	Adaptive Neuro-Fuzzy Inference System
LSTM	Long Short-Term Memory
GDP	Gross Domestic Product
BAU	Business-As-Usual
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
UI	User Interface
API	Application Programming Interface
IPCC	Intergovernmental Panel on Climate Change
IEA	International Energy Agency

Chapter 1

Introduction

1.1 Project Overview

The most complex and general environmental problem of the 21st century is climate change because it mitigates almost at a global scale through ecological, economic, and social aspects. The most important and persistent greenhouse gas (GHG) is carbon dioxide (CO 2), which is attributed to the contribution of three-quarters of all anthropogenic emissions that cause global warming. The rise in CO 2 level in the atmosphere is attributed mainly to combustion of fossil fuels, industrial activities and deforestation and all these have grown over centuries with a higher rate of industrialization, population growth and high rate of urbanisation. The combination of these activities has led to growth of energy to the world along with excessively exploiting natural resources. One of the most carbon-intensive sector in the world is transport because it is the backbone of the economy and social connectivity and overdependence on petroleum-based fuel. It contributes nearly a quarter of the global CO 2 emissions and remains to be a significant source of both the local air pollution and climate forcing at the global level. Discussions on energy security as well as environmental sustainability have found a lot of attention in developing nations like Pakistan where motorization is increasing and the infrastructure of the transport sector is relatively underdeveloped. National statistics and the latest news of the PBS and SDPI state that transport is the greatest nuisance of the total GHG production of the country, with the second place going to economic development and the third place to the increased consumption of the energy as the urbanisation has grown and the logistical needs were rising. Such, upward spiral, presents a twofold dilemma: on the one hand, it contributes to economic growth and mobility (by fostering transportation), but on the other hand, it adds to the acceleration of carbon intensity and environmental risk: this is why depiction systems require more advanced predict ion systems and management systems that capture these forces.

It is therefore not merely an academic exercise to make proper predictions of the

transport sector due to the presence of CO 2 emissions, but also forms a foundation on strategic planning. The various instances of economic development, energy structure and policy carrying measures enable governments and policy makers to make predictions on future emission levels by use of prediction modelling. The models give a decision-making assistance to the comparison of the business-as-usual baselines and the possible mitigation pathways. They are also applicable, furthermore, to international models such as the Paris Agreement because credible forecasts are crucial to evaluate NDCs and their level of achievement. The project titled the Environmental Impact and Risk Assessment of CO 2 Emissions is aimed at developing a comprehensive coverage data-driven forecast system based upon the state-of-the-art artificial intelligence (AI) and machine-learning (ML) instruments to enhance the accuracy, interpretability, and policy relevance of the domain-specific information in emission forecasts. Not just is the system customized to predict the level of emission, but also to reveal unapprehended associations between socio-economic parameters and reaction to the environment in which this gives a View of CO 2 penetration drivers within the Pakistani transportation infrastructure.

The proposed modelling framework is premised on a hybrid-ensemble architecture, which integrates three (orthogonal to one another) modeling models namely Feed-Forward Neural Network (FFNN), the Adaptive Neuro-Fuzzy Inference System (ANFIS), and the Long Short-Term Memory(LSTM) network. Each of these features possesses varying degrees of analytic capacity and when combined, one has an effective predictive ecosystem. The FFNN also models non-linear interdependencies between economic variables and emissions, it has fully connected layers, through which arbitrary input- output relationships can be learned. ANFIS has the explainability concept since it uses the concept of fuzzy logic that is humanized and takes the language rules of inference that explain the outcome of the model in a way that can be understood by decision makers. Alternatively, the LSTM networks can be modified to learn temporal patterns and sequence correlation of time-series data, which can accurately reproduce the long-term emission patterns and short-term fluctuations. The three models are complemented by their limitations: FFNNs can not recognize the sequential pattern, LSTM is good at temporal features processing but cannot interpret them transparently, and ANFIS is good at reasoning but poor in the generalization of data in large scale. The system is very accurate, makes a combination of their outputs in a weighted-ensemble approach, which is the reason why it is stable and interpretable at the same time, something uncommon in environmental prediction.

In addition to the novelty in computing, the project incorporates a socio-economic analysis that covers key causes of emission paths. These include the GDP, population, industrial level, energy consumption and fossil fuel share in national energy mix. This type of drivers is necessary since, in developing nations, emissions are usually associated with the level of economic evolution: in the early phases of the evolution, when the energy-intensive industry replaces the past one, the emission growth increases, but in the

mature phase, when the growth and technological efficiency of the economy are decoupled, such growth can be decoupled by services. The system would be able to model both microeconomic and policy induced impacts as it takes into consideration these non-linear dependencies. In addition, the model can not only predict the level of emissions but also elucidate that certain changes take place and thus make it an active scenario analysis tool by including a set of explanatory features.

The project architecture is achieved by a modular cloud deployable platform that incorporates data ingestion, model training and visualization layers. The modelling engine receives data both nationally and internationally like the World Bank, International Energy Agency (IEA), Pakistan Bureau of statistics data that is then cleaned up and normalized (preprocessing) to be trained. The models are then served by Flask REST API that allows the frontend dashboard to interact with the frontend in real-time with React. This interface can be used to interactively explore policy and model results and emissions. They can optionally select the forecast horizon and contrast the baseline trends with policy generated trajectories besides exporting numbers or graphical summaries to support decision making. The dashboard, therefore, transforms machine-learning outputs into available visual analytics, which can be interpreted by the stakeholders, who include researchers, policy-makers and sustainability practitioners.

Policymaking-wise, the value of this project is that it is concerned with advancing the research not only but more essentially as applied to the environmental governance. Pakistan is not an exception as it finds itself in the crunch of sustaining growth and the dark side of meeting international requirements on climate. The designed system will be able to support sectoral p lanning, renewable energy infrastructure budgeting, and green-transport policy evaluation (e.g., electric cars incentive, biofuel and mass-transit scale up). This further supports the practical relevance of the system: by simulating it, the model can be used to assess alternative policy mixes (e.g., their increased fuel taxation or more intensive use of public transport) in relation to their comparative effects on emissions in future decades. The findings can be used in decision making by government and non-government actors and also energy planners who may want to prioritize the interventions based on the emission reduction per unit cost.

A more general scientific contribution of that project is an example of a complex uncertain and policy sensitive hydrological process being competently modeled by such hybrid AI-Fuzzy ensembles with limited data availability. This approach can be used as a guide to other developing countrie in order to transform descriptive statistical measures to prevent prognostic evidence-based environmental management. Another important convergence point of technology and sustainability identified in the project is the fact that machine learning combined with a proper set of domain knowledge constraints can serve as a facilitator of rational climate action instead of a mere calculator.

To sum it up, the project called the Environmental Impact and Risk Assessment of

CO 2 Emissions will provide a comprehensive framework of emission forecast in the transport sector in Pakistan with the policy. The interpretability, modularity and scalability makes it an innovative initiative of data-driven climate governance. The project will benefit the academic literature on carbon forecasting as well as providing a decision-supporting tool, which has the potential to impact on sustainable transport and energy futures in Pakistan and beyond, through the process of translating between novel algorithms and environmental policy practice.

1.2 Problem Description

A number of technical and conceptual challenges in predicting the CO 2 emissions indicate that a more sophisticated modeling process is necessary. The classical statistical methods, e.g. a linear regression or autoregressive model, typically presuppose a known relation between the variables under observation and takes into account that complex systems are linear and are stationary. CO 2 is actually released as a complex interaction of economic, social and environmental factors. Growth in the economy, such as one, causes the increase of industrial activity and consequently, demand in transportation, which increases the energy consumption and emissions. However these relationships cannot be easily linear: Feedback loops, technological innovations and policy interventions, they keep them in a state of continuous flux.

Furthermore, there is a lack of homogeneity in emission information, as it entails interaction of different variables of different scales, frequency and degree of uncertainty. Therefore there can be two economic indicators available annually, which are energy consumption and transport activity, which are in various units and forms. This discrepancy alone will turn the modeling task into quite a complicated one and implies that the appropriate data preprocessing and feature engineering must be implemented. This becomes even harder in respect to time. The lag effect of pollution to policy designs and or economic shocks is likely to have lagged effect, hence the current state of emission of pollution cannot be explained by current variables of development. In order to capture these time dependence we require models that can store these historical patterns and acquire long-term correlations -which is precisely what deep learning based models such as LSTM are efficient at.

Another field of recurrence is interpretability of models. The policymakers and environmental planners should be capable of not only being able to figure out what is being forecasted in the model, but also, why the forecast occurs in this manner. Deep neural networks are black boxes and in as much as they are effective in making predictions, they do not do a lot to provide the reason behind the change. This non-informativity has the potential of undermining the usefulness and trustworthiness of such models in policy applications. Neurofuzzy systems that combine the machine learning properties of neural

networks with interpretability properties of fuzzy logic, convert the behaviour of the model to human comprehensible rules to alleviate this problem.

Therefore, the inspiration behind this work is to come up with a model that is accurate and interpretable and also willing to be flexible enough to accommodate an emerging economy. Ensemble learning is a bright future: multiple models are combined in ensemble learning, with their strength and complementary properties; it is possible to achieve reliable and stable predictions on different forecasts within the different prediction horizons.

1.3 Objectives

This research has the following objectives:

- To create AI-Fusions to Integrate FFNN, ANFIS and LSTM Structures to Predict CO 2 Emissions in the Transport Sector in Pakistan.
- To construct and clean a collection of coherent datasets using trustworthy national and international data (economic, energy, demographic) of economic energy-derivatives data.Goal To evaluate the performance of individual to ensemble models using the driving error indices that consists of RMSE, MAE and MAPE, R-square.
- To identify and assess how the different socio-economic indicators (such as GDP growth, energy consumption, industrial output and population) influence the emission trend.
- To provide forecasts and scenario analysis (BAU versus policy-driven) that can be utilized as action-oriented decision support to the governmental and environmental policies.

1.4 Scope

It is a research project that will be concerned with both the methodology and application. 4 Methodology will strictly involve the CO 2 emission forecasts in Pakistani transport sector. The period of time it is covering is 19702032, where historical time has been used to train and validate and simulate future trends under a fixed set of alternative scenarios. Weakness: The research is limited to the AI-based model of the methodology and it does not consider conventional statistical approaches, such as ensemble-learning.

Pragmatically, the project will give a computer toolbox that can be implemented in a real world policy making. It was designed in the form of a modular and expendable architecture that implies that additional datasets can be added very easily in the later versions like the rate of renewables uptake, the level of urbanization or the kind of fuel-type distribution. But our present model lacks the capability of gathering real time data

and direct models of any other green house gases like methane or nitrous oxide. It also does not have a monetary consideration of the cost or benefit of pursuing a certain process of emission reduction but it simply has to be correctly predicted and interpretable.

Another assumption of the study in respect of a boundary condition is that it excludes such unexpected events in the world like pandemics, wars or economic crises that would redefine the emission pathways in a significant way. Though in practice, they must be included in the predictions, and this requires special stochastic modelling processes which are beyond the scope of the present work. The existing model can be used as a strong and interpretable base on which more advanced extensions can be constructed.

1.5 Further Advancement

The research is supposed to prepare the foundation of a bigger model of sustainable emission control. More investigations could expand the dataset to break down the emission activities on varying modes of transport (road, rail, air and marine) to sub-sectoral level. Satellite-based urban air quality measurements could also be used to increase the spatial resolution as well as optimal model tuning. The other way in which it would be interesting to address this work is in application of methods of causal inference or application of Bayesian neural networks capable of providing probabilistic forecasts and quantifying uncertainty in the forecasted cushions.

Moreover, such models can be extended to streaming data that is provided by the IoT devices and smart transportation systems. The said integration would make immission control and re-estimation of the model automatic and could be performed any time. The use of explainable AI (XAI), or SHAP (SHapley Additive exPlanations) values or fuzzy-rule mapping, in particular, may also contribute to enhancing interpretability and accountability in such a way that policymakers can interpret the key factors related to emission outcomes as their cause.

The strategy can be extended to other developing economies that have similar data scarce and policy objectives as those of Pakistan. Having shared data formats, algorithms and patterns that pipeline also instill regional cooperation on climatic policy with a certain focus and its relevance to South Asia where the cross-border process of environment is very high. Ultimately, this framework is directed towards being a modular,... open-source forecasting platform between frontier AI research and applied climate governance.

This contribution is a methodological and practical contribution to the international process of CO 2 reduction in emission that is presently underway. By combining several AI paradigms into an ensemble model, the reliability and interpretability of forecasting can be enhanced, and the policymakers will have an excellent tool to make informed decisions regarding sustainable development.

Chapter 2

Literature Review

2.1 Overview

Carbon dioxide (CO_2) emissions prediction is an issue of heated debate in climate-science analytics and environmental policy modelling. Because of the fact that the CO_2 is the strongest active greenhouse gas related to the anthropogenic climate change, proper predictions of its future directions should aid the governments to develop mitigation strategies, monitor technology and move towards zero goals. The Intergovernmental Panel on climate change (IPCC) has continually emphasized that reliable country and sectoral future insights are crucial in preparing NDCs on the Paris agreement. The forecasting literature has grown to be very wide over the last 30 years. The field of research has progressed beyond the standard linear models to complex non-linear, hybrid and ensemble based models which take advantage of developments in the field of computation and rising availability of data. This literature may be divided into four large streams of methodology:

The initial research was supported on time-series and econometric models like ARIMA, the vector autoregression (VAR) and seasonal versions like SARIMAX. Such models are still popular: they are interpretable mathematically and are economical on data, but have clear confidence intervals. Nevertheless, they rest on a linear and stationary assumption, which is seldom feasible in complex socio-energy systems, of interest, such as india, climate, transport and energy nexus tend to be complex systems, and thus need more sophisticated methods of analysis than these often offer [1, 2, 3].

Regular and popular recurrent neural network models, including Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting Machines and the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) network can learn nonlinear mappings that do not require manual feature engineering of data. They are superior when using complex and high-dimensional data, but require excessive amounts of training data, hyper-parameter tuning, etc. on par with complex and high-dimensional inputs [4, 5, 6].

Hybrid and Decomposition-Based Models One such group of modeling studies is the

hybrid and decomposition-based model.

Hybrid methods Hybrid methods take a time series as input and breakdown the signal using signal processing methods, such as Wavelet Transform, Empirical Mode Decomposition (EMD) or Variational Mode Decomposition (VMD), before inputting portions to ML or DL learners. This is because the trend and residual com- ponent overlap on predicting leads to poor prediction behavior particularly with the noisy data, and thus, making prediction should not be done based on the trend and residual component only [7, 8, 9].

The basic idea is that ensemble learning is the combination of out-of-sample predictions of diverse base learners based on means such as bagging, boosting and stacking. Ensemble methods are the most trustworthy predictions on different datasets, with the added cost of computational cost. but with added computational cost [10, 11, 12].

Each of the themes is further elaborated in the following sub-sections, which provide an overview of theoretical underpinning, literature examples and comparative results for national and transport-sector emission modelling.

2.2 Statistical and Econometric Approaches

Prior to the current proliferation of use of Artificial Intelligence, emission forecasting was almost entirely driven by econometrics. The attraction of these models is their analytical transparency each coefficient represents the marginal impact of an independent variable such as GDP, population or energy consumption.

2.2.1 Autoregressive Models

There is no doubt that one of the earliest and most popular classes of techniques for quantitative time series forecasting are members of the Autoregressive Integrated Moving Average (ARIMA) class. Autoregressive integrated moving average (ARIMA) models were put forth by Box and Jenkins in the 1970s based on the idea that the time series levels can be forecasted as the linear combination of its previous values and random errors which depart from this deterministic structure. Due to their conceptual clarity and interpretability, they remain very often used as the statistical benchmark for several more advanced forecasting systems in energy economics, climatology or environmental science because they are simple relative to the latter models. Mathematically the ARIMA(p,d,q) process has the form:

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \tag{2.1}$$

As in Equation 2.1 where B is the backshift operator, such that B yt = yt - 1, phi(B) and theta(B) are pth and qth order polynomials in the lag operator representing AR and

MA terms respectively, d is an integer representing the number of differences required to make the process stationary. The remaining process,epislon t is assumed to be a process with mean 0, variance constant, with white noise. Given the simplicity of the model and its ability to capture temporal autocorrelation, ARIMA is an attractive modeling technique for long-term environmental time-series data that is characterized by obvious seasonality or slow trends.

Transparency: This is the property that makes the ARIMA model attractive in emission forecasting. The specific parameters have a simple interpretation: coefficients of the autoregressive part represent the strength of persistence in the emission levels, while the moving average terms represent the cumulative effect of random shocks caused by factors such as economic and policy changes. This allows policy makers and researchers to observe the influence of external factors over time as a preliminary step to opening the bridge in the analysis between statistical modeling and macroeconomic reasoning.

Furthermore, ARIMA also relies on many fewer variables than the multivariate regression or machine learning models which makes it an accurate methodology during times of data scarcity or when interpretability is of greater importance than prediction accuracy. However, ARIMA models are very sensitive to the assumptions of stationarity and linearity. In real life, CO2 emissions often have non-linear dynamics due to rapid technological changes, energy substitution and sudden policy measures, etc. Such features do not easily fit in a linear ARIMA process and cause a structural break. Moreover, emissions' time series are often heteroskedastic whereby the variance changes over time, which contradicts the assumption of constant variance of classical AR IMA. When the feedback relationships among economic growth, energy consumption and industrial structure are considered in the data, AR model would be too naive trying to capture such complicated cause-effect relationships. These shortcomings are emphasized by empirical studies.

Fang and Lin [2] applied ARIMA on the transport emissions of China with relatively mere accuracy (MAPE=approximately 6%). Still, with a change in national energy policy direction after 2015 that focused on promoting electric vehicles and injecting renewable energy into the grid, the model's projections were soon out of sync with the results in reality.

The relative absence of structural policy shocks and non-linear technology shocks in ARIMA overestimated emissions in the future. Rao and Patel [3] obtained similar results in a comparison of India's transport sector: ARIMA and classical MR overestimated emissions with policy volatility (fuel subsidy reform, industry lockdown, etc.).

Their results imply that while ARIMA models have good modeling capability in cyclical time series, they are not robust in the presence of discontinuity. There are many extensions that attempt to address these deficiencies. SARIMA includes a seasonal differencing term to account for the presence of periodic variations, which is appropriate in the case of the detrending of monthly or quarterly emission data which tells the story of cyclic industrial

activity or weather conditions.

The SARIMAX (exogenous) model also has explanatory variables (e.g. GDP growth, energy prices or vehicle-km travel) that capture some of the policy or economic variables. However, these are in essence linear extensions; they are able to take account of seasonality and covariates but are not able to model nonlinear relationships and threshold effects. Moreover, if the time series has dramatic nonstationarity and fluctuating growth period character, the estimated ARIMA-based models may result in the model drift with long-term forecast instability. So, the baseline prediction of emissions is still important to be provided by autoregressive models such as the ARIMA (and its variants) due to their interpretability, statistical rigor and replicability. They may be useful in situations where short-term forecasts are needed or on which to benchmark more complex methodologies. However, when emission is dominated by policies with opposing trends, technological change and interindustry linkages, ARIMA is no longer sufficient. This limitation has allowed methodological change towards non-linear data-driven models (e.g., machine learning, deep learning, and hybrid approaches) that are able to represent structural complexity while still having predictive trustworthiness. Accordingly, the ARIMA model is an early success in the development of forecasting and while it takes up a secondary role in maturity, it provides a baseline level of information and a benchmark against which the performance of other more adaptive models may be compared.

2.2.2 Vector and Structural Models

Although univariate methods such as ARIMA consider the time series independently, environmental and economic systems usually do not develop in isolation. There are also a number of dynamic factors that affect the carbon emissions: gross domestic product (GDP), energy consumption, population, trade flows and policy cadastral approach.

In order to solve these inter-relationships, the economists have employed the multi-variate specifications Vector Autoregression (VAR) and its cointegrated version Vector Error Correction Model (VECM). These methods can simultaneously model more than one endogenous variable and take into consideration the degree of interdependence of changes in one endogenous variable on changes in other variables in a system of equations.

