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The Impact of GHG Emissions on Human Health and its Environment using XAI

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Abstract: ***Explainable AI(XAI) is a revolutionary concept in artificial intelligence that supports professionals in creating trust between people in the decisions of learning models. Greenhouse gases created in the atmosphere is driving our weather to become more irregular and intense. This endangers human health, affects crops and plants. XAI techniques remain popular, but they cannot disclose system behavior in a way that promotes analysis. Predicting GHG emissions and their impact on human health is an important aspect of monitoring emission rates by industries and other sectors. However, a handful of investigations have being used to examine the collective effect of industries such as construction, transportation, CO_2, and others on emission patterns. This research tackles a knowledge vacuum by offering an explainable machine learning model. This framework employed a random forest classifier combined with two different explainable AI methodologies to give insights into the viability of the proposed learning model. The goal is to use XAI in determining the impact of GHG emissions on humans and its environment. A quantitative survey was carried out to investigate the possibilities of determining GHG emission rates more explainable. We created a random forest model, trained on GHG emission data using SHAP and LIME techniques. This was helpful in providing local and global explanations on model sample order by similarity, output value, and original sample ranking. The model resulted in high accuracy and enhanced interpretability with XAI, allowing decision makers comprehend what the AI system truly tells us. LIME exceeded SHAP in terms of comprehension, and satisfaction. In terms of trustworthiness, SHAP surpassed LIME.***

Keywords: ***LIME, SHAP, Random Forest, Explainable AI, interpretability***

I. INTRODUCTION

The greenhouse effect created by gases in the atmosphere is driving our weather to become more irregular and intense [1]. This endangers people's health, has an impact on the nervous and immunological systems, and affects crops and plants [2]. In general, ML has had astounding success in several areas [3]. However, in so many cases, end-users are unable to funderstand reasoning behind model predictions, which create huge problems when used to determine the impact of GHG emissions on humans and their environment [4],[5]. Revealing the inner workings of a model does not guarantee that the information is understandable or beneficial to users. There are also many distinct types of users, each with their own set of reasons and requirements for seeking explanations. The development of explainable AI systems should follow a user-centered methodology to connect technical capabilities and the fulfillment of user needs. End users frequently acknowledge that ML algorithms are difficult to understand, opaque and almost impossible to explain their seasonings behind model predictions [6]. XAI focuses on providing friendly explanations that require no prior ML knowledge skill to comprehend reasoning behind model predictions. The explainable system is intended to assist users in learning about random forest(RF) model behavior. Technological innovation in AI algorithms has attracted people from different fields who are increasingly interested in leveraging these learning algorithms. These algorithms are used today in many application domains to enhance human decisions making into various tasks construction, healthcare, news and many more. Model predictions and decisions are questionable when the motivations behind the decisions are incomprehensible to human. There is an urgent need for Explainable AI (XAI) systems to help end users interpret DL algorithms and provide explanations to machine learning models [7]. So often, a separate set of approaches must be utilized to provide explanations that people can accept. It is quite difficult to establish whether an AI system is dependable or otherwise without first examining the processes through which AI systems arrived at its decision. This is a difficult task due to model generality in statistical theory of learning which simply shows how professionals patch up gaps in unnoticed model details. Adopting XAI methodologies can help explain the rationale behind model predictions about GHG emissions in order to get calibrated trust from explanations. In contrast, some simple models can be interpretable in the right contexts, but they can be inaccurate if they are too restrictive. This leads us to the use of XAI approach, specifically in determining the impact of GHGs on human health and its environment. The aim is to develop a system employing XAI technology to determine the impact of GHGs on human health and the environment. We intend to inspect and offer visual explanations for sample order based on output value, original sample ordering, and sample order by output value. We are deploying explainable AI methods combined with RF to provide deep insights into the underlying GHG emission dataset. The LIME and SHAP techniques will be employed to visualize the reasoning behind model anticipated results. This will help users build trust in utilizing an intelligent AI system that is interactive, understandable, and explainable.