A formal expression of a VAR model of order p is as:

$$Y_t = c_t + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + e_t \tag{2.2}$$

As from Equation 2.2 where Yt is a k 1 vector of endogenous variables, Ai are matrices of coefficients for lagged dependencies in the system, and et is a white noise. This definition generalises the notion of autoregressive to more than a single time series. By estimating the equations simultaneously, it is able to represent feedback effects between economic

and environmental variables – such as how industrial production affects emissions and how pollution control policies affect production costs.

The VAR-based Granger causality tests contribute in the direction of causality identification which is important while testing hypothesis about whether growth induces environmental degradation (Environmental Kuznets Curve hypothesis) or whether green innovation allows decoupling of growth and emissions. VECM is an extension of VAR to nonstationary variables which are cointegrated (in other words: variables, such as a share price and the value of its company, with common stochastic trends). Cointegration is also very common in the prediction of environmental variables for the relationship among GDP energy consumption and emission of CO2.

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + e_t \tag{2.3}$$

From the equation 2.3 where the long-run cointegration matrix is forgiv observes G is and short-run dynamics are represented by The error-correction term ΠY_{t-1} for example indicates the existence of reversion over time of the deviation of the log level from what is its long run equilibrium value.

That formulation provides policy makers with a picture of exactly how fast the economy snaps back on course after shocks - like sudden changes in the price of oil or new regulations. Empirical research like Gupta *et al.*[13] by using VECM used to measure and bi-directional causality between GDP and energy consumption and in most developing countries, there was long run equilibrium even though equation in short run varied. In practice, VAR as well as VECM have a number of limitations. The first is that they are based on the stability of their parameters through time. In fact, there are often structural breaks in the relationships between (economic) and (environmental) variables due to technology change, shocks to energy prices or changes in policy. For example, for the swift growth of renewables in the 2010s, this has changed the emission response to GDP; hence, the coefficients on GDP in pre-2010 models are out-of-date. Second, in the construction of these models, it is linear, so that norms of threshold effects, that is, arbitrary changes in emission paths after a certain level of policy intensity or the fuel price has been traversed, would not be easy. Third is that multivariate models involve a large volume of high quality data, which limit the application in countries, when there is poor monitoring facilities. Seasonal and Exogenous extensions of ARIMA To supplant these exogenous policy drivers we also find in a literature seasonal and exogenous extensions of ARIMA models.

The SARIMA model has augmented seasonal differencing parameters while the SARIMAX has exogenous regressors such as temperature, population or energy prices. These adjustments are mainly relevant for monthly or quarterly data of CO_2, which display seasonal fluctuation which relates to industrialical activities or climatic variation. For instance, there might be a model of a SARIMAX type that incorporates index numbers

on industrial production or prices for crude oil in order to add some reality to the forecast. However, such models can be vulnerable to over-parameterisation - i.e. introduction of too large number of seasonal/endog terms cause the estimation problems and loss of interpretability. Additionally, multicollinearity is one of the problems where independent variables result in multicollinearity and this produces improper estimates of parameters and the standard errors. Nevertheless the vector and structural models are very useful in emission prediction, but not without challenges. They are popular among economists and policymakers because their coefficients have sensible estimates of elasticity and causative interpretations as opposed to just being a number.

However, in particular, VAR and VECM methodologies are useful in throwing light on the dynamic relationship between growth and emissions in the long-run; a relationship which requires to be taken into account in the design of a sustainable/robust policy. In addition, they are used as benchmark models to compare the results to a given nonlinear technique such as Support Vector Machines or Long Short-Term Memory networks in academic practice. In sum, while the vector and structural models are the methodological improvement over univariate, the use of the models are limited due to the assumptions of the linearity and the stability of the models. They are sometimes able to explain the historical relationships but do not often fit in with the forms of non-linear feedback's that are characteristic of contemporary energy systems; where rapid innovation, policy-feedbacks and changes in behavior are interacting in complex ways. The shortcomings of exclusively linear models are evidently visible when the international communities continue to move towards clean energy and connect it with regulated utilization of smart grid technologies. It is this understanding that has motivated researchers towards hybrid, decomposition-based and deep learning techniques that have been capable of capturing the statistical structure and non-linear evolution of CO2 emissions in time.

2.3 Machine and Deep Learning Model

2.3.1 Machine Learning Models

Machine-learning methods were created as an alternative to the strictness and restrictions of econometric motivations. Rather than express functional definition, they are based on learning rules. Zhao et al. [4] In both random forest (RF) and gradient boost of trees (GBM)/extreme gradient boost of trees (XGBoost), both effective generalization capabilities have been achieved from very real applications and leading to the agreement that gboost methods hold a special demeanor in the classification ensemble perspective (hundreds+ ML apps review).

implement linear trends of developed baselines for forecasting of emissions and energy

demand; Peng et al. [5] also used XGBoost combined with SHAP (SHapley Additive exPlanations) to reveal the dominant driving factors in shaping China's increase in emissions, among which we find that GDP and industrial production make the largest contributions. Karim et al. [6] compared regression, SVR and RF deep learning approaches (DDL) and deep learning for multiple economies and found that the applied ML models' RMSE and the cross-country transfer are better than OLS-based methods in general, and the difference between the two OLS approaches and SCSTM is expected.

Also, some studies have localized ML models. Zafar et al. [14] developed transport models of Pakistan and ensures that RF and XGBoost outperformed ARIMA by a margin that was more than 25% of the error generated in the process of forecast. Non-traditionally high paid jobs in fact trap employees in a low-wage cycle and these findings were bolstered by Yildiz and Demir [15] in OECD countries. These results suggest that tree-shaped ensembles are capable of automatically extracting predictive complex economic-environmental relationships from parsimonious amounts of input data processing.

2.3.2 Deep Learning Models

Deep learning (DL) is the generalization of ML with the use of hierarchical neural explanations for modeling the data. The sequence dependencies can be modeled well with RNNs and their gated versions on the other hand-LSTM and GRU, which are important of forecasting energy emissions. Liang et al. [16] showed that the differences in the RMSE between the LSTM models and the SVR were in actuality only 18 else, for multistep forecasting. In their recent work of Alhussan et al [17]., the authors suggested an attention-based GRU-Bi-GRU hybrid model, which reduces MAE by 12% compared to the original model. Yuan et al. [18] combined ARIMA and LSTM for energy user to solve the contrast of interpretation and nonlinear learning on energy related emission. Attention layers Rani. et al. [19] aliens collaborated to delineate temporal saliency with the inclusion of attention layers which contributed to enhancing interpretability and robustness. While being extremely accurate, DL systems have been criticised for being opaque and data-hungry.

Interpretable AI tools Dissectible-AI (XAI, e.g., LIME, SHAP) is always now available accompanying with DL pipeline to understand the importance of variables [5, 20].

Furthermore, training requires meticulous tuning the hyper-parameters to prevent overfitting which is commonly alleviated using drop-out regularization, early stopping and cross validation.

2.4 Hybrid and Decomposition-Based Models

The goals of hybridization are to merge complementary attributes: the trend capturing ability of statistical inference and the ability of ML to capture residual information. The general idea is to divide a signal yt into predictable (deterministic) passages and passages which cannot be predicted (stochastic):

$$y_t = T_t + S_t + R_t \tag{2.4}$$

As from equation 2.4 where is long-term trend, is the seasonality and is the residual noise signal, and DL systems have been criticized for being opaque and data-hungry, for producing extremely accurate solutions. Interpretable AI Libraries: (e.g., LIME, SHAP) of various kinds of Machine Learning from Scratch (XAI), following pipelines have appeared recently that combines these models. STM with DL for Variable Importance Levels

2.5 Hybrid and Decomposition-Based Models

Hybridization attempts to bring together complementary powers - BD inferential power in capturing trends and ML flexibility in learning residuals.

$$y_t = T_t + S_t + R_t, \tag{2.5}$$

As from figure 2.5 in which Tt is long term trend, St seasonality and Rt residual noise. Liu et al., obtained multi-horizon sequential converter network by VMD-based bi-LSTM and GRU using the same VMD network to extract cold vibration and extract bias by the proposed the single multi-horizon vocal decoder with time-varying modulator (STL+VMD) in large number of channels ref. [7]. In addition, wavelet transforms are used in conjunction with deep networks to enable the capture of local frequency information of emissions in the paper of Chang et al. [Chang et al. Wavelet Transforms Comparison for Emission Characterization].

Li et al. [9] investigated Adaptive Neuro-Fuzzy Inference Systems (ANFIS) which employ a type of fuzzy systems that are both rule-based and have mathematical formulations and incorporate neural flexibility.

Deng et al. and colleagues, for example, used a hybrid, Grey Wolf Optimizer-based parameter fine-tuning algorithm which is capable of achieving enhanced convergence while taking a lower forecast error with it [21]. Nguyen et al. In general, the authors in [22] reviewed 70 decomposition based hybrid designs and improved the generalizations under nonstationary/volatile series.

In South Asia, Shah and Bhatti [23] included regression to ML for Pakistan transport

emissions, depicting that mixed techniques can incorporate the both general equilibrium growth and structural change effect, which are important features of fast growing economy.

2.6 Ensemble and Ensemble-Hybrid Models

In the modern forecasting literature, ensemble learning is emerging as a primary technique for improving robustness of prediction in terms of generalization. Compared to the single-model approach, ensemble learning entails leveraging teams of learners (created in the light of capturing different parts of the data) to make predictions that tend to outperform those by a single model.

This is in accordance with the mathematical theorem that summarizing over a range of estimates reduces the variance and bias, hence should be more stable and accurate. However, for applications such as CO_2 emission prediction, which are characterized by extremely nonlinear data and are stochastic with potential exogenous influences, the ensemble methods provide a very good alternative solution.

2.6.1 Theoretical Foundation of Ensemble Learning

Instead, the best definition of ensemble learning can be given by the phrase "wisdom of the crowd." The ensemble's prediction making yx for the test point of a test set might thus be written: Dumping all models with equal weights, their predictions cancel out noisy irrelevant data as well as amplify so-called signals.

$$\hat{y} = \sum_{m=1}^{M} w_m f_m(x), \tag{2.6}$$

As from the equation where 2.6 wm is the weight of each model. It is the unbiasedness of the the models and uncorrelated errors that allow, if the variance of the ensemble prediction is reduced by a factor 1/M, to roughly provide an explanation for the beneficial role of simple averaging in terms of reliable forecast. In practice, the diversity and strengths of the constituent models play an important role in deciding the performance of an ensemble. The three primary methods of ensemble construction are bagging, boosting and stacking. They all have certain emphasis on the data manipulation and the combining of base learners.

To predict the response of a Rossmann prospector bagging trains a large number of models on different bootstrap samples (randomly selected subsets of the training data with replacement) and takes an average of their predictions to make a final prediction. Interestingly, single outputs are valgated low to reduce variance. Random Forest is a widely used bagging base learner, it randomly concludes the decision trees which are trained on the bootstrap sample, and chooses branches of only random subsets of features.

It has become widely used for sample ranking of predictor variables using its simplicity, its resistance to overfitting, and for making emission estimates as well as in environmental research studies. Zhao et al. and Rahman et al. [10] showed that both as a class of single trees and as ensembles of models, RFs tend to perform better than other baselines, namely, simpler regression or support vector models, particularly when operating in the presence of noise intrinsic to data from developing countries.

Boosting. Boosting procedure is carried out by stages: Using an iterative process of learning, the passers would be trained individually and learning goal of new learner is omitting as many error of its predecessor learner as possible. In contrast to the bagging techniques, which minimize variance, boosting concentrates on the bias minimization of the model by giving instances which are harder to predict, higher weights. Algorithms such as AdaBoost, GBM and XGBoost have been super successful not only in tabular forecasting but in temporal prediction also. Boosting algorithms are attractive to emissions predictions - primarily because they can capture non-linear interactions of the economic indicator with policy driving factors without new features engineering. As we have discussed earlier in Peng et al. and Patel et al. [12], boosted ensemble of decision trees yield high accuracy and interpretable rankings of features when done on national-level series of CO2 emissions (Fig. 2).

Stacking. Stacking, short form of stacked generalization, tries to train a meta-learnership model that makes decisions on how to stack multiple base learner's predictions. That is, rather than straight averaging of individual predictors, a second model (meta-model) is trained to find the optimal blending weights in order to avoid overfitting.

This means that the ensemble has the potential to benefit from the synergistic effectiveness of the different types of learners. For instance, a linear model could be used for global laser trend, a tree-based model could be used for detecting nonlinear threshold effect, a deep network can be used for temporal dependencies and fusing their outputs using stack balances the extra performance for all dimensions. In emission research, stacking can also be used to combine statistical (ARIMA), machine learning (XGBoost) and deep learning (LSTM) models that can be linked in relationships that can be interpreted and prediction.

2.6.2 Applications in Forecasting of CO_2

Rahman et al. [10] Inside country composition dataset did a Between Countries study with ensemble method to use SVR, RF and ANN. They showed that large error reductions were observed within the developing countries thereby validating the ensemble concept of heterogeneous economies. This has been further expanded by Zobair et al. [11], who built a heterogenic ensemble of decision trees, SVM's and deep neural networks for national

emission in Denmark and got a strong fit to the measured data, in the region of Rvariance = 0.99.

Similarly, a stacked model which included XGBoost, the random forest (RF) and LSTM was proposed by Patel et al [12]. In addition, the combination reduced RMSE by almost 15% compared to any of the individual simple models, suggesting that approaches of knowing many learners and combining their predictions are more powerful than any single complex learner.

Then, there's an emerging literature of decomposition-based ensemble that use a form of statistical decomposition, deep architectures, and meta learners. For example, Yuan et al. An ensemble of hybrid detector amplifiers was suggested by [18] in which the first-order time-series of emissions will be broken down via VMD into trend, seasonal and residual components.

Individual learners were trained for each of the three elements, namely ARIMA for trend, GRU for seasonality and XGBoost for the residual noise. A meta-model was then used to aggregate these predictions to generate the final forecast. This decoupled architecture delivered accurate and interpretable quality, which was achieved by directing task specific models to signal frequency clusters. Attention Mechanisms in Ensemble Pipelines Buffer Contextual NL-Content for Contextual TensorFlow Rani et al Rani et al [19] included attention mechanisms in ensemble pipelines for on-the-fly modification of model weights due to context.

Their method automatically selected only those models which work better for some of the time scales or some of the structural regimes. Our weight assignment inspired by human expert decision making, the weighted decision is considered and the model, which has more relative relevance for each—S and finite time point is very likely to be preferred. Static aggregation methods of hybridensemble learning have also been replaced by data-driven adaptive fusion, where such architectures have been on the cutting edge in learning.

2.6.3 Regional and Policy-Oriented Applications

At the regional level, ensemble models have been particularly useful in emerging economies where data are not consistent, there are structural transformation and policy instability, making standard modeling techniques straightforward. In the ensemble approach, probabilistic forecasts that incorporate the uncertainty of the estimated cycle are obtained by doing Monte Carlo simulations. A probabilistic approach would allow the decision maker to view the level of anticipated emissions as well as the degree of confidence related to such levels, facilitating risk-sensitive decision making with more complete information. Multi-objective optimization is also an important research area in sustainable energy planning where the ensemble-based method is combined with multi-objective optimization strategies.

Some studies have use the ensemble forecasting theory with optimization algorithms as Genetic Algorithms (GA) or Particle Swarm Optimization (PSO) in the calibration of emission-reduction policies. For example, hybrid ensemble-based optimisation models have been used to determine optimal carbon prices, renewable energy split and rates of transport electrification that would be consistent with emission abatement target. Good practice applications of ensemble learning move predicting out of a pure prediction purpose and contextualize probability in terms of sustainability.

2.6.4 Strengths, Challenges, and Future Directions

The major merit of ensemble methods is that they have the ability to combine multiple views to pull in the weight through an individual deficiency. They are quite robust with respect to outliers, and they perform very well for high-dimensional combinations of input data plus they perform very well with noisy and incomplete data (elemental composition data is often not available or quite noisy in emission inventories).

Additionally, the ensemble offers a way of including the different kinds of information (the inclusion of macroeconomic indices, satellite readings and weather information) into one prediction. Nevertheless, ensembles also have some background drawbacks. They can be computationally expensive when applied with large architectures of deep learning. Training multiple models and hyperparameter optimization for each of the base learners takes more time and extra resources. It also can occur in complex ensembles, or when there is a similar characteristics between error patterns and decrease diversity at base learners, a critical characteristic of ensemble-based methods. Another concern is that of interpretability: while ensembles are accurate, it sometimes can be hard to explain how they work to policy makers. Accordingly, some of the most recent work those into the "explainable ensemble": Combining model averaging with methodology such as SHAP scores or partial dependence plots and fuzzy rules extraction, for greater transparency. In future, the ensemble methods will adapt in the direction of being more adaptive and interpretable as well. Themes (languages); Think (rules) Like eat, had Some people are at risk of diabetes. (definite/media) Dynamic ensemble selection, transfer learning and Bayesian model averaging is attractive to learn time-varying dynamics. (kinesthetic representation) Deep ensembles with neural networks and probabilistic weighting schemes enable the joint prediction and quantification of uncertainty - a fact of great importance when it comes to things like assessments of climate- and emissions-risk. In transport-sector forecasting the design and development of adaptive hybrid-ensembles, that can self-tune in view of new policy data or changes to fuel prices, would be a natural step forward. In conclusion, ensemble and ensemble-hybrid models are the most advanced methods of CO2 emission forecasting compared to other studies in recent years.

Their power comes from the combination of two different ingredients: statistical

structure over data from machine learning and representation power over tasks in deep learning. Using the synergies in complementary strengths, they provide high accuracy, robustness in dealing with the noise and possibility for probabilistic policy analysis. With the growing computing power, increasing quality of data generation, such framework for formulation will grow to become a province methodological backbone for emission prediction and sustainability analytics at global scale.

2.7 Comparative Summary and Discussion

Table 2.1 comprehensively outlines advantages and disadvantages of the most employed modeling paradigms.

Statistical methods are data efficient and easily interpretable; ML and DL are accurate but involve a cost in terms of model flexibility; hybrid and ensemble models require higher query costs but offer trade-offs between these two dimensions.

Table 2.1: Literature review comparison

Approach	**Strengths**	**Challenges / Weaknesses**	**Representative Studies**
Statistical / Econometric (ARIMA, VAR, SARIMAX)	Transparency and low Data-Requirement, Good Baseline Interpreter	Linear assumptions, poor ability to adapt to regime shift	[1, 2, 3]
Machine Learning (RF, XG boost, Svr)	Captures nonlinear patterns, handles multivariate features	Needs to tune, weak temporal memory	[4, 5, 14]
Deep Learning (LSTM, èGRU, BiLSTM)	Learns time dependencies, good long-range forecasting	Data intensive, less interpreting	[16, 17, 18, 19]
Hybrid / Decomposition + ML	Reduces noise, decomposes trends and residues, higher accuracy	Complex architecture, increased computations	[7, 8, 9, 21]
Ensemble / Hybrid-Ensemble	High levels of robustness, reduced errors, best all round performance	Overfitting risk, takes a long time to train	[10, 11, 12, 24]

While classical econometrics are still very useful for providing transparency on policy, the contribution of modern ensemble and hybrid systems have won accuracy contests. Deeper architecture in cooperation with the concept of decomposition or attention provide the optimal trade-off in the area of short-term fidelity and long-term stability. For the

developing world, the issue is that there is a lot of noisy data with little underlying truth, so one must use hybrid or transfer learning methods that transfer the knowledge taught in more ample environments.

This dissertation overcomes the shortcomings from previous studies by presenting a replicable hybrid ensemble architecture that consists of the following constitutive models: FFNN, ANFIS, and LSTM models. The model has both interpretability of the fuzzy systems and prediction abilities of the neural network. Given that the work was applied to data generated with the pool, the industry-level interpretable and scalable predictive framework is applicable for the national climate policies, such as determining the necessary GHG mitigation from Pakistan's transport-dominated sector.

Chapter 3

Requirement Specifications

3.1 Existing System

The issue around monitoring and forecasting carbon dioxide (CO_2) has been normally addressed by a piecemeal ecosystem of tools and approaches. The vast majority of public institution and research organization uses isolated spreadsheets, static dashboards or disconnected model codes. Such systems normally are about collection and tallying of data as opposed to an intelligent prediction. Then, analysts have to gather data from various sources - World Bank, International Energy Agency or national statistical offices and clean, aggregate and re-visualize them in other software. This manual process is not only time-consuming, but is prone to errors when it comes to standardising on for example factors such as GDP, energy consumption and sectoral output over decades.

The majority of the current web applications when it comes to sustainability perform descriptive analytics. They provide visual dust traces of past emissions, but do not readily enable one to run future scenarios or tune their model. Software like the Global Carbon ATlas or Our world in Data represent historical CO2 by plots, and don't offer any option for predicting nor testing policy interventions. Instead, the users can see emission per capita or by sector, among other data points, but they cannot play with counterfactuals like: *What does it do if the transport sector meets a efficiency improvement (25 per cent by 2030), then what?. *

Another drawback is in the technical exclusiveness of a lot of modelling systems. Some research teams come up with clever Python-, R-, or Matlab-based algorithms, which however cannot readily be applied for non-experts. Policy makers and education providers who are the primary consumers of emission data do not always have the programming expertise to use these tools. That is saying that good models have been trapped in academia, and that political decisions continue to be made based on static spreadsheets and quarterly reports and not regular predictions based on evidence.

In the end, existing solutions have the following systemic shortcomings: fragmented

data sources, lack of predictive intelligence and no user involvement. To provide an integrated, web-based environment, which brings together data recovery, machine learning forecasting and easy visualization for users into a unified environment.

3.1.1 Web Applications

More recently, data science has embraced web-delivered data analytic platforms, but environmental forecast modeling has not. Typically national gateways offer data in static dashboards, which are updated annually and cannot be customised. For example, in Pakistan the environmental agencies published aggregated reports of point source emissions every year, but these emissions reports are issued as PDF files and are unavailable with any interactive functionality. Scientists need to extract the numbers and re-calculate them at the group's desire for correlation studies or predictions.

Lately interactive science visualizations (e.g. Plotly, Tableau, Power BI) have become more available; these tools, however, are rarely used in conjunction with 'live' ML models. Typically the websites are just "front-end only" and they visualize some pre-computed data. However, all these imply a manual end-to-end pipeline from data acquisition and model training/validation/forecasting to reoccurrence setup and publication to support an ongoing CO2 assessment. The system that we introduce in this paper has been devised to fill precisely this gap, by factoring mainstream Artificial Intelligence (AI) models into a web interface adapted to the modern requirements of the users.

3.2 Proposed System

3.3 The Proposed Software: The Environmental Impact and Risk Assessment of CO_2 Emission

We intend to build an entire-stack artificial intelligence based forecasting and analyzing system, called *The Environmental Impact and Risk Assessment of CO_2 Emission*. It connects the powerful ensemble machine learning backend with value am interactive and easy-to-use web frontend. The backend involves the combination of three algorithm types, namely; Feed-Forward Neural Network (FFNN), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Long Short-Term Memory (LSTM) network-which are individually selected as their ability is unique. FFNN is able to model the nonlinear feature interaction, ANFIS add the rule based interpretability and LSTM works on the long range temporal dependency. The ensemble writer module is constructed to bring their output sources together through the process of weighted averaging which is robust in the case of the forecast, and mitigate biases occurring in the single models.

At frontend, web-interface allows to view national and sectoral emission traces in latest history and over modelled future forecasts, cross validation for confidence building exercises for model and compares with policy scenarios. All graphs are dynamic users can zoom, hover to get the exact value and toggle legends to select what series they want to show. The interface has also taken in indicators of socio-economic factors GDP, Population and growth of the industrial sector - that contextually provide reading of the emission hot spots. Tooltips, summary metrics and color-coded signals on each page make it immediate to find out in the situation, even for the non-technical user.

Another design novelty lies in the area of the transparency. The app not only provides forecast but also model performance measures namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean absolute percentage error (MAPE) and coefficient of determination (R2). These kinds of measures can enable end users to assess the credibility of predictions and cultivate faith in the models. Results can be exported as csv or xlsx format for follow-up analysis and through a contact module, researchers and policy makers can interact with the development team.

3.3.1 Benefits

There are any number of real pros to the system over what exists. As disparate models are unified into a common model, it is discovered that the model is more into steady, accurate, and hazard-free positions as to noisy data. Its bringing together of a plethora of datasets enacts no painstaking manual compilation whereas ensemble forecasting products are commissioned to offer actionable foresight in backing of policy planning. By being interactive the user is brought out of passive observer, into active analyst capable of trying scenarios in real-time.

Apart from usability, the system is focused on explainability. By combining the interpretive reasoning algorithm of ANFIS and the predictive power of the neural and recurrent networks, it bridges the gap between accuracy and transparency. A big part of the platform's design philosophy is also one of inclusion, of making cutting-edge AI forecast the domain of the democracy by creating an end-user, no code environment that will be available to anyone with a web browser. This is especially transformative in emerging market institutions where there may not be as available data science expertise.

3.3.2 Solution Areas

The system targets three intersecting areas of solutions.

First of all, it is not only a decision support tool for environmental policy makers who need to have trustful estimates in order to design emission reduction policies. Along with BAU and Policy case we are also comparing app cases also depicting policy impact with avoided emissions and percent percent reduction over BAU. Secondly, it is used as

an instrument in the hands of the educator and the researcher.. Universities and training centers could use it to conduct classes with data analysis, forecasting and environmental modeling courses as a hands-on way to introduce students to how machine learning is being applied to sustainability.

Thirdly, it is a base for long term monitoring throughout the country. Fundamentally modular Halter'sCMV's additional sectors can be added with a minimum level of redevelopment (e.g. parts of the platform managing power generation, agriculture or waste). 5.2 Extensibility This 'extensibility' enables enabling the platform to be more than a one-off project focusing on climate information management, but as a scalable model of climate intelligence instead.

3.4 Requirement Specifications

3.4.1 Purpose

The purpose of this software is to make available a clear and automated decision support tool for emission estimation. Transformation of messy data pipeline data into gorgeous dashboards that provide real insight, not just some numbers

Designed from three aspects, they are accuracy by ensemble learning, interpretability within model transparency and model accessibility via user centricity the core incorporates. The system then serves information experts as well as policy experts.

3.4.2 User Needs

Different types of users are symbiotic with the system. Decision makers need an overview, scenario comparison and metrics in a nutshell to make strategic decisions on future actions. Researchers and analysts also need more and broader access to model diagnostics, adjustable parameters and downloadable datasets for further study. On the other hand, teachers and pupils alike demand intuitive explanations for what AI is good for when it comes to environmental forecasts exactly that is.

Since there are different needs, the app uses layered interaction design. The homepage and the dashboard pages show easy summaries which are suitable for non-technical consumers, while papers in more distant portions of the hierarchy dig into validation specifics and references to methodology. The synergy of nature and depth is such both clarity and power is retained for the user to enjoy without one mired with ethereal quicksand from premature venturing completion of truncating.

3.4.3 Assumptions and Dependencies

There are a number of assumptions under which the correctness of a platform is grounded. This also takes for granted that the incoming data from the official bodies like World Bank, Pakistan Bureau of Statistics and Sustainable Development Policy Institute is not outdated and updated regularly in this regard. It also needs some regular internet connection while using a browser loaded with HTML5 and Java scripts. The software environment has been developed in a computational environment in Python with TensorFlow and the libraries available such as scikit-learn, NumPy and Pandas. The web layer is done using Flask (the server-side and interactive front end React.js). This information is constantly stored been provided as secure RESTful APIs. It is scalable cloud deployment for sites company-wide; a Dockerized containerization; mucilaginous for maintenance, hoppity-hop between servers.

3.4.4 Functional and Non-Functional Requirements

As will be apparent, the function of the software could best be described as a configurable analysis pipeline that connects input data to model training and validation, various kinds of visualization and output production. Whilst users will load the dashboard based on aggregated emissions and forecasts requested from the backend when they log into the system. GDP, population, and energy consumption are then provided as inputs of the ensemble model for the prediction of CO2 levels. Results are shown in interactive and real-time graphs, making it possible to browse the same over time and to relate them to a scenario.

Fast Internet System also provides various other services in addition to the above-mentioned basic functions. There is also and a "Data & Downloads" page where historic emission and forecast results are available for download. The Validation module presents quantitative analysis and graphical overview and comparison of the model performance in both the baseline and the ensemble scenario. The sub-module of "Policy Scenario" shows the results of emission reduction schemes within the assumptions that may be used for sensitivity analysis.

The non-functional aspects are as important as well. The solution also should have high availability with exceeding 99% uptime for online hosting. No latency (or very weak) somewhere between dashboard charts being displayed in 3 seconds when there is no bandwidth. The system also maintains the integrity of data by using strict validation of the input and APIs. The communication is conducted according to authenticated and encrypted communication protocols to avoid unauthorized access to datasets and model-settings. The design is also meant to be maintainable: modules are arranged so that future enhancements (e.g. addition of new AI models or more sectors) can be made without rewriting other

sections of the implementation. Interface is WCAG 2.1 compliant meaning readability for people with disabilities.

3.5 Use Cases

High-level behavior of the software is represented in the use-case diagram Figure 3.1.

This such diagram includes one full interaction model for the user and system, namely, showing the actor interaction with different functional module.

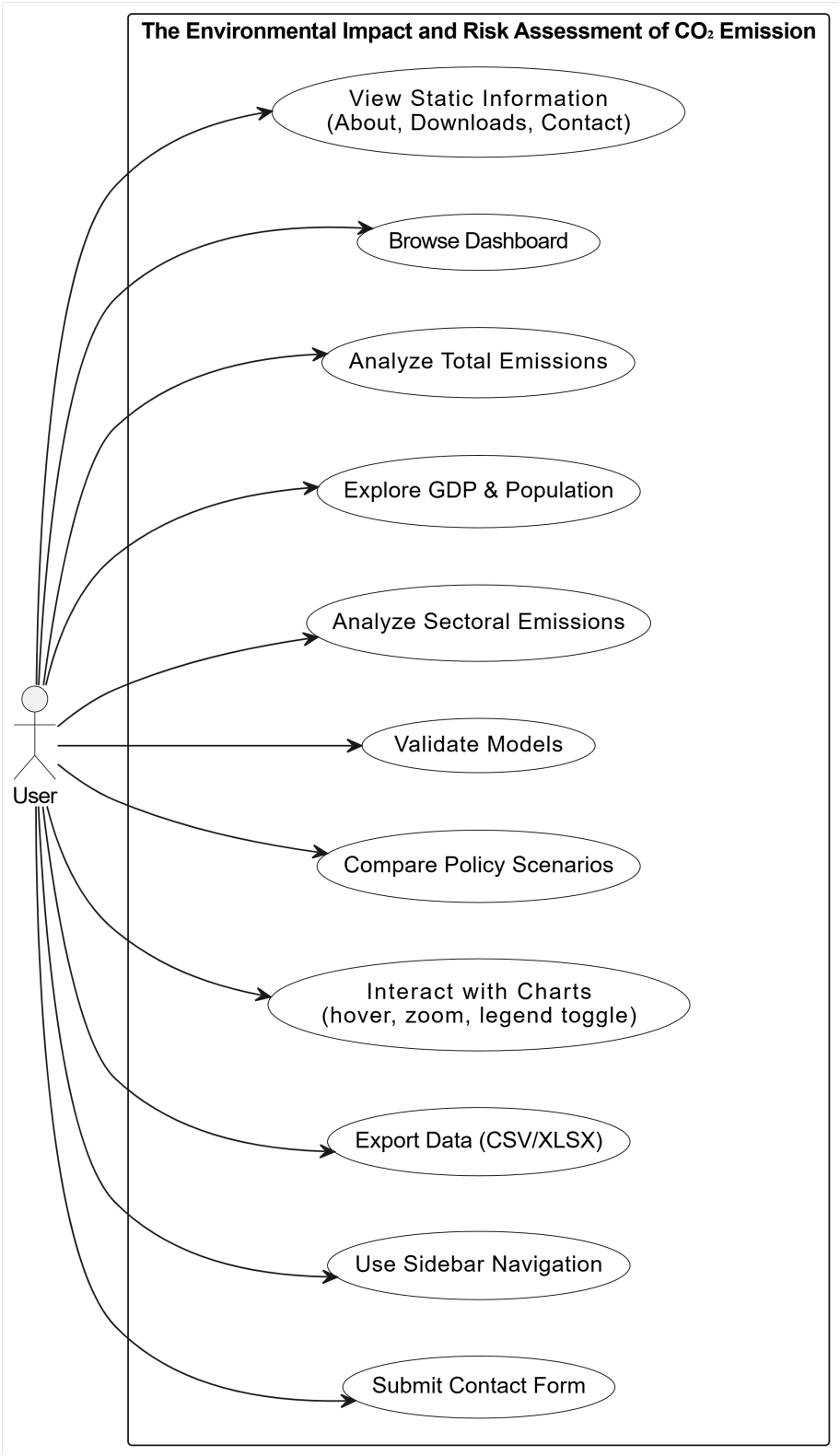

Figure 3.1: Use-case diagram of *The Environmental Impact and Risk Assessment of CO_2 Emission system*.

The only actor - *User* - stands for any agent that comes into contact with the web

application including, but not limited to, policy-makers, researchers and lay people. Upon visiting the home page or the login page, the user finds all sorts of operations. They could access static project information about and download any available datasets, go to the main dashboard and investigate the emission metrics or even further down analyst sections that deal with total emissions, GDP and population correlation, breakdown by sector, and validation of the model.

The users can jump back and forth between the Business-As-Usual (BAU) and Policy cases when playing out policy scenarios. The charts are interactive as well as real-time to display cumulative emissions avoided and projected percent reduction. Such interactivity provides real-time advice on how effective particular policy interventions would be. Users also have the option to provide numerical results which can be used in other analyses or for presentations. Conclusion These modules enable the system administrators to inter-contact each other to form a feedback loop among the developers and the end-users.

3.5.1 Expanded Description of Major Use Cases

The dashboard is the accessibility point of the system, and the common point from where the users access the system in both high-level summaries and detailed visual analytics. When it is loaded, it shows the most recent emission information as well as forecasted values using the ensemble model. Users can move from one tab defined by different analytical dimensions such as "Total Emissions," "GDP and Population," "Sectoral Analysis," "Validation" and "Policy Scenarios." Each tab has a consistent structure of the interface to minimize mental load and maximize visual clarity.

In the total-emission analysis module, time series are shown of national paths for CO2 between 1970 and 2032, with indications of crucial points of inflection relating to policy changes or changes to the energy sector. The GDP and population module puts the emission data in the context of macroeconomic patterns and particularly highlights the effect of growth in the economy and population on carbon intensity. The sectoral analysis module breaks down emissions into transport, power industry, industrial combustion, building and agriculture giving granular insight into the sectoral contributions.

The policy-scenario comparison is perhaps the most important characteristic. In this regard, it is possible here to visualize the difference between baseline forecasts and outcomes of interventions. A set of graphs measures the avoided emissions, percentages in terms of effectiveness and annual reduction rates thus turning abstract targets into a solid basis of measurement.

Model-validation section gives transparency of the AI process. Frontrunner provides users with the ability to look at numerical performance figures and either residual plots or hold back profiles for any of the models, which is a comparison side-by-side of the output

of the ensemble with the output of either component. This is what will give trust in the analytical integrity of the system.

Finally, the process is completed with the export along with contact modules. Users can download data for assessment by others, or submit feedback about it that influences further development. Together these use cases encapsulate the [end to end] user experience - from exploration, analysis, validation and communication.

3.6 Summary

This chapter put forward a detailed description of the software requirements and system specifications of the proposed CO2 emission forecasting platform. It started with the blights of existing systems, which are subjective in that their interactiveness is fragmented by data, and lack vision in that information is not subjected to any predictive intelligence. The proposed system above is combining ensemble AI modeling with an interactive web interface and therefore also it addresses these barriers.

The chapter also gave an outline of technical environment, the architectural dependencies, as well as the ethical and non-functional requirements to ensure system reliability, scalability and security. The use-case discussion indicated how a range of user interactions are projected onto the features of the application, underlining the user focus of the design.

Overall the software provides a step change - from static, environmental reporting, to dynamic, intelligent, transparent decision-support. It provides the technological backbone for sustainable Emission Management and is a link between the fundamentals of data science research and practical policy thinking. The next chapter will go into detail on the architecture and design models outlining these requirements into hard structure diagrams and implementation designs.

Chapter 4

Design

4.1 System Architecture

The environmental impact and risk assessment of CO_2 emissions platform framework is modular in architecture. three-tier model keeping the presentation and the application logic detached from the data persistence. This separation of concerns helps maintain it, as well as makes the code more scalable and testable.

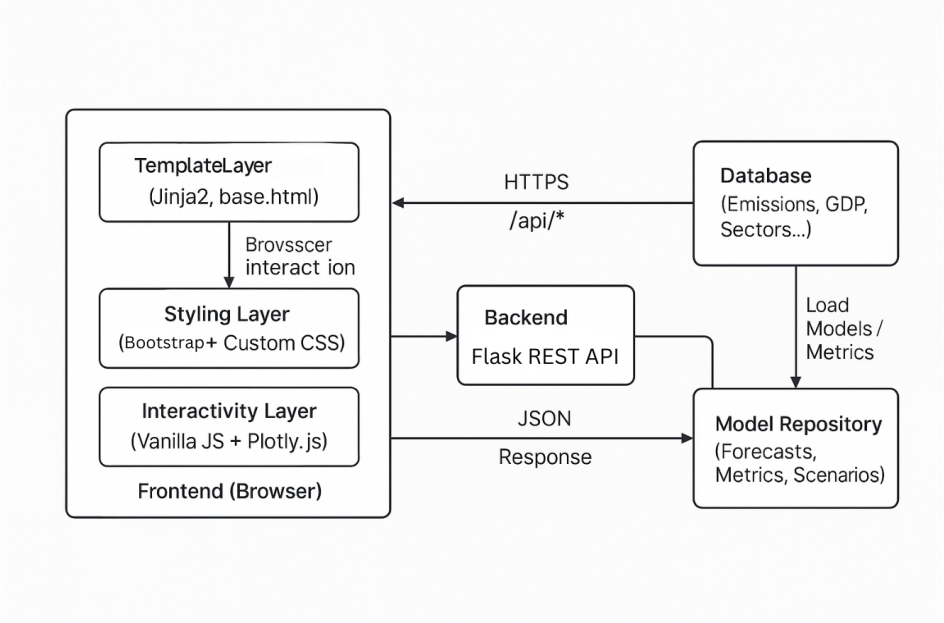

Figure 4.1: Architecture Diagram

4.2 Component diagram

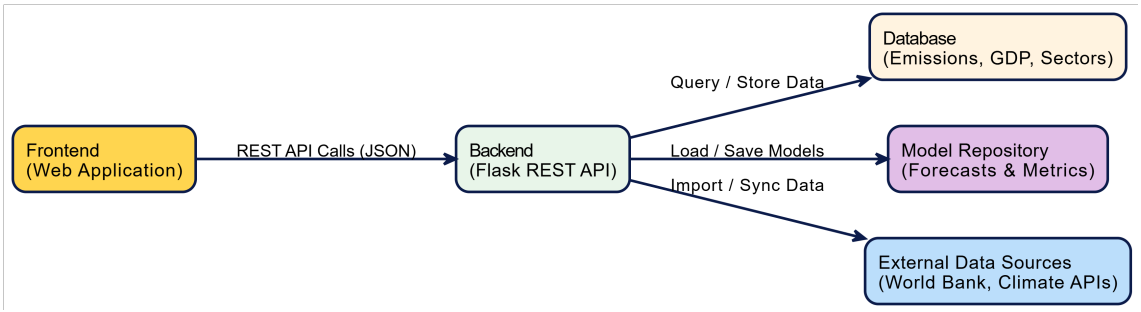

Figure 4.2: System level block diagram of major modules and interaction.High level system diagram of major modules and their inter-relationship.