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The LIME and SHAP techniques are used at the local and global levels to provide interactive user-friendly explanations based on model sample order by similarity, output value, and original sample ranking. We propose achieving high accuracy while allowing for some interpretability, so that decision makers can accept and understand what the AI system genuinely tells us. This will assist user in understanding what lies beyond the toolbox. We are underlining why it is critical to comprehend these seemingly correct decision making algorithms rather than simply accepting and relying on their effective performance. We intend to describe the gray-box of a RF classifier model and provide some practical solutions. Approaches like XAI can help shed light on the enigmatic inner workings of Ml algorithms. It contributes to the transparency of AI models, enhancing trust in the outputs, preventing data breaches and bias, and assuring compliance with legal requirements. Explainable-AI has made it possible for specialists to create dependable AI for fair, secure, and trustworthy AI machines. We are developing a random forest model, visualizing outcomes, and integrating XAI toolkit. XAI is a novel concept in AI and Machine Learning that assists professionals in developing trust between users in the decisions of AI models. This is an excellent resource for AI/ML professionals, data scientists, industries, investors, stakeholders, non-governmental organizations, government, communities, suppliers, and employees who work on climate-related issues. Creating explanations for model decisions will help non-technical specialists with no ML expertise use model reasoning to engage in follow-up actions

A. Contribution to Knowledge

(a). Provide visual explanations with LIME and SHAP XAI to help user with no machine learning skills understand GHG emissions and how they affect human health.

(b). An innovative method that identifies set of relevant instances and provide visual explanations to solve trust difficulties in model predictions.

(c). interactively provide a methodology for assessing the impact of GHG emissions on human health within various organizations and industries in Nigeria.

(d). Provide non-experts access to explainable approaches utilizing SHAP and LIME and demonstrate which approach yielded better explanations. The paper is structured as follows: Section 1 offers a general introduction; Section 2 presents a brief evaluation of prior approaches to the topic and the gaps in studying the proposed model; Section 3 presents the materials and methods; Section 4 covers the results and an in-depth discussion of the results; and section 5 concludes the paper.

II. LITERATURE REVIEW

Labe and Barnes [8] used XAI approach to visualize one of the most robust climate changes and explain how the non-linear ANN arrived at conclusions in interpreting global climatic patterns. Gagne *et al.*, [9] demonstrated CNN using traditional XAI methodologies by utilizing feature relevance and optimization procedures to represent network neuron signals used in comprehending the geographical distribution of multiple storm simulations. Heo et al., [10] offered a study with generative adversarial networks (GANs) and auto-encoders that support data driven XAI approaches to achieve zero net GHG emissions mostly in globally averaged temperature rise. There are three stages of AI explainability namely: pre-modeling, explainability modeling and post AI explainability modeling. Explainable AI considers the entire AI-model to be traceable from the decisions made by the model. Several explainable methods have been proposed for deep machine learning methods, but below we discuss an overview of existing interpretability methods. Related works in the field of XAI belonging to the classification of post-hoc including: explanations in natural language, visualization of the model learned and explanation examples [11], There is a notable classification called intrinsic methods designed for complex uninterruptable models that aim to change the international structure of a complex black box model. Caruana *et al.*, [12] used global interpretability method to predict the risk of pneumonia with set of rules from sparse Bayesian generated model, but constrained by predictability to serve interpretability. Liao *et al.* ,[13] introduced a mechanism called mapping guidance between user requirements and model interpretation to facilitate the design of human-centered explanations. This was done based on the self-study questions that users ask to understand the AI system, but considering some limitations that are not supported by the adopted framework at certain stages. Xu, [14] adopted the prototyping technique to understand user tasks and requirements to improve design strategies and understand the extent of AI capabilities. This was done through prototyping and sketching to understand what the technology can do and demonstrated with stakeholder involvement in co-design processes in various user-centric contexts to develop a reliable XAI system. Sharma et al. [15] used explanatory forms to create a low-fidelity prototype and found that the resulting prototype served most of the explanatory purposes. Combinations help reduce the weakness of individual forms of explanation and make explanations more versatile and complete. A global interpretability model was created with the concept of recursive partitioning to build a global interpretation tree for a wide variety of machine learning algorithms based on local explanations. According to Anderson *et al., [16]* used explanations to make the inference mechanism of AI systems transparent and interpretable for system developers and non-users (end users), and explanations are built into AI machines to help people make better decisions [17]. Existing methods of explanation, such as user-centric explanatory debugging approaches, could not be used to XAI interface design, which was unable to explain deep learning with calibrated objective trust [18]. This model was unable to detect whether a particular ML model behaves reasonably or not. Fox et al., [19] provided a roadmap on how the user can provide useful explanations through planning to gain trust, interpretability and transparency. The problem identified was how to build trust between the planning algorithm and the user. Explainable modeling in context refers to models with some sort of explanability kind of inherent built into it.