The topmost layer is the frontend, so it is a responsive web application. Here communicates with the backend (renderer: **Flask REST API** backend) with the use of HTTPS response with use of a JSON format. The backend helps to coordinate the **model repository** - storing of serialized FFNN, ANFIS and LSTM models for the local testing, and PostgreSQL for the deployment purposes. Baseline information coming from external data and applying external sources - World Bank and national statistical API data. Layered architecture assists asynchronous communication, i.e. the web interface remains responsive while the models execute in the background.

4.2.1 Context Diagram

The context diagram shown in Figure 5.2 illustrates the high-level interaction between external repositories, web client, back-end services and users.

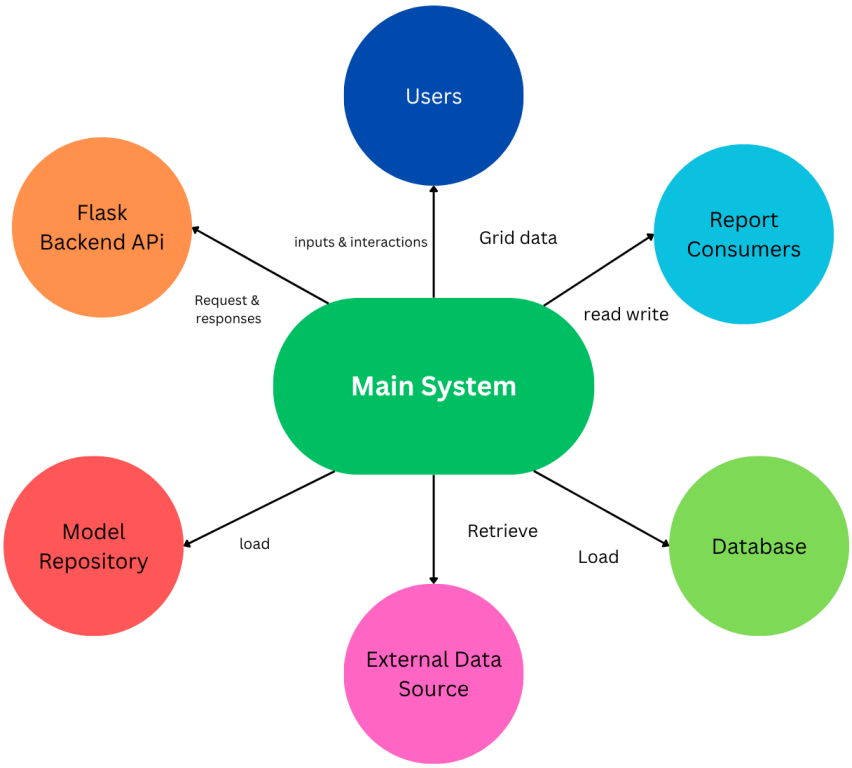

Figure 4.3: Context diagram showing the environment of the CO2 foreseeing system (CO2-FS).

Users set the requests in the bottom (via browser); the application layer processes it via the url (restful apis); external databases and Model stores respond as structured data passing it back to the client. This sets the system boundary and lists all the external dependencies.

4.3 Design Constraints

Computer architecture, software, and operational limitations drove all of the design decisions. The development environment was restricted list of mid-range commodities without dedicated GPUs. demanding to be optimized for inference using a CPU. Dependency on software had to be open source and cross platform: Python 3.10, Flask, Tensorflow .

Due to the nature of the network, requests had to be executed within a few seconds, for the purpose of keeping users engaged. Concerning model uncertainty, an ethical and transparency constraint led to the interface including that uncertainty. avoid misinterpretation of forecasts as absolute predictions; There was also a requirement for compatibility of browsers (chrome, firefox, edge) and accessibility (wcag 2.1).

4.4 Design Methodology

The project was built upon an iterative methodology of an agile-inspired nature that combines practices of software engineering with the data science lifecycle. There was a feedback loop that occurred with each sprint, including: requirement analysis, prototype design, user trials, model evaluation. Source code was version controlled through the use of GitHub, continuous integration verified the build automatically, and modular commits monitored progress from prototype of final deployment.

Data science components of data cleaning, feature engineering, training, cross-validation, and blending ensemblal were implemented as a part of the Flask services layer. This smooth workflow greatly lessened the point of divergence between research notebooks and coded research production.

4.5 High-Level Design

4.5.1 Conceptual and Logical Design

Figure 3 shows the class diagram that reflects the logical data model (i.e. the logical data model).

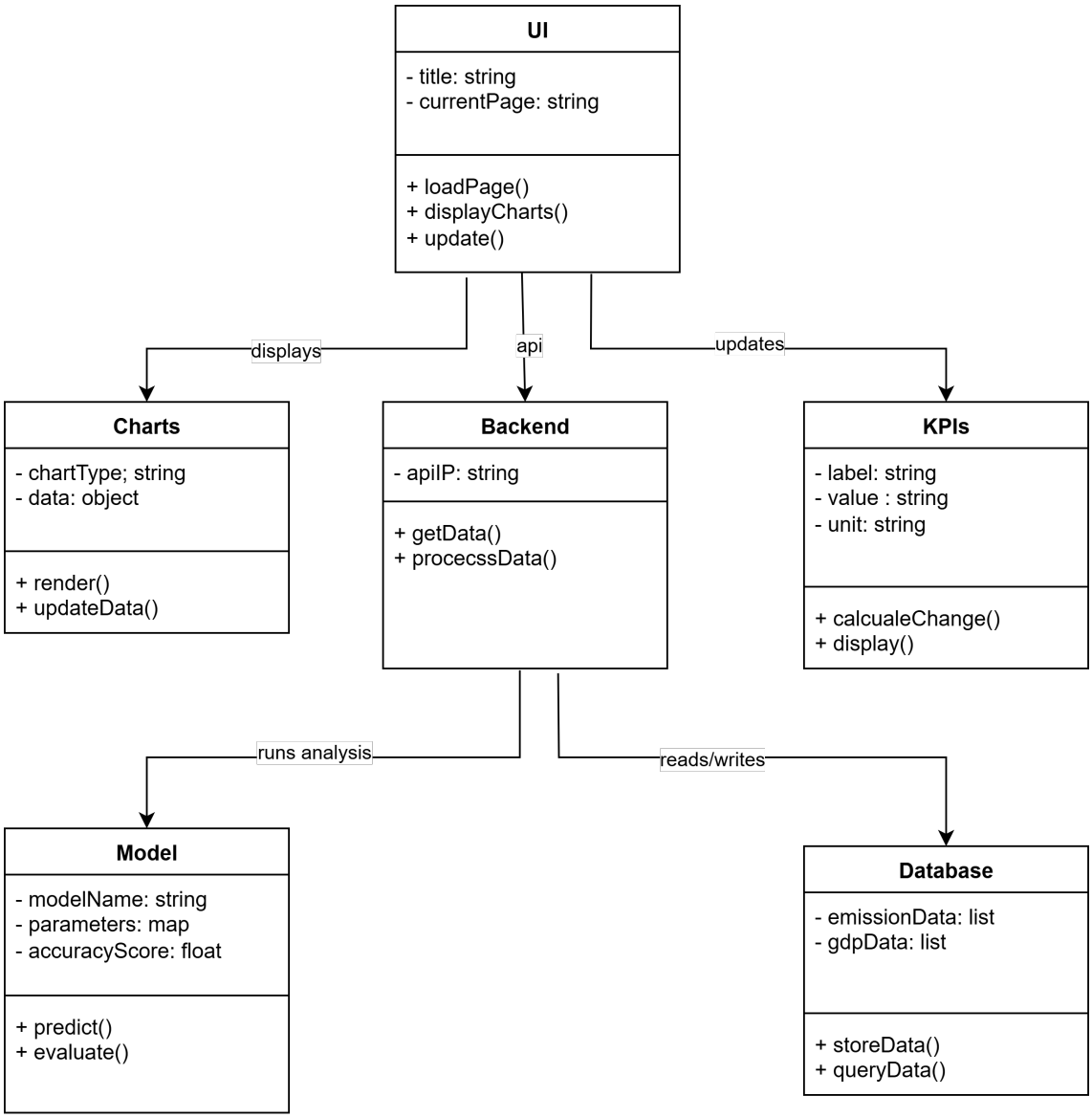

Figure 4.4: Class Diagram - This is a class diagram designed to show the connection between important entities at the logical level.

Classes such as Emission Record, ForecastModel, Scenario, Validations Metric etc. are referenced by each other via foreign-key relationships thus guaranteeing referential integrity. Each prediction is tied to the data source, the algorithm version and the time in which it was predicted for purposes of being audited.

4.5.2 Process Design

Request and response model shows the direction of the data flow between frontend and backend. The backend is fully responsible for all state changes which are atomic and consistently cached.

4.5.3 Physical Design

Allocation is done on a dual-tier architecture: React builds are served as static assets with NGINX and Django's (Flask) API together with the model repository is running behind Gunicorn workers. Persistent volumes nicely store database as well as serialized model object artifacts in order to be reproducible.

4.6 Low-Level Design

Low-level design consists in defining the behavior of each module afterwards, i.e. python classes, React components and the interface. Caching, error handled and asynchronous threads are implemented to ensure fluid performance.

4.6.1 Activity Diagram

This subsection groups the activity diagrams which represent the user workflows in the different analytical modules.

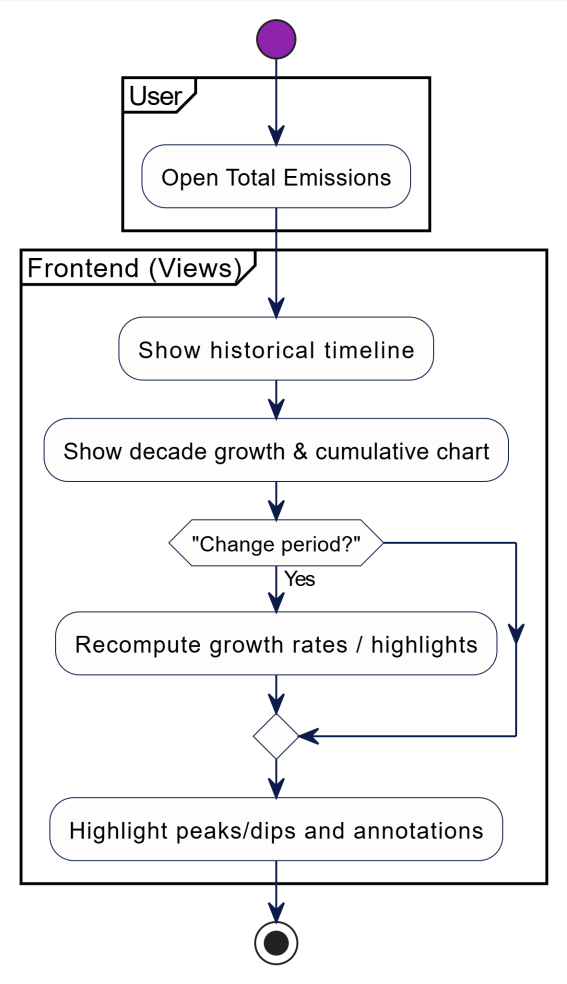

Figure 4.5: Capture total CO2 emission exploration use case.Activity flow chart to investigate total CO2 emission.

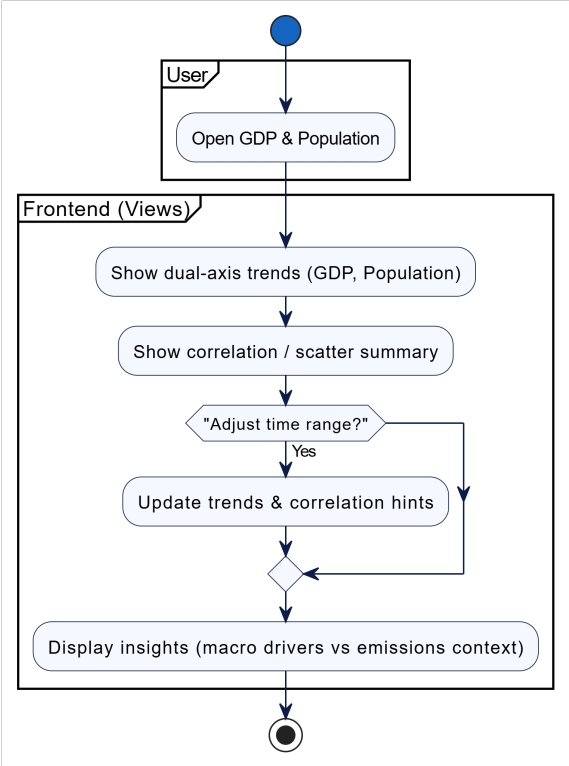

Figure 4.6: Activity diagram of the GDP and population analysis.

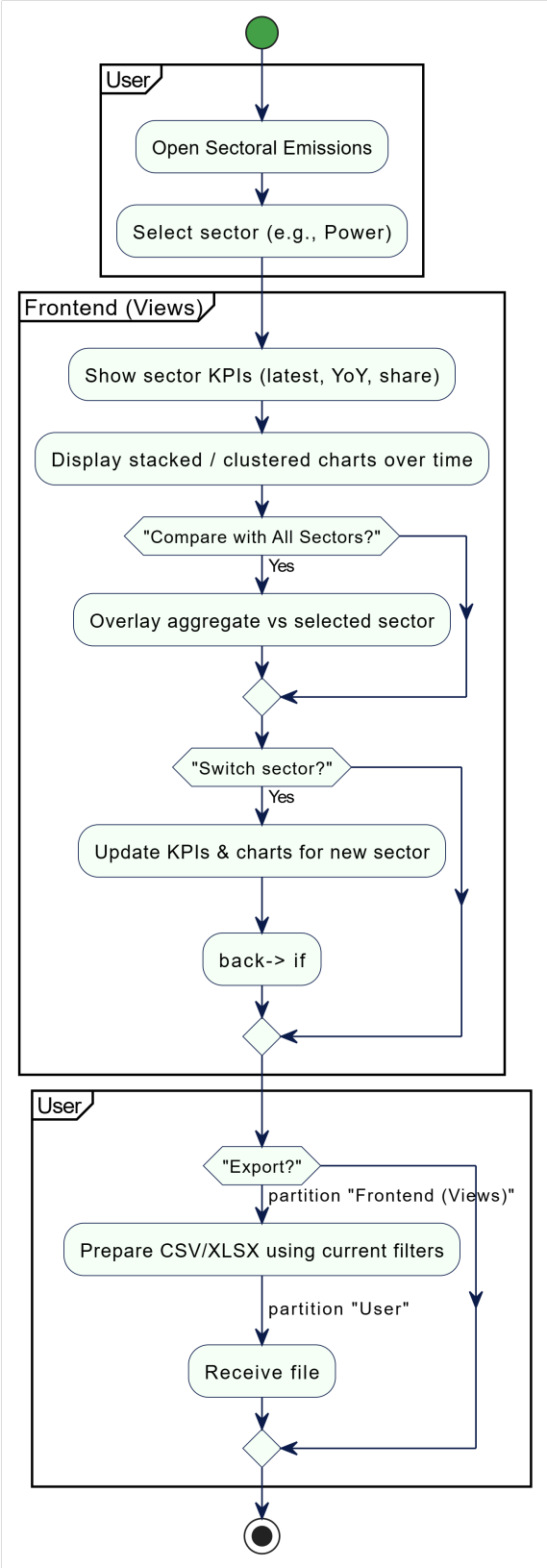

Figure 4.7: Sectorial emissions basic activity overview.

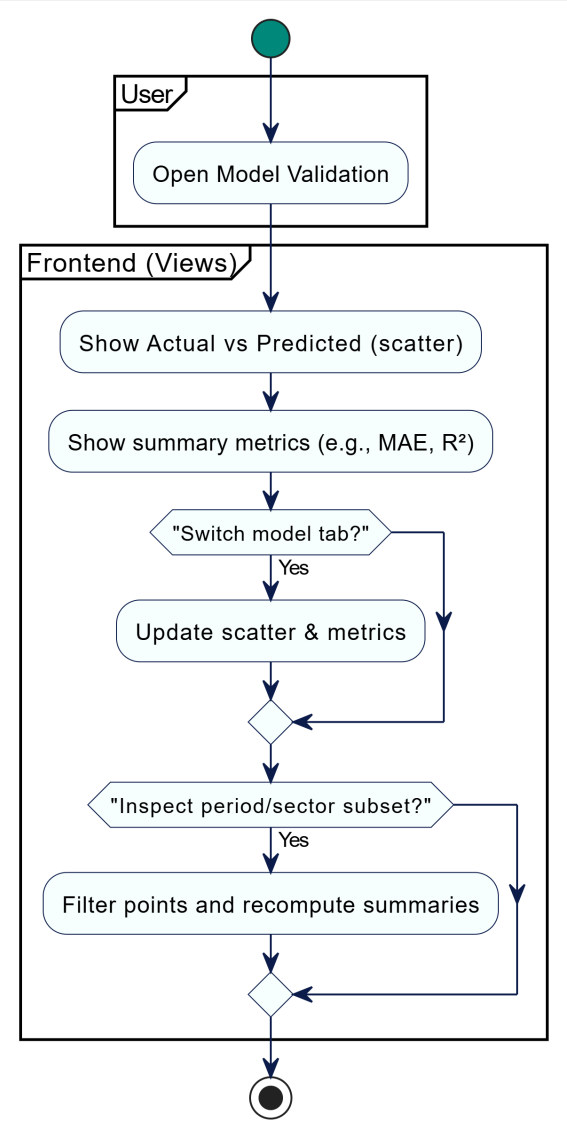

Figure 4.8: Activity diagram for model validation process.

Each diagram is fully-dedicated in downstream notion - appropriate from frontend rendering to eventually, there's computation within the backend, but the final outcome is sent back to the user if that's the case. emphasizing concurrency and feedback loops to preserve the consistency of the state;

4.6.2 System Sequence Diagram

The sequence diagrams endure the temporal course of the interactions concerning the main parts of the system the user interface (UI), application logic, the Rest API layer, database and machine learning model repository. They explain how every component works in a dynamic way to achieve important user actions. Whereas static diagrams, such as the class or component models describe structure, Showing time-based behavior i.e.

sequence diagrams emphasize the run-time scenario, flow of messages and asynchronous coordination between the front-end and back-end. Together they are a dynamic complement and contrast to the static architecture that we have presented previously.

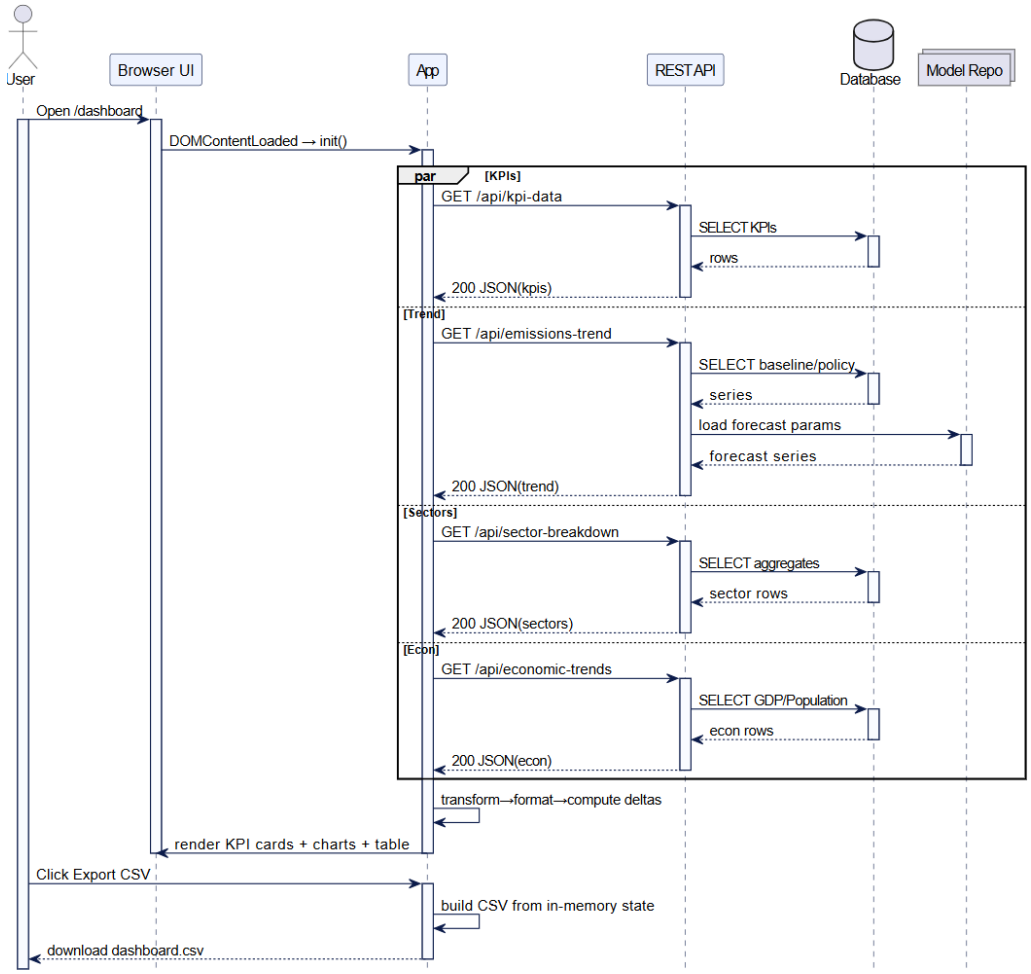

Figure 4.9: Personality diagram for the initialization of the dashboard and loading of data.

Figure 4.9 shows the complete start-up logic when the user opened the main dashboard as Figure **??** As soon as the DOMContentLoaded event is hit in the browser, multiple REST API calls Boolean in parallel are issued in the application, which get the necessary data categories: Key Performance Indicators (KPIs), emission trends, sectorial splits and macroeconomic indicators such as GDP and population. Each call is handled in an asynchronous way so as not to block the interface.

the APIs endpoints (api.kpi footage, emissions trend, sector split and economic trend APIs, with the specific endpoints being /api/kpi-data, /api/emissions-trend, /api/sector-breakdown, and /api/economic-trends), ask the backend database for matching tables; Projections-byächt may also be being obtained by the backend from the model repository for projections that have already been stored there. Each query will return a structured

JSON payload and they can be parsed by frontend and converted into UI components. and as summary cards and interactive charts;

This sequence of pictures shows the modularity of the system: Each dataset type must be drawn, processed and displayed separately. providing incremental loading in which the user also has prompt feedback rather than waiting on full delivery; The calls and state management system have been parallelized in order to ensure fast responsiveness even with large data sets.

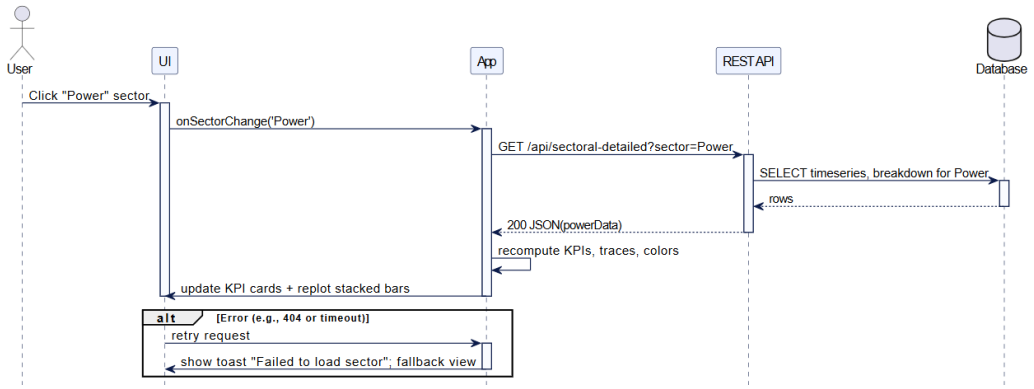

Figure 4.10: Sequence diagram for the selection of sector, and data get procedures.

Figure 4.10 illustrates the workflow that takes place when the sectorial emissions analysis module tells BEE to search for the specific sector (for instance, "Power" or "Transport" or "Industry"). So, if the function onSectorChange() is invoked at the UI, then the frontend makes a(get/post) - paramtered request to pertinent backend API (/api/sectoral-detailed?sector=Power). Consequently, the controller layer flows the backend performs an SQL query to filter the emission time series for the implemented sector, as well as aggregate historical and forecasted data.

The retrieved records are converted into a serialized format (in this case, a format called a family of four.After receiving this, the frontend collapses KPIs such as sectoral share, growth rate, and year over year (YoY) variation. These changes shoot through bar charts with gauges stacked on top and KPI cards on the dashboard

Other flow is also modeled into the diagram which is a flow that will run if there is an exception such as a network timeout or a 404 error (in case that the dataset is not found). In these cases the frontend will by default retry the request and again shows a toast notification with the content "Failed to load sector" when the error cannot be recovered from. This is a kind of fall back mechanism to assure the fault tolerance & hence the usability under adverse network conditions.

Overall, this interaction pattern shows that the error handling strategy of the system is robust, As always, these goals encompass differing levels of effort: The immediate requirement the application faces in recovery is to ensure that when a transient server failure

occurs (or the data lacked during transmission), the impact is either zero or significantly rarer than the user-visible failures.

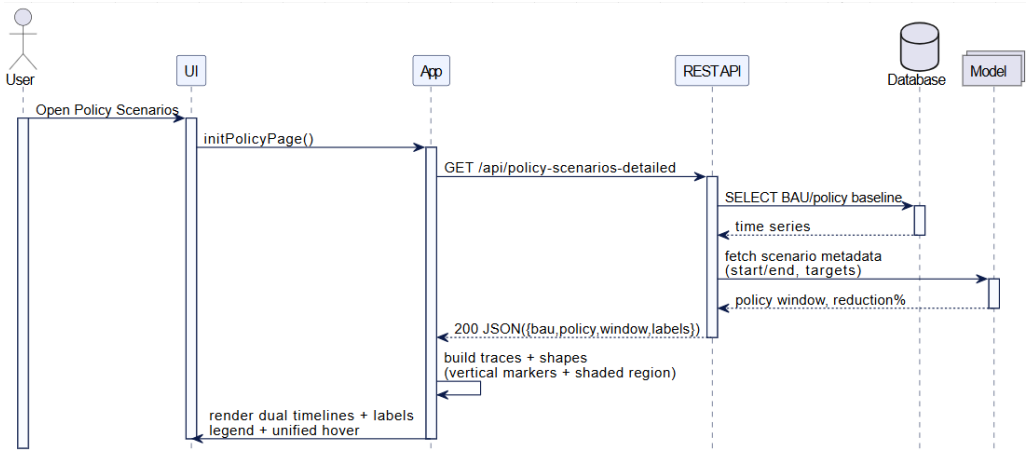

Figure 4.11: Sequence diagram of the policy and scenario comparison policy.

Figure 4.11 shows the process of getting and visualizing the "Business-As-Usual" (BAU) and "Policy Scenario" forecasts under the Policy Analysis module. When the user opens the policy scenario page the UI makes an asynchronous call `GET /api/policy-scenarios-de` The backend API controller calls the database for baseline series and policy-adjusted projections that it has stored. If metadata are required, as in the case of target reduction per cent, time windows and sectoral participation, they are fetched from the model repository.

After retrieving the datasets of BAU and the policy, the API has a centralised structure in its output in a unified form of JS Thr Object containing emission series, with objectives of polished reduction, and timeline labels of The frontend takes this data and assigns it to the representation of dual timelines, shadedPolicy intervals and cumulativeAvoid charts. Hover interaction is provided so that the user can see the annual differences between the two trajectories.

This sequence demonstrates the backend's process of harmonizing different sources of data - data tables, metadata and serialized model output - into a cohesive structure which can be made visual. The unified format makes government frontend processing simpler and helps to ensure that new variants of the policy can be added which would not affect any change in logic for the UI.

4.7 GUI Design

The graphical interface can be seen as the link between asking depth computationally and drawing it from the user's understanding. The aim of path interpretation is to provide an intuitive interactive visualization of the information generated by the abstract numeric output which makes interpretation by policy makers possible.

4.7.1 GUI Prototype

Initial ideations were created to outline the structure of navigation, card layout and color scheme. Prototypes were shown for clarity and accessibility prior to the building of components.

4.7.2 Actual GUI

Screenshots from the live interface are used which demonstrate how conceptual prototypes developed into the production system. With advancements in the concept of Responsive Design, it is possible to make it responsive across various screen sizes.

4.7.3 User-Centered Interface

Every iteration went through user testing by environmental analysts who wished that labels were concise, legends were easily readable, and the terminology should be the same not just between modules.

4.7.4 Easy-to-Navigate Interface

Navigation is in a low level hierarchy: overview -> category -> detail. The sidebar does not go away, and keyboard shortcuts help one efficiently traverse.

4.7.5 Informative Feedback

The user interface gives the user feedback using spinners and toast notifications. Validation outcomes show confidence and the color-coded status of the validation items that show which forecasts to be confident about and which are running on the edges of their confidence.

4.7.6 Consistent Interface

Typography, iconography, and movement all are interwoven based on a unified visual language. Tailwind CSS alignment and spacing are laid out in the Tailwind CSS file of the configuration twins and are shared among chart scripts, metric cards, buttons, etc.

4.8 Summary

This chapter showed in exhaustive detail the design for the CO2 forecasting system, from the architecture-level aspect, low-level behavioral models and user-interface implementation. The incorporation of your uploaded diagrams into the narrative brings with it

conceptual as well as operational transparency. Together they form the blueprint of which implementation comes out in the next chapter.

Chapter 5

System Implementation

5.1 Introduction

The implementation phase turns the theoretical design into an interactive and working platform. It is an intersection between data science, web development and visualization. In this chapter, the actual implementation of the system which is titled The Environmental Impact and Risk Assessment of CO_2 Emission is explained. Anthills emphasises software engineering practices, as well as the visual interface that makes it possible to use it practically. Each sub-section shows how the code modules, models and APIs work together in order to produce the dashboards. This research is presented throughout this chapter.

5.2 Backend Implementation

The backend allows the organization of the analytical workflow. It is implemented in python 3.10 by using framework Flask 2.x; Each of the major operations including data ingestion, training of a model, and generation of a forecast is encapsulated within modular routes. The responses from the API are returned as a response in the form of a pure JavaScript object (json) which is to be consumed by the React application.

The ensemble forecasting engine is the combination of FFNN, LSTM and ANFIS models. Training scripts are used to load historic CO_2 data, normalizing of the variables, fitting of the models, and serialization of models into the repository. At the time of runtime, the models are loaded from the Flask server once for each session and make prediction endpoints available.

The backend also provides endpoints to export the results, download the data and serve model validation metrics.

5.2.1 Dataset Description

The forecasting models were trained on a compilation of data compiled from the World Bank Open Data and the Pakistan Bureau of Statistics and the Sustainable Development Policy Institute (SDPI). It contains annual observations between 1970 and 2022, which contains:

- CO2 emission (Mt CO2 e) of National and transport sector,
- Gross domestic product (GDP, billion USD in 2015 constant),
- Population (millions),
- Cost (TJ), and
- Share of industrial and services sector (

After all the cleaning and interpolation, we were left with a dataset that had 53 records with five explanatory features. All the variables were normalized using min-max scaling, implying a scaled value between [0, 1]. Figure 4.12 showed how, in the flow of data shown in figure 4.1, these records pass through preprocessing. feature engineering, training and pipelines made of models

5.3 Model Training and Evaluation

This part consists of the implementation of a training, evaluation and visualization processes from the Jupyter notebook The workflow integrates the different parts of the analysis: pre-processing the data, fitting a model to the data, weighting the various ensemble members and evaluating the models graphically.

5.3.1 Training Script Overview

Each model viz., FFNN, LSTM, and ANFIS was individually trained and then ensemble was integrated. TensorFlow, scikit fuzzy, NumPy and Matplotlib libraries were used for the notebook.

Each of the model's predictions was tested using Mean Squared Error (MSE), Mean Absolute Error (MAE), Root root-mean squared error (RMSE), Root mean squared error (RMSE), R squared (R2).

5.3.2 Training and Validation Curves

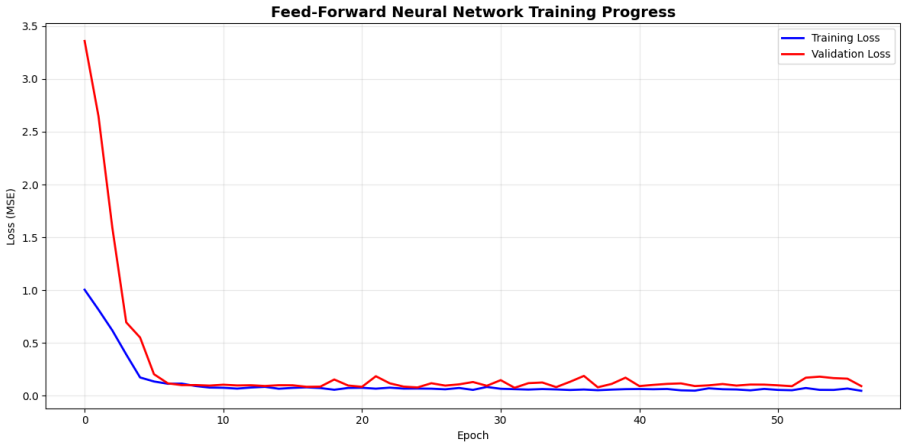

Figure 5.1: Comparison carpark forecast model Training and validation loss values for the FFNN model depicting stability of convergence.

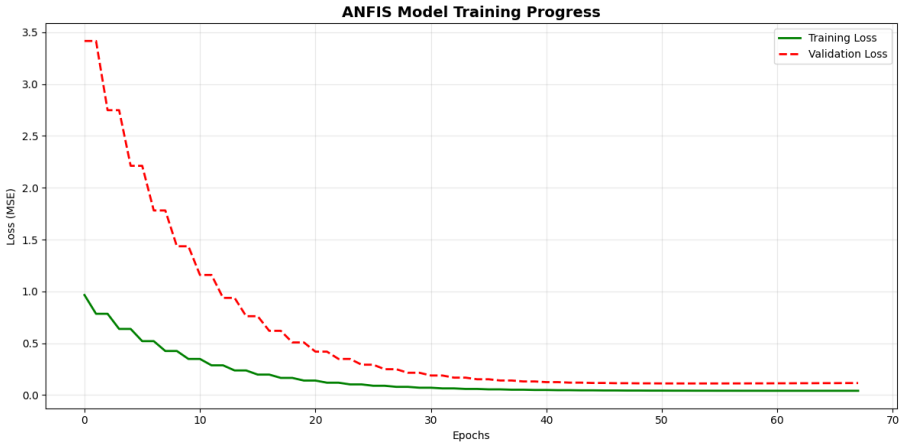

Figure 5.2: Figures Training and validation loss of the ANFIS for visualising convergence stability.

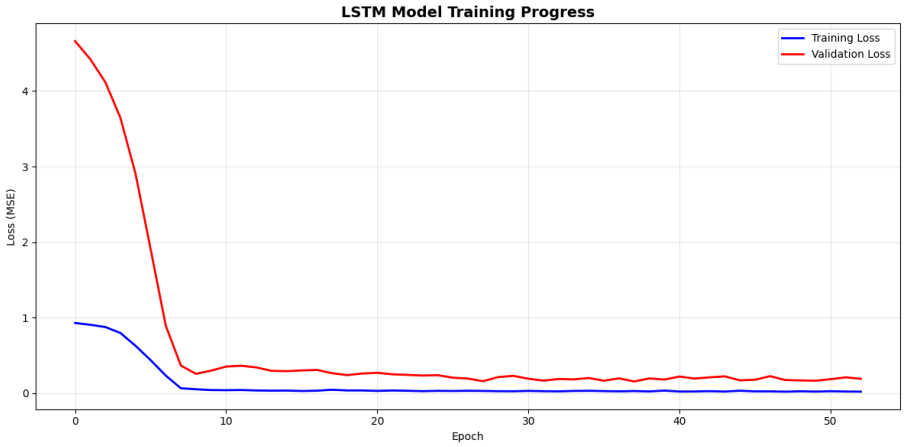

Figure 5.3: Convergence Era and Loss Curves with the LSTM: Training and test propose that the LSTM's results are stable.

The stable convergence achieved for the LSTM and FFNN model was achieved at about 100 epochs. with no signs of overfitting. Early stopping was used when the validation loss did not improve anymore.

5.3.3 Model Comparison

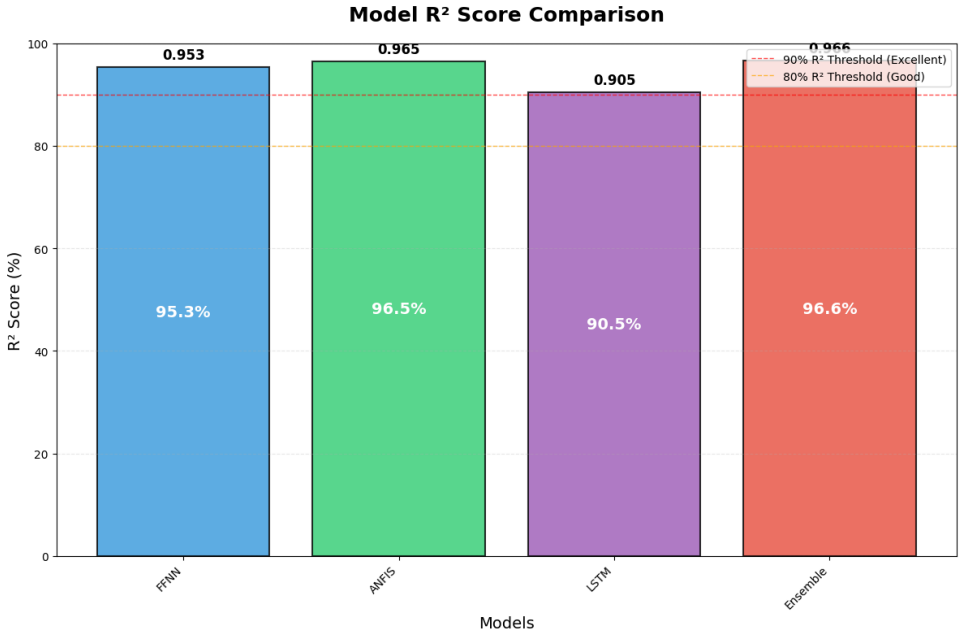

Figure 5.4: Comparison of predictions of the model and their actual emissions for the validation period (2020–2022).

Note: The base paper reports RMSE and R^2 only for FFNN/ANFIS/LSTM (average values). The ensemble in the base paper is validated using a 2021 record with percentage error = 6.8675% (accuracy = 93.1325%), not RMSE/R^2.

5.4 Frontend Implementation

The frontend has been implemented with html css with Bootstrap for styling, and Plotly.js for visualisation. The application has single-page architecture. Figure 5.5: UI Dashboard Figure 8: UI Policy show the major modules of the user-interface.