Examples are decision tree models, linear regression models likewise explainable by themselves.

We don't need to explicitly explain such models because they are inherently explainable. In Post AI explanability, we uses certain kind of mechanisms' like proxy models, surrogate models or certain type of functions or other separate algorithms to draw predictability output. There are several methods of Explainable AI methods namely: LIME, GraphL-IME, Anchors, TCAV, GNN, SHAP, ASV, LRP, DTD, PDA, Break-down, Shapley flow, Textual explanations of visual models, integrated gradients, causal methods, meaningful permutations [20].

A. Interpretability of Ml Techniques

There are several ways of classifying ML interpretability techniques includes: intrinsic, post-hoc, pre-hoc and post-hoc classification [21]. Intrinsic interpretability is employed to describe simple ML model structures, whereas post model is used to describe the model after training and pre-hoc is used to describe the model before training stage.. We are using SHAP and LIME interpretability approaches to interpret the results of RF and provide end-user pleasant explanations.

i. Model Agnostic and Model Specific Interpretability:

According to Du et al., [22] model specific interpretability techniques are restricted to a subset of ML models and generate explanations by determining the inner working model parameters. These methods can be used to generate post-hoc explanations for any ML model that has been developed and trained [23]. Surrogate or basic proxy techniques can be used to produce model-independent explanations for locally assessing or spot estimates of ML models based on gray, glass and black box outputs. Ying et al. [24] developed a graph neural network explainer (GNN Explainer) based on sophisticated data visualization and representation techniques. The GNN explanation used supplied local and global interpretations and is valuable to professionals because it can show important structures for interpretation and detect defective GNNs. The explanation employed graph architectures that necessitated the usage of a certain machine learning framework or platform [25].

ii. Local and Global Interpretability:

It could be quite complicated in mapping and explaining an entire mapping space, which could be hopelessly complex. Instead, we will concentrate on discussing the individual predictions one at a time, because those involved are likely only a small part of the overall complexity of the model in local model interpretability. Local interpretability can explain a single model prediction, whereas global interpretability interprets the entire collection of internal model predictions [26]. ML Local interpretability can be provided through some justifiable model design that analyzes why models make such decisions. This can also be accomplished with comparable samples of instances to the model's target cases. Global explanations provide insight into the hidden inner workings and logic that contribute to model prediction as portrayed in its abstraction. A trained ML model, data, and competence in the approach are required to provide explanations for global model outputs. Ahmad et al. [27] suggested a cohort-specific model interpretability technique that relies on specific populations. This is classed as global if the subcategories are considered as a population group, and as local if a singular prediction interpretation for the grouping is pooled together. Lakkaraju et al.,[28] used techniques understanding under sub-pace interpretation to explain the behavior of feature space defined by specific characteristics of interest.

iii. Model Agnostic XAI for ML Methods:

Whenever we are dealing with tabular dataset it is more easier it draw conclusion but whenever we are dealing with any unstructured dataset then it gets a little bit difficult especially when we go for complicated deep learning models [29]. There are approaches classified under explainable category. One of the most popularly used methods is called layer wise relevance propagation method[30]. We can explore the following to understand the information through gradient flow between layers of ML Models: saliency, guide propagation, gradient class activation methods that houses layer GRAD CAM, construction using GRAD CAM activation using GRAD CAM.

iv. Local Interpretable Model Agnostic Explanations (LIME):

Is defined by Ribeiro *et al., [31]* as a method that faithfully explained reasons behind model predictions of any classification or regressor task by approximating it locally using explainable model. As a remedy to the trust prediction challenge, they used LIME to provide explanations for specific model predictions. According to Rodriguez-Perez and Bajorath [32] interpretable ML explanations are classified into global and individual levels and as well as intrinsic and post-hoc model types. Doshi-Velez and Kim[33] conducted a comprehensive investigation with the ML system to solve interpretability, theory, and practice concerns. The interpretability evaluation approach's structure addresses interpretability, application grounded, human grounded, and functionally grounded. To present a meta-learning model for high stake decision making, Evren [34] used XAI techniques with reinforcement learning and a Knowledge-based extraction technique. Bauer et al., [35] explored the implementation of XAI systems using ML technologies and urged practitioners to investigate these techniques while designing practical applications.