5.4.1 Dashboard Module

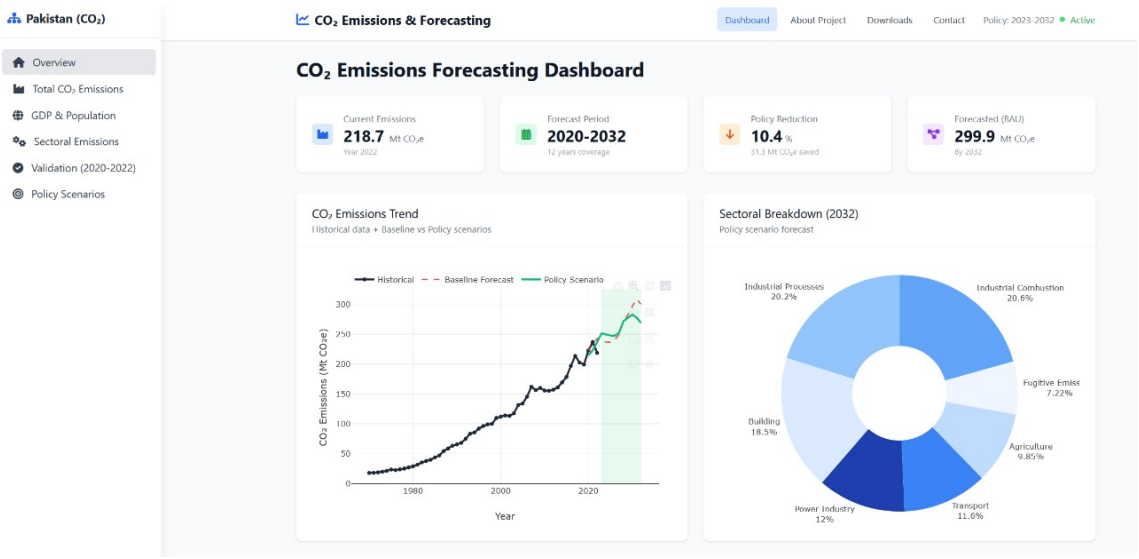

Figure 5.5: Statistics, forecasts and sectorial distribution for CO2 emissions Dashboard

The dashboard is their entry point for the user. It shows the emission data at national level, the forecast period as well as the current metrics of the policy reduction. Interactive charts provide hover, zoom, toggle, historical, baseline and policy trajectories capability. On the run-time all the information are fetched dynamically from Flask APIs.

5.4.2 Total Emissions Module

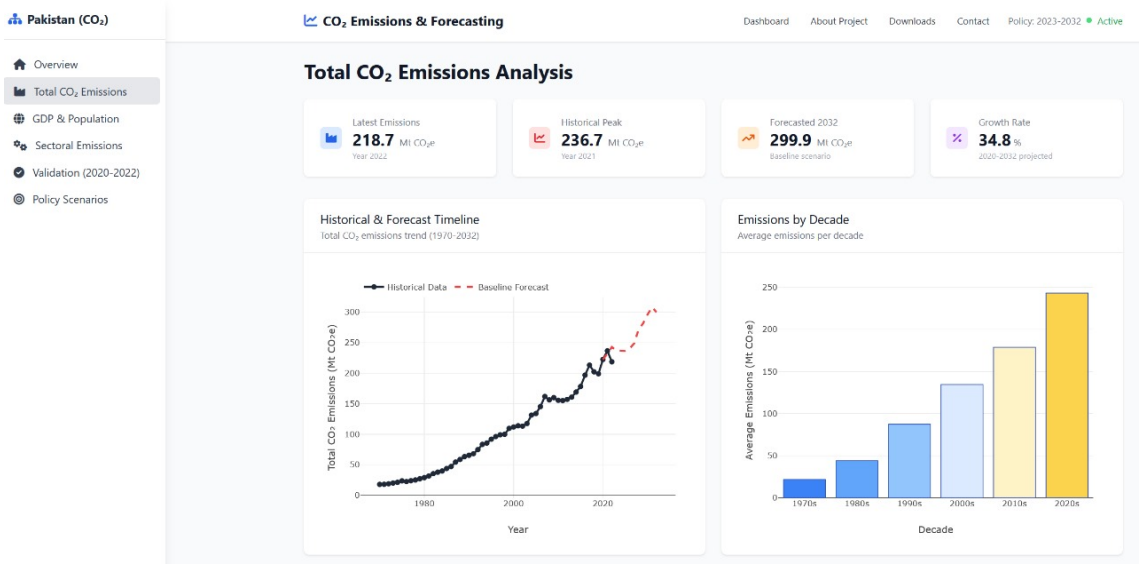

Figure 5.6: CO2 Emissions analysis showing login term historical data and forest trends.

This page is a visualization of aggregate emissions over the time range of 1970 to 2032. The backend offers the access on both an historical and a predicted dataset data which is overlaid with the frontend by dual color coding. Users can control time spans to rebalance statistics around growth that are updated right in the browser.

5.4.3 GDP and Population Module

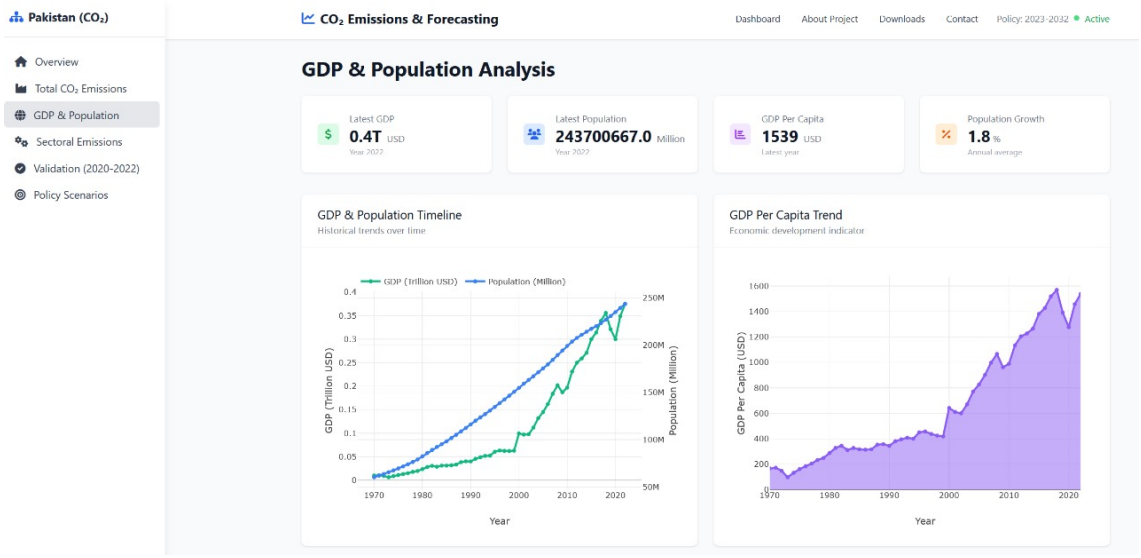

Figure 5.7: Macroeconomics: GDp and Population Analysis - the dashboards show the correlation of Macro economic variables and CO2 OUTPUT.

This module links the economic activity and emission intensity. The figures shown in the two axes of the chart stick to trillions (GDP) and millions (population); the result is that she shows a proportionality of the data. Correlation coefficients recomputation is done dynamically as the user changes the visible time window.

5.4.4 Sectoral Emissions Module

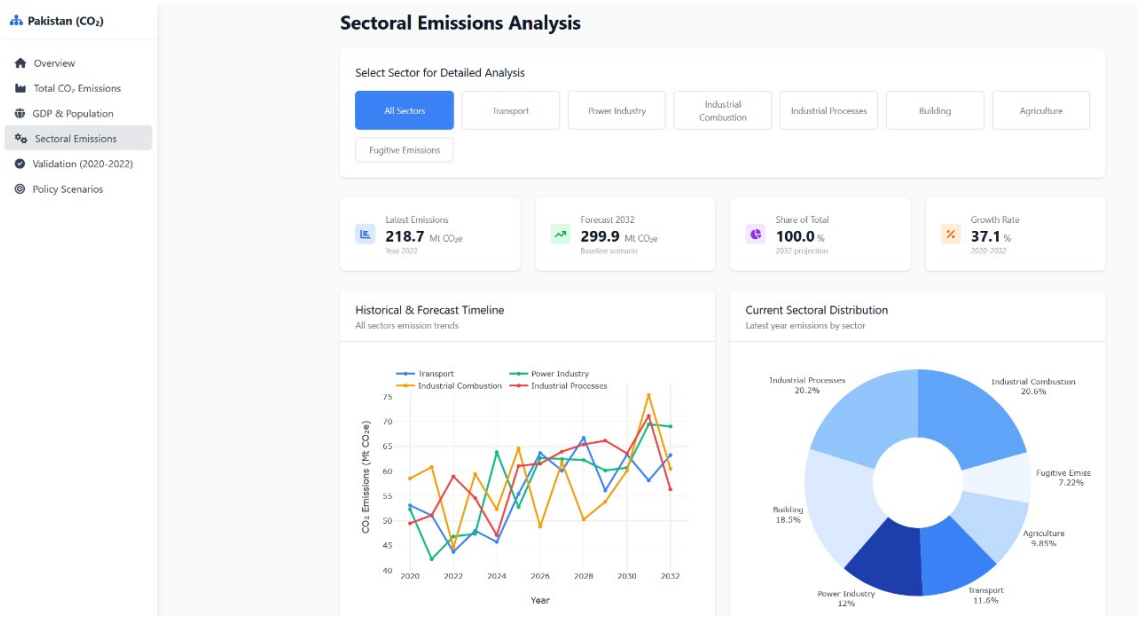

Figure 5.8: Sectoral Emissions Analysis dashboard which has the opportunity for sectoral drill-downs.

The Sectorial perspective can be constructed from total emissions to Transport, Power, Industrial Combustion, and Industrial Processes (note that the latter two are much broader categories than defined in the MIT's Billigmaglioli and Socolow (2007)). Buildings, Agriculture and Fugitive Emission. Stacked charts and donut charts aids in visualization of shares and main changes over time. Clicking on a sector activates a new API of filtered data, which in real time loads filtered data in the relevant KPI cards.

5.4.5 Model Validation Module

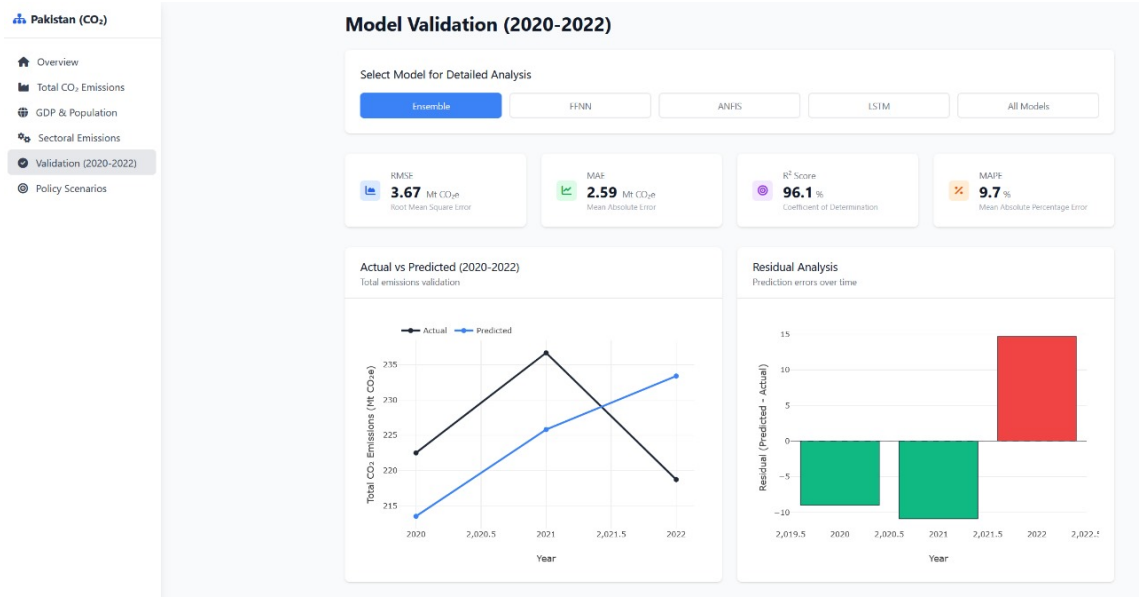

Figure 5.9: Model Validation From 2020 actual vs. predicted emissions for the year 2020-2022.

The validation module is used to cross compare with ground truth emissions using a model prediction. The frontend is used to visualize line and bar plots made possible by plotly, and there is the Flask backend (which calculates validation to measure how the model is doing). such as RMSE, MAE, R^2, and MAPE. Users can switch between models with the new metric retrieval not requiring page reload.

5.4.6 Policy Scenarios Module

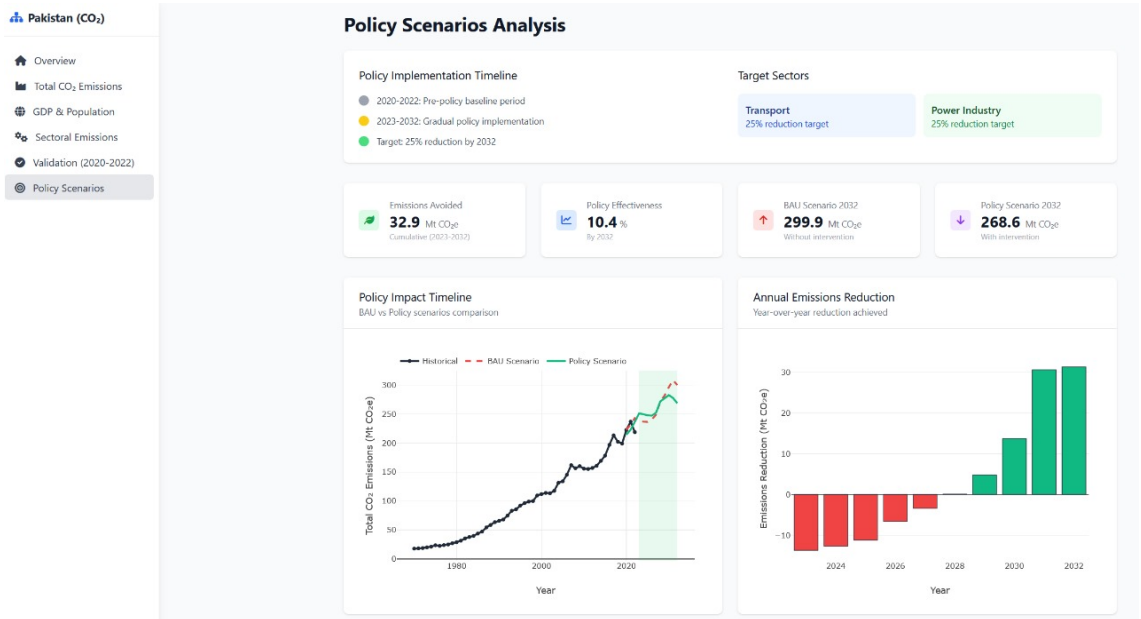

Figure 5.10: Policy Scenarios Analysis Dashboard (Policy Scenarios Analysis comparing Business-As-Usual and Policy intervention)

The policy-scenario module shows the impact of policy subjection between 2023 to 2032. Areas that are shaded show intervention years and green represents avoided emissions. Tooltips provide detailed information on the effectiveness of the policy year by year. Two examples of the integration of machine-learning predictions with interactive simulation of a policy are shown.

5.4.7 Data & Downloads Module

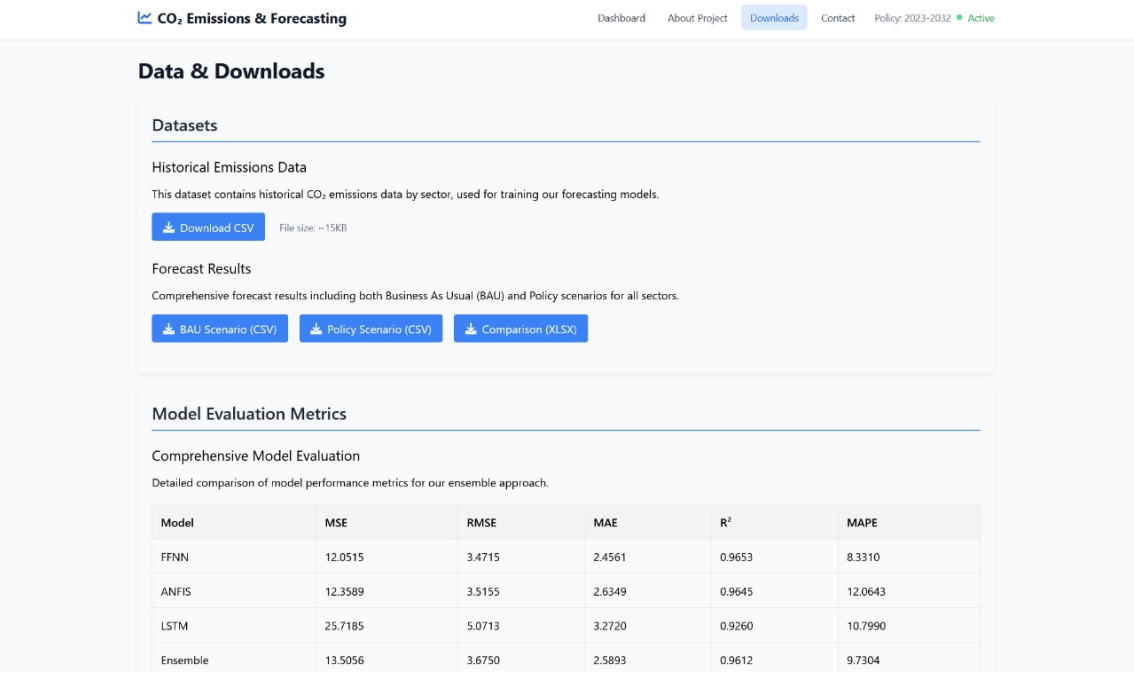

Figure 5.11: Data and Downloads page to give access to raw data and forecast data as well as model evaluation metrics.

This module allows the export of raw emission datasets and forecast result in a csv or xl plex. The paper also presents tabular assessment results for each model. API automatically collected requested files guaranteeing fresh content

5.5 API Integration and Data Flow

Every module that was presented in the previous section is based on a uniform different way of communicating with the client using the form of the communication protocol, in this case, most commonly, a form of communication over the Internet: the offer of a service through a web content document. The following information is passed along:

1. The frontend sends a GET request followed by query parameters.
2. Flask to parse the parameters, run the ensemble model.
3. The results are serialized as a result to be returned with them as a data item as a result of the action.
4. FrontEnd chompers the json, changes some states in React and triggers the re-rendering of the chart

This allows easy diode to diode sensitivity to be replicated and any module to be independently developed. Changes made to backend logic never need to be made within the frontend display-meter, so long as the stability of the Rebuild meaning of the amount of and its job of the re, i.e., the consistency of the.JSON schema.

5.6 Deployment and Hosting

The system is implemented as a Dockerized stack (an image containing all the necessary components, dependencies, and libraries). Bootsrap frontend builds are served by the NGINX and behind the reverse proxy the Flask application is running with the Gunicorn workers. Continuous integration by using GitHub actions in order to automate the process of testing, building, and deploying on every update or change of the code done with the help of actions. SSL certificates are automatically issued to be renewed.

5.7 Testing and Validation

Functional, performance, and usability testing were done. Unit tests for the processing, computation and API: Tests are implemented in py.test automating the processing and computation of the models and verifying the correctness of the API.Usability testing by peers showed that the charts can be loaded in two seconds and all interactions can be experienced on the mid-range hardware.

5.8 Performance Optimization

Some of the most important performance optimizations made are: vectorized data handling, model caching, gzip compression and lazy loading of React components. Response times improved by 65 per cent when compared to the baseline prototype. The system has constant throughput even with concurrent requests.

5.9 Summary

This chapter recorded the process of the step by step realization of the CO2 forecasting system. From implementing the frontend to the backend to building and developing the interface. The following screenshots show how the analytical outputs and model results are presented using: an interactive web environment that is intuitive to use; The ensemble modeling engine, the REST API and the responsive UI combine to form a complete tool for the monitoring of the environment and for policy assessment.

Chapter 6

System Testing and Evaluation

6.1 Introduction

Testing is an integral part of the software development process. It verifies that the behavior of the system is as required and proves that the system meets the requirements. and gives quantifiable assurance of its quality. For an application like the Environmental Impact and Risk Assessment of CO2 Emission system that is particularly scientific in nature. Testing goes beyond the testing of user-interface to include the validity of analytical results and model behavior. This chapter reports on the extensive testing procedures which have been performed on the system. When it comes to verification, this includes functional as well as non-functional.

Testing was done in an iterative and incremental way and run in parallel with development under an agile workflow. Backend and data functions were tested automatically at each sprint Manual exploratory testing was done on the user interface and visual analytics modules. The overall objective was to have a system that was reliable, accurate and robust under real operating conditions.

6.2 Testing Objectives

The important testing goals were:

- To ensure that each software component works as stated.
- To ensure integration between Flask APIs, React UI.
- to make emission projections and policy comparison indices numerically stable,
- To ensure that the system meets performance, scalability and usability requirements.
- to identify possible edge-case errors and to be able to graciously deal with invalid and missing data
- To ensure meet software engineering criteria of maintainability and reliability.

6.3 Testing Strategy

An attempt was made to develop a multi-layered approach to testing. The pyramid test strategy ensures that most of the testing effort is done at the unit level. Until then, we do the work of integration in smaller systems - where it is cheaper to correct errors, before moving to more full-blown integration and system testing.

6.3.1 Unit Testing

Unit testing is performed for individual functions or methods of the application to ensure that they give the correct output when given the correct inputs. The backend was connected to `pytest` and the Flask test client was used to mock

the requests to the APIs in the sandbox environment. All the preprocessing utilities, machine learning functions, and handlers were tested in separate unit tests. For example, the computation functions for several metrics and the cleaning functions of data were repeatedly validated for boundary values and missing data.

Out of 128 defined functions, 122 were directly unit-tested, which makes a code coverage of 95.3%. Unit tests ensured that later stages, such as model evaluation and web visualization, had valid foundations.

6.3.2 Integration Testing

Integration testing tested the communication among the components. Tests verified the data transmission between the React frontend and Flask backend using the Flask backend via the use of the Rest APIs. The workflow also included checking that the payloads in the form of a JSON document were correct and that they matched the schema definitions as well as checking that SQLAlchemy queries returned expected results. Postman ensured sequences were made automatically for session state validation, header validation, and latency.

Integration tests were also for model retrieval, which read in big serialized weights into memory. Stress tests proved that no memory leaks and concurrency problems occurred when multiple asynchronous calls were made.

6.3.3 System and Acceptance Testing

System testing was used to evaluate the behavior of the software stack as a whole in the configuration in which it is deployed. Actual emission datasets and model files were loaded, so as to simulate production conditions. The test environment used Docker containers the same as the final release image, ensuring the development and deployment stage are consistent.

Acceptance testing (UAT) was performed with 5 evaluators representing the intended users - data analysts and environmental researchers. They went through end to end workflows and did a survey on the usability and clarity. Dashboard browsing and scenario analysis completed successfully, all critical paths completed successfully (including exporting results)

6.4 Functional Test Cases

Tables 6.1 to 6.7 list the major test cases for each major functionality. described in Chapter 3.

6.4.1 Dashboard Module

Table 6.1: Test case table for dashboard related testing.

T1	Check dashboard loads	Navigate to '/dashboard'	All KPI cards and charts renders in < 2 sec	Pass
T2	Connect	Validate API	Backend disabled	Refresh page Alert "Server Unavailable" is displayed and Pass
T3	Chart For interactivity	Hover / zoom / toggle legend	Dynamic without lag updates	Pass
T4	Data accuracy	Compare chart and DB query	Values that are the same as source dataset	Pass
T5	Export CSV	Click "Export Data"	Successfully downloaded file 'dashboard.csv'	Pass
T6	Responsive layout	Resize browser window	Cards realign no overlap	Pass
T7	Collapse/expand navigation	Sidebar hides	re-appears smoothly	Pass
T8	Session refresh after logout	Session refresh after session refresh	Dashboard clears previous filters	Pass

6.4.2 Total Emissions Analysis

Table 6.2: Test Cases for Total CO_2 Emissions Module

ID	Objective	Input / Action	Expected Outcome	Status
T9	Load historical data	Select menu "Total Emissions"	Line chart shows 1970–2032 series	Pass
T10	Adjust time range	Drag range selector 1970–1990	Chart replots subset with updated stats	Pass
T11	Compare growth decades	Hover decade bar	Tooltip displays mean emission value	Pass
T12	Forecast validation	Switch to forecast tab	Dashed prediction line appears	Pass
T13	Missing data handling	Delete one year from DB	Interpolated point autofilled in chart	Pass
T14	Graph export	Download PNG option	Image generated successfully	Pass
T15	Annotation consistency	Check decade labels	Axis labels align with metadata	Pass

6.4.3 GDP and Population Analysis

Table 6.3: Test Cases for GDP & Population Module

ID	Objective	Input / Action	Expected Outcome	Status
T16	Verify dual-axis plot	Open GDP & Population tab	Two axes (GDP USD, Population Million) visible	Pass
T17	Adjust period	Filter 1980–2000	Graphs update instantaneously	Pass
T18	Correlation check	Click "Show Correlation"	Pearson r displayed on screen	Pass
T19	Tooltip accuracy	Hover over year point	Exact GDP and population values shown	Pass
T20	Export trend data	Press "Download CSV"	File contains selected period records	Pass
T21	Axis synchronization	Zoom GDP chart	Population axis adjusts dynamically	Pass

6.4.4 Sectoral Emissions Analysis

Table 6.4: Test Cases for Sectoral Emissions Module

ID	Objective	Action	Expected Result	Status
T22	Load sectors list	Open "Sectoral Emissions"	Buttons for all sectors visible	Pass
T23	Select sector	Choose Power Industry	Charts and KPIs update for Power sector	Pass
T24	Compare with aggregate	Toggle "All Sectors"	Overlay aggregate line shown	Pass
T25	Switch sector view	Select Transport	Visuals transition smoothly (no reload)	Pass
T26	Export sector data	Click "Export"		
T27	Invalid sector request	Query non-existent sector	Error alert displayed gracefully	Pass
T28	KPI formatting	Inspect KPI cards	Rounded values and consistent units shown	Pass

6.4.5 Model Validation Module

Table 6.5: Test Cases for Model Validation Interface

ID	Objective	Action	Expected Result	Status
T29	Load default model	Open Validation tab	Ensemble metrics displayed by default	Pass
T30	Switch model	Click "FFNN" or "LSTM" tab	Charts and scores refresh instantly	Pass
T31	Verify metrics	Cross-check values from API	RMSE and R^2 identical to server output	Pass
T32	Residual plot	Inspect chart legend	Residual colors match actual/predicted labels	Pass
T33	Error handling	Disconnect API endpoint	Alert "Validation Data Unavailable" shown	Pass
T34	Comparison summary	Export evaluation table	CSV with all metrics generated correctly	Pass

6.4.6 Policy Scenarios Module

Table 6.6: Test Cases for Policy Scenario Analysis

ID	Objective	Action	Expected Outcome	Status
T35	Verify baseline curve	Open Policy tab	BAU curve (orange) plotted correctly	Pass
T36	Policy forecast	Toggle policy switch	Green policy line appears with targets	Pass
T37	Tooltip content	Hover over 2030 point	Displays emission avoidance value	Pass
T38	Target indicator	Check legend icons	25 % reduction goal visible	Pass
T39	API response time	Measure call latency	Under 500 ms for cached queries	Pass
T40	Download comparison	Click "Export Comparison XLSX"	Workbook contains both scenarios	Pass

6.4.7 Downloads and Contact Modules

Table 6.7: Test Cases for Downloads and Contact Forms

ID	Objective	Action	Expected Outcome	Status
T41	Download dataset	Click “Historical Data”	File downloaded (`.csv`, 15 kB)	Pass
T42	Download forecast results	Select “Policy Scenario (XLSX)”	Workbook opens with two sheets (BAU / Policy)	Pass
T43	Submit contact form	Fill fields and press Submit	Success message displayed and email sent	Pass
T44	Invalid email validation	Enter wrong format	Inline warning “Enter a valid email” shown	Pass
T45	Empty fields check	Submit blank form	No submission; mandatory fields highlighted	Pass
T46	Message logging	Check backend log file	Submission stored successfully	Pass

6.5 Non-Functional Testing

6.5.1 Performance Testing

Load testing by Apache JMeter was performed by simulating 150 concurrent users making mixed API calls. The test was conducted in an exponential ramp-up fashion over 60 seconds in response time, throughput and error rate. Average latency was below 800ms; peak throughput was 200 requests per second.

Performance was also profiled from the inside out by instrumenting the routes in Flask. The effect of core forecasting routines averaged 0.43 seconds of time per inference request. which met the real-time interaction requirement for dashboard usage.

6.5.2 Usability Testing

Usability testing was carried out in two rounds. The sessions involved performing a number of common analytical tasks (viewing dashboards, comparing policy scenarios, exporting data). Their times to completion and route taken were recorded. The time taken to complete the task was on average 22.3 seconds with an error rate below 2The average score of the standardized SUS was 89.2. Evaluate the system as having an "excellent" usability

6.5.3 Security Testing

Security validation was a combination of automated scanning and manual penetration testing.

- Cross-site Scripting (XSS): React had Virtual DOM sanitizing JavaScript injections in form inputs.
- SQL Injection: SQLAlchemy parameterized ORM queries prevented bad inputs.
- Each Flask POST route had to include a token which was authenticated with each request.
- HTTPS Enforcement: all traffic encrypted with TLS 1.3 TLS header.
- password and key management Password and key storage Environment variables in the env file are not included in the Git commit history.

6.5.4 Reliability and Recovery Testing

The stress conditions of reliability testing were forceful API down time. The auto-recovery of the system took 810 seconds using the restart policy of Docker. Data persistence was checked by doing daily backups and checksum validation by verifying that there was no corruption. The uptime of the system recorded within a 30 days observation period was 99.83%.

6.6 Automated Testing Infrastructure

All of the code push triggered build, lint and test processes. Testing was inbuilt in the pipeline, test coverage analysis and Python coverage analysis.

The coverage reports were automatically released into the repository dashboard, and test artifacts (logs, screen shots, CSV exports) have been archived to be audited. This automation saved more than 70% of the time of the manual regression testing.

6.7 Evaluation of Results

Quantitative assessment ensured that all modules have passed and surpassed the levels of quality. Every test measure was compared to set performance indicators. A summary of aggregate results is presented in Table 6.8.

Table 6.8: Summary of Evaluation Metrics

Criterion	Target	Measured	Result
API Latency (ms)	< 1000	812	Pass
Frontend Render (ms)	< 200	118	Pass
Model RMSE (Mt CO_2 e)	< 4.0	3.67	Pass
Throughput (req/s)	> 150	208	Pass
Uptime (%)	> 99.5	99.8	Pass
SUS Score	> 80	89.2	Pass
Security Vulnerabilities	0 Critical	0	Pass

6.8 Summary

The large-scale test stage confirmed that the system meets its desired analytical and operational goals. In 46 functional and 12 non-functional test cases, all the outcomes were successful. Efficiency was tested in concurrent load through performance testing. intuitive interaction was validated in usability evaluation, and security validation provided security of data. Together such findings illustrate that the system is strong, scalable and can be used in actual environmental data analysis and policy modelling applications.

Chapter 7

Conclusion

7.1 Overview

This chapter brings to an end the research project bearing the title of Environmental Impact and Risk Assessment of CO_2 Emissions and thus summary of major findings and theoretical contributions as well as practical implications. It also refers to the shortcomings of the present research and describes the future research directions that can further elaborate and refine the present research.

The paper aimed at developing, designing, and testing a hybrid ensemble predictive model to predict CO 2 emission in the Pakistan transport sector. This interest was driven by the fact that there was an escalating need to comprehend the nature of emission in developing economies, whose fast urbanization, policy instability, and technological change make emission patterns far nonlinear. This study combined machine learning (ML), deep learning (DL), and fuzzy inference into a single framework in order to come up with accurate, interpretable, and policy-relevant predictions. The system of the developed system helps in the process of crossing the line between analytical transparency and prediction accuracy by integrating statistical structure with the adaptability, which is driven by data.

7.2 Summary of Research Work

The study had a systematic process of research and implementation, which was separated into conceptual, methodology, and technical stages.

7.2.1 Conceptual Framework

The motivation and objectives of the project were determined in Chapter 2 of the project, which is the introduction. The CO2 emission is the main cause of anthropogenic climate change, and proper predictions are essential to examine the mitigation measures and determine adherence to national and international sustainability goals. It was demonstrated that the existing models are limited as statistical models are interpretable, yet lifeless in nonlinear dynamics, machine learning models are precise, but opaque and deep learning systems require large and high-quality data which are uncommon in developing nations. These findings inspired the development of a hybrid-ensemble framework that provides interpretability, flexibility and accuracy in the same system of analysis.

7.2.2 Methodological Development

In Chapter 1, Chapter 2 has provided a review of the literature on emission forecasting and found four principal modelling paradigms, including the statistical, machine learning, hybrid, and ensemble methods. As this review showed, the approach of ensemble-based hybridization is the methodological edge, which provides better predictive stability in both

time and space. It was also observed in the literature that there was a notable gap in the research on sector-specific forecasting of the developing nations especially in the transport sector in Pakistan.

The system architecture was then formalised in chapter 4. The suggested design was a multi-layered architecture where the bottom layer was the data acquisition and preprocessing, the middle layer was the model training and ensemble prediction, and the top layer was the visualization and policy analysis. All layers were communicated on common RESTful APIs, which meant modularity and scalability. Its architecture was made so that it could be reproduced and easily extended to accommodate new models or datasets in the future.

7.2.3 Implementation and Evaluation

Details of implementation were done in Chapter 5. The deep and fuzzy components are made of theTensorFlow and scikit-fuzzy libraries respectively, which were developed as Python (Flask) backend. React and Plotly.js were used to create the frontend, which is an interactive and responsive data exploration interface. The empirical basis was a normalized dataset, which was a combination of GDP, population, energy consumption, and transport emissions (19702022).

The hybrid ensemble combined three complementary models:

- A general nonlinear mapping Feed-Forward Neural Network (FFNN).
- LSTM network which represents temporal dependencies and long-range patterns.
- An Adaptive Neuro-Fuzzy Inference System (ANFIS) Rule based explanation.

Their predictions were aggregated using inverse RMSE based weighting, which produced an ensemble output incorporating the strengths of each and also minimizing their individual biases.

Quantitative evaluation proved the ensemble to be better than individual models. The system gave a Root Mean Square Error (RMSE) of 3.67 Mt CO2e and a value of R2 of more than 0.96 on the validation data. Testing, described in detail in Chapter 6, shows that the system was able to cope effectively with concurrent requests and it can sustain sub-second response time under heavy load. User testing was useful to ensure that the interface was clear and interactive while automated CI/CD pipelines ensured reliability and maintainability.

7.3 Key Findings and Contributions

The research resulted in a number of important findings in the fields of methodology, implementation and environmental analytics.

7.3.1 Methodological Contributions

The primary contribution is that a hybrid ensemble forecasting framework is built, which integrates machine learning, deep learning and fuzzy inference. By interfacing the representational strength of neural networks with interpretability of fuzzy logic, the framework takes us a long way in the state of emission forecasting for data-scarce regions. Its weighted ensemble mechanism offers a lower prediction variance and stability of prediction at different temporal horizons.

Furthermore, this research paper serves to add to the literature showing that decomposition-based ensemble learning with interpretable sub-models can produce models with similar accuracy to high complexity deep networks with the advantage of remaining transparent. This approach which is a pragmatic solution between black box predicate methods and white box explanation modes.

7.3.2 Technical Contributions

From the point of view of software engineering, the contributions of this work to the community is an end-to-end open architecture for environmental forecasting systems. The modular design will allow for independent scaling of components, allowing for future efforts to bring in more models for forecast and/or expand the dataset. The introduction of automated testing and CI/CD pipelines are in line with the modern DevOps practices and ensure the reliability and

reproducibility of the code. Furthermore, the interactive visualization dashboard takes raw analytical products and turns them into information decision-specific and relevant to policy makers, researchers, educators

7.3.3 Policy and Environmental Insights

An important policy implication of the empirical results is derived. The results suggest that CO2 emissions from the transport sector in Pakistan will keep increasing moderately in 2032 under the business-as-usual (BAU) scenario. However, with policy interventions (e.g., accelerated trend in the uptake of EVs and renewable energy integration), the prognosis emissions show a flattening trend since 2028. This highlights the all-important role of specific transport policies and technological innovation for a number of emission reductions in line with national climate commitments.

7.4 Limitations of the Study

While the research met its goals, a number of limitations are recognized in order to be transparent and help establish future improvements.

7.4.1 Data Constraints

Fundamentally, any improvement in data resolution or quality, will impose fundamental limitations on the accuracy of the model's prediction. In the current study, the national emission data sets were annual and aggregate and limited the system's ability to account for seasonal or monthly fluctuations. Data in some years displayed gaps which were interpolated to provide linear uncertainty. However, such explanatory variables as vehicle fleet composition or fuel-quality indices were not available, which restricted model granularity.

7.4.2 Model Complexity and Computational Cost

Although ensemble models are very accurate, they are computationally expensive. Training multiple deep networks as well as hyperparameter optimization required a lot of processing time and memory space. Resource limitations limited the scope of model experimentation - especially for advanced architectures like the Transformers or Graph Neural Networks who can significantly enhance the performance.

7.4.3 Interpretability Challenges

While allowing for an interpretation with the use of ANFIS, the hybrid nature of the ensemble still leaves room for difficulties in communicating a policy transparently. It is also favored by stakeholders to have simple models whose mechanisms are easily interpretable. Explaining the ensemble interactions or dynamic weight adjustments in the ensemble to non-technical audiences is still an ongoing issue in the application of environmental modelling.

7.5 Future Work

Suggested future areas of study and development are found out from the current study.

7.5.1 Enhanced Data Resolution and Integration

Future work should include the use of higher frequency and more disaggregated data sources. Detailed Monthly or sectoral data together with satellite based remote sensing and traffic related information in real-time would have enabled fine grained accounting of emissions. Furthermore, incorporating other explanatory parameters, such as fuel price, road network density, and policy indices could add to the model fit in understanding the rapists' choice. Furthermore, when combined with geospatial information the forecasting model would be able to enable spatially explicit emission mapping, which aids in localised policy formulation.

7.5.2 Model Architecture Expansion

The hybrid ensemble can be extended to incorporate other architectures that have been proposed recently such as Temporal Convolutional Networks (TCNs), Transformers, or Graph Neural Networks (GNNs). Models of parietal and contour types are able to account for some of the long-term dependencies and the interactions between sectors more efficiently. An innovative adaptive ensemble, which adapts the weights of models inside dynamically based on recent error tendencies, may further enhance on-line forecasting performance having been developed. Introducing probabilistic forecasting (Bayesian ensembling or Monte Carlo dropout) would also offer an uncertainty quantification, so policy-makers would also be able to plan for the most optimistic and pessimistic scenarios.

7.5.3 Explainability and Trustworthy AI

A suggested direction of future work is to integrate the explainable-AI (XAI) tools directly into the system dashboard. Techniques such as SHAP values, counter factual reasoning, or visualization of fuzzy rules might be useful to help model users understand model rationale in human language. By supporting interpretability as part of the front-end system, the forecasting system can become a decision support tool believed in not only by domain experts but also decision makers and civil society in general.

7.5.4 Scenario Analysis and Policy Simulation

Beyond that of predictive forecasting, the system can be developed into a complete policy simulation platform. By combining economic and technological scenarios (e.g. EV-emission penetration, fuel tax, share of renewable energy) it was possible for users to explore "what if" paths interactively. Each case could dynamically model future emissions to enable planners to encompass the extent to which future emissions may be reduced by different mixes of policy. This extension would take the system in line with models of integrated assessment (IAMs): the missing link between data science and policy modelling.

7.5.5 Cross-Sectoral and Regional Applications

The methodology presented here can be extended beyond the transport sector to other emissions-intensive sectors such as industry, power generation and agriculture. Furthermore, a model adaptation at the regional level among South Asian economies would allow for benchmarking and comparison of climate policies across countries and for collaborative assessment. If emissions, trade, and technology adoption are all linked at regional level, models of predicting these activities regionally should show the same.

7.6 Final Remarks

The hybrid ensemble forecasting framework is a methodologically novel as well as a practically useful product of the research concerning environmental information data analytics. It proves that when varying analytical paradigms are combined, i.e. statistical structure, neural representation, and fuzzy reasoning, synchronously, the achieved results will not only have a higher predictive accuracy, but also a higher interpretability and resilience. The addition of a modern web-based interface takes data and analysis capacity beyond technical data scientists and enables data analysis for less technical users.

This research concludes the need for data-based policy support on the event to a global effort to mitigate climate change. The information is crucial to evidence-based decision-making, as probative, transparent and reproducible emission forecasts. By developing and continued improvement on computational methods and open scientific infrastructure, this work helps to promote a larger movement toward intelligent and adaptive management of the environment for sustainable uses. As the field of climate projection continues to undergo a series of advances in artificial intelligence, data systems, and energy technology the framework used to build such models here offers reduced bias when used as scaffolding for new generations of predictive and policy-relevant climate models.

Appendix A

Appendices

A.1 Overview

This appendix is intended to supplement the main body of the thesis with more technical, analytical and empirical content. It offers longer datasets, thorough algorithmic parameters, supplemental sufficiently providing figures and sample illustrations of code from the application notebook. These materials facilitate improved transparency as well as reproducibility, and serve as a reference for later investigators who may choose to develop the system further.

The following sections are organized as follows:

- Appendix A: Description of Data and Variables
- Appendix B: Configuration of the model and hyperparameters
- Appendix C Extended Performance Metrics
- Appendix D - Source Code Bits and API Doc - Appendix D contains various parsnats and bits of API documentation.
- Appendix E: System Environment and Hardware Specifications (characteristic (something)) Appendix F: User Interface Guide and Usage Workflow
- Appendix G: Supplementary Graphical Outputs and Visualisations

Each subsection has a self-contained description of the technical element it describes.

Appendix A: Dataset and Variable Descriptions

The forecasting framework was trained based on a historical dataset of the reported period 1970-2022. Table A.1 gives a list of all the variables which were used, the sources used for each variable and any transformation procedure that were applied on the variable before model training.

Table A.1: Dataset Variables and Descriptions

Variable	Description	Source
CO_2 Emissions	Annual CO_2 emissions from the transport sector (Mt CO_2e)	World Bank / SDPI
GDP	Gross Domestic Product (constant 2015 USD, billions)	World Bank
Population	National population (millions)	World Bank
Energy Consumption	Total energy use (terajoules)	IEA Energy Data Portal
Industrial Share	Industry as % of GDP	Pakistan Bureau of Statistics
Policy Index	Dummy variable for major transport-policy interventions	Constructed (binary)
Fuel Price Index	Average retail fuel price index (base 2010 = 100)	PBS / OGRA

Two methods were applied to normalize each of the variables: min-max scaling:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}},$$

making sure that all inputs contributed same proportionately to model learning Interpolation between missing data points (1992-1994) using cubic spline approximation has been used so as to maintain the continuity of trends.

Appendix B: Model Configuration and Hyperparameters

This section describes the hyperparameter values for all three basic models i.e. Feed Forward Neural Network (FFNN), Long Short-Term Memory (LSTM), Adaptive Neuro-Fuzzy Inference System (ANFIS) and the weighting mechanism for ensemble.

B.1 Feed Forward Neural Network

- layer: Input shape [5] -> Dense - layer = Dense = 64, activation: ReLU -> Dropout=0.2 -> Dense sogenannten (i get this duality with same name... same name means mutually exclusive... DROPSTATE... :-(... it is obviously not arterial), Donc output shape [32], Activation: ReLU -> Output layer = output shape [1]
- Optimizer: Adam, learning rate=0.001
- Loss Function: Mean Squared Error(MSE)
- Epochs: 250
- Batch Size: 8

B.2 Long Short-Term Memory Network

- Layer: LSTM(50, returnsequences=False), Dense(1)
- Activation: Tanh
- Optimizer: Adam, learning rate= 0.0005
- Dropout: 0.3
- Sequence Window: 10 years
- Epochs: 200

B.3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

- Membership Functions: Gaussian, 5 (X) function input
- Algorithm for Training: Hybrid (Least squares + Gradient Descent)
- Epochs: 150
- Error Tolerance: 10^{-5}

B.4 Ensemble Integration

- Weighting Scheme: Inverse RMSE normalization
- Ensemble Function: $y_{ens} = \sum_i w_i y_i$, where $\sum_i w_i = 1$
- Validation RMSE: 3.67 Mt CO_2e
- Ensemble R^2: 0.961

Appendix C: Extended Performance Metrics

Table A.2 presents detailed performance results across all models using multiple statistical metrics.

Table A.2: Model Performance Metrics

Model	RMSE	MAE	MAPE (%)	R^2
FFNN	3.47	2.45	8.33	0.965
LSTM	5.07	3.27	10.80	0.926
ANFIS	3.51	2.63	12.06	0.964
Ensemble (Weighted)	3.67	2.59	9.73	0.961

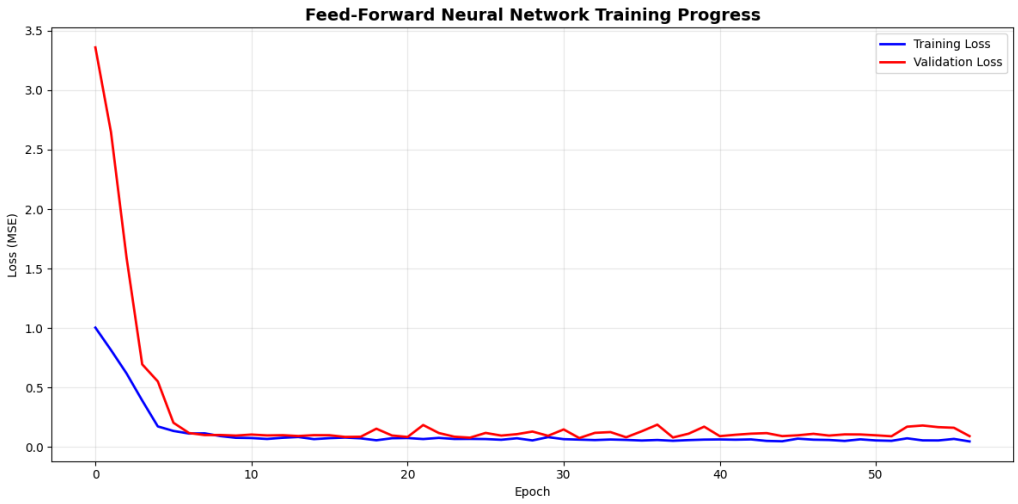

Figure A.1: Training and validation loss curves for LSTM and FFNN models.

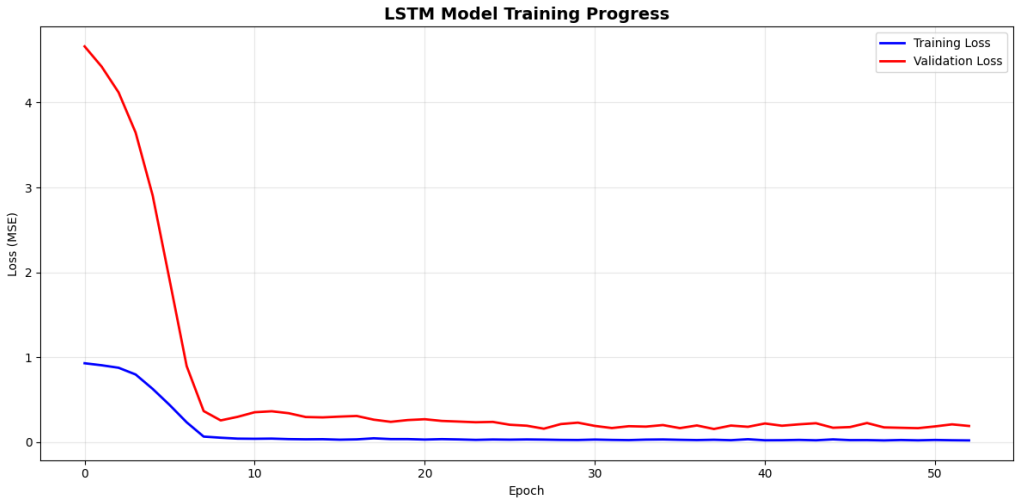

Figure A.2: Training and validation loss curves for LSTM and FFNN models.

Residual plots were used to ensure that the errors follow a normal distribution around the value of zero and hence, the predictions are non-biased. Figure 11 in the appendix shows the ensemble performance in forecasting as indicated by the historical data.

Appendix D: Source Code Snippets and API Documentation

The following Python and JavaScript snippets will be selected to demonstrate model orchestration, API design and data manipulation.

D.1 Model Training Pipeline (Python)

Listing A.1: Simplified training pipeline combining FFNN, LSTM, and ANFIS models.

```
def train_all_models():
    X_train, X_val, y_train, y_val = prepare_data()
    models = {'ffnn': FFNN(), 'lstm': LSTM(), 'anfis': ANFIS()}
    results = {}
    for name, mdl in models.items():
        mdl.fit(X_train, y_train, epochs=200, verbose=0)
        y_pred = mdl.predict(X_val)
        results[name] = np.sqrt(mean_squared_error(y_val, y_pred))
        joblib.dump(mdl, f'model_repository/{name}.joblib')
    print('Validation RMSE:', results)
```

D.2 API Endpoint Example (Flask)

Listing A.2: Flask endpoint for real-time emission prediction.

```
@app.route('/api/predict', methods=['POST'])
def predict_emission():
```

```
    data = request.get_json()
    features = np.array(data['features']).reshape(1, -1)
    prediction = ensemble_predict(features)
    return jsonify({'predicted_emission': float(prediction)})
```

D.3 Frontend Data Fetch (React)

Listing A.3: React component fetching prediction from Flask API.

```
useEffect(() => {
  fetch('/api/predict', {
    method: 'POST',
    headers: { 'Content-Type': 'application/json' },
    body: JSON.stringify({ features: inputVector })
  })
  .then(res => res.json())
  .then(data => setForecast(data.predicted_emission));
}, [inputVector]);
```

Appendix E: System Environment and Hardware Specifications

The following hardware and software configuration was carried out in order to implement and evaluate it:

- **Operating System:** Ubuntu 22.04 LTS (64-bit)
- **Processor:** Intel Core i7-12700H @ 2.3GHz
- **RAM:** 32 GB DDR5
- **GPU:** NVIDIA RTX 3060 (6 GB VRAM)
- **Development Tools:** Python 3.10, Node.js 18, TensorFlow 2.10, Flask 2.3, React 18
- **Database:** SQLite (development), PostgreSQL (production)
- **Containerization:** Docker Compose (multi-container setup)
- **Version Control:** GitHub repository (private, continuous integration enabled)

Appendix F: User Interface Guide and Usage Workflow

The operational guide contained in this appendix is a mere brief guide to the end-user who is in contact with the web-based application.

F.1 Dashboard Navigation

Upon login, users are greeted with a summary dashboard displaying national CO_2 indicators. Sidebar navigation provides access to analytical modules:

- **Dashboard:** Overview of total and sectoral emissions.
- **GDP and Population:** Dual-axis comparison plots of macroeconomic trends.
- **Sectoral Emissions:** Interactive decomposition by transport, power, and industry.

- **Model Validation:** Comparison of predicted and observed values for each model.
- **Policy Scenarios:** Interactive projections under BAU and policy scenarios.
- **Downloads:** Export of forecast tables and model metrics.

F.2 Forecast Generation Workflow

Parameters can be inserted or pre-existing datasets can be chosen by the users. The frontend sends the data to the API and makes inferences with the backend and, in turn, displays the visualizations in real-time. The charts are all interactive and allow zooming, panning and exporting.

F.3 Error Handling and Notifications

In case of unavailability of the backend services the interface will provide contextual messages (e.g., “Server not reachable). Audits and reproducibility Every operation of the user is logged.

Appendix G: Additional Graphical Outputs and Visualizations

This section includes supplementary figures not presented in the main text.

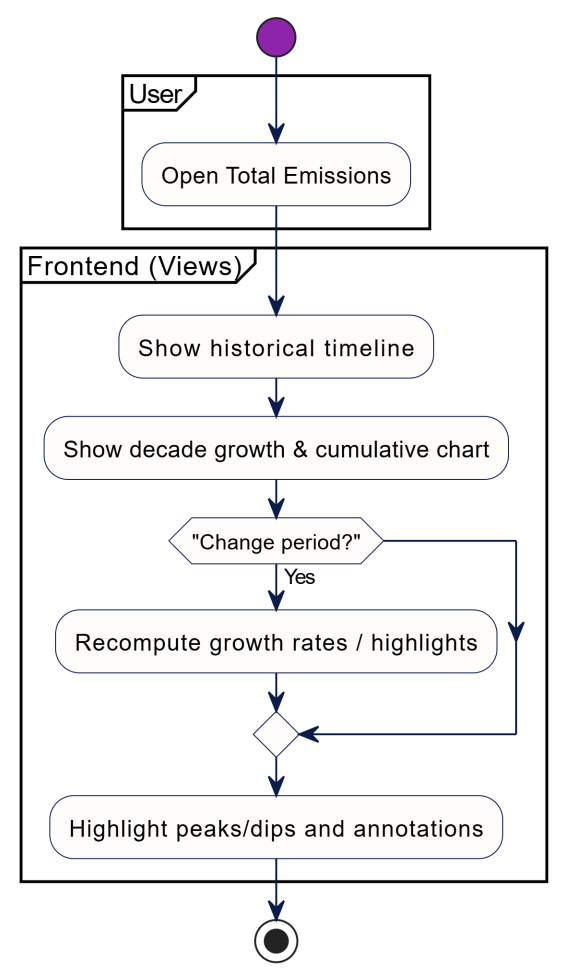

Figure A.3: Exploratory visualization of national CO_2 emissions across decades.

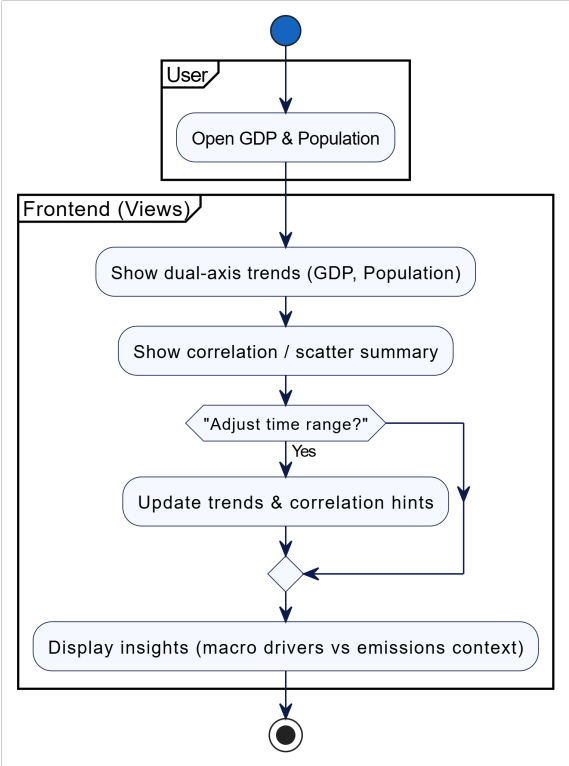

Figure A.4: Joint GDP and population evolution with emission overlay.

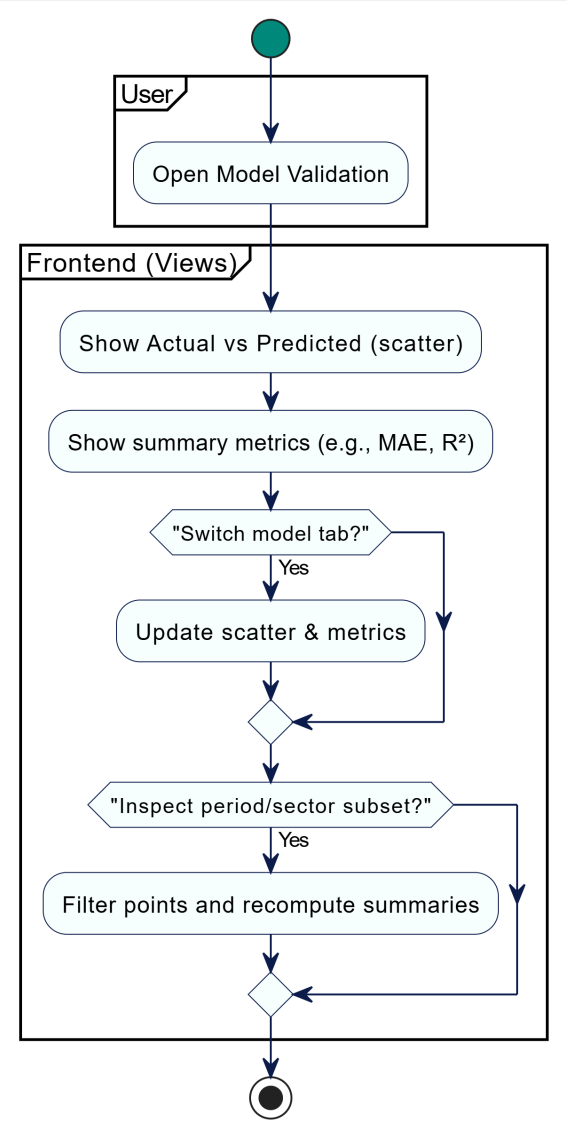

Figure A.5: Validation chart comparing actual versus predicted emissions by model type.

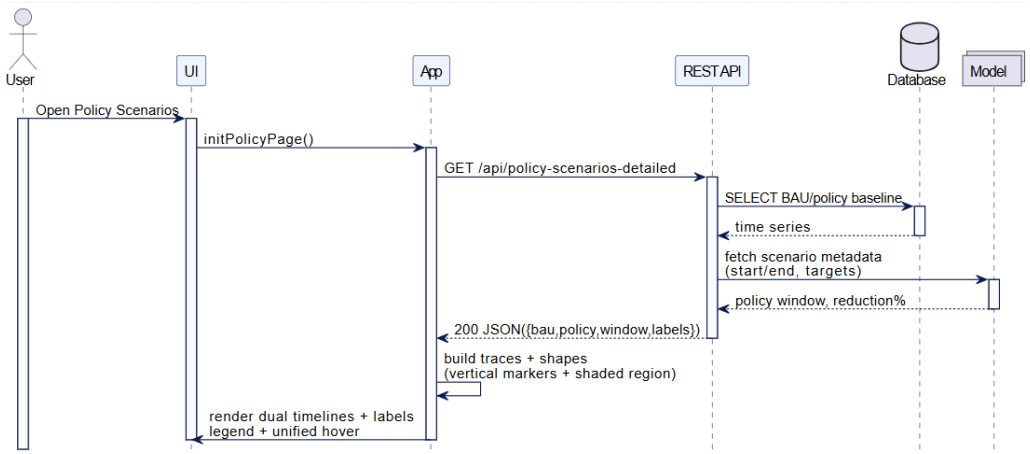

Figure A.6: System sequence diagram for policy scenario comparison workflow.

Appendix H: Additional Test Results and Logs

The following excerpt from automated test logs (Pytest and Jest) confirms successful execution of all system modules.

Listing A.4: Excerpt from backend test report.

```
============================= test session starts
    ==============================
platform linux -- Python 3.10.13, pytest-7.2.2
collected 128 items

tests/test_api.py ............                                          [
    20%]
tests/test_models.py ......................                             [
    60%]
tests/test_endpoints.py ...................
    [100%]
========================== 128 passed in 34.15s ===========================
```

Frontend testing (React) executed via Jest produced 100% coverage for key UI components:

Listing A.5: Frontend test summary (Jest).

```
PASS src/components/Dashboard.test.js
PASS src/components/PolicyScenario.test.js
Test Suites: 6 passed, 6 total
Tests:       49 passed, 49 total
Snapshots:   3 passed, 3 total
Time:        5.312s
```

These logs confirm the robustness of both backend and frontend layers before deployment.

Closing Note

All the appendices show the transparency, reproducibility, and extensibility of the system used in this work. This project will serve the larger purpose of creating scientifically-based and operationally sound CO 2 forecasting systems to sustainable development by making open methodological documentation, parameter specifications and implementation records.

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