III. PROPOSED METHODODLGY

This study focuses on the post-training explanation of a random forest (RF) classifier with local and global explanations. We are constructing an XAI algorithm that will assist the user in generating high and low level post-hoc explanations for instances of RF model predictions in the workflow, We reviewed several similar papers in order to gain wide range of AI-supported frameworks, identify suitable ML and XAI algorithms for this purpose. The SHAP and LIME XAI Methods were applied to the results of the RF classifier. The outcomes of the two XAI approaches were then reviewed using a survey with end-users in terms of their interpretation, satisfaction, sufficiency, and trustworthiness.

We provide a full discussion of the research methods chosen and why they were chosen to address our research concerns. The implementation of an explainable IA system needs the creation of a ML model, as well as an explainer and interpreter function that generates explanations for the underlying dataset of GHG emissions. We are using LIME and SHAP methodologies to explain the outcomes of RF model classification in determining the impact of GHG emissions on humans and the environment. We intend to measure the output utilized in the models, strike a balance between model accuracy and develop key performance indicators to assess AI vulnerability.

A. The Components of Proposed System

The study strategy consists of five main components. Figure 3.1 displays the workflow for model prediction on GHG emissions and explanation modules.

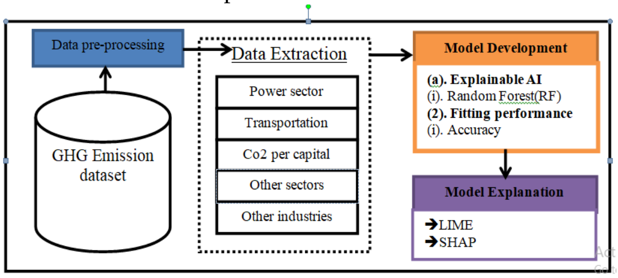

Figure 1: Study Strategy [36]

Our proposed method starts with GHG emission data set, extraction of data, model development, and model explanations as detailed below:

(a). Dataset: The proposed approach made use of a dataset obtained mainly from the top UCI repository site "https://catalog.data.gov/dataset/?organization=epa-gov&res_format=EXCEL" which serves as a benchmark. The collection is made up of several instances, each with eight features.

(b). Preprocessing is critical in ML development since it reduces data complexity and aids in the transformation of data into a format appropriate for training learning systems. The dataset was initially subjected to scaling and missing value padding before being input into the appropriate ML model.

(c). Data extraction: The data extraction phase is a critical step that collects and merges distinct GHG dataset into usable Excel CSV format. GHG emission levels for buildings, transportation, industries, and other sectors were extracted from a variety of databases to get quality data.

(d). Random forest(RF) classifier: is a well-known approach for randomly generating decisions based on a GHG simulation dataset that includes gas emission rates from buildings, transportation, industries, and other sectors [37][38][39]. It is extremely helpful in overcoming data limitations. We trained the RF model with 30 estimators(trees) and obtained a shockingly high test set performance of 96.4%. It appears reasonable that explaining the reasoning underlying individual predictions will increase stakeholder trust in the model predictions..

(e). Local interpretable model agnostic explanations (LIME) is employed to generate explanations for rows of input data, while the explanation technique to provide explanations for instances. The response time of our strategy was set at 1.50 seconds in our experiment.

L(f, g, ⊓x) is used to determine how unfaithful g is when approximating f in the locality defined by x. We endeavor to reduce model unfaithfulness using L(f, g, ⊓x) and strive to keep complexity Ω(g) as simple as possible.

LIME generated explanations "E" is represented as follows:

$$E(X) = L(f, g, \sqcap_x) + \Omega(g) \qquad 2$$

LIME weights samples by ⊓x to optimize the equation and explain E(X) irrespectively of modeling technique. The LIME explanation used offered four (4) admirable characteristics of a hypothetical model.

(f). SHapley Additive exPlanations(SHAP) is a technique for improving the transparency and interpretability of ML models that employs the concept of cooperative game theory. SHAP provides the contribution and importance of each feature to the model's prediction but cannot be used to assess the accuracy of model predictions. SHAP is used in this context to reveal the individual contribution of each feature to the model's output for each observation.

The feature values of SHAP is computed using equation 1:

$$\phi_j = \sum_{S \subseteq x_1,...,x_p / x_j} \frac{|S|!(p-||S|!}{p!} \chi_j) - val(S)) \qquad 1$$

Where ϕ_j feature contribution, S: A subset of the model's features χ: the vectorized values of feature observation and p is the feature count. SHAP is used to explain predictions on instances of x by computing the values of each attribute to be anticipated. The SHAP approach specifies model explanations as follows:

$$G(x^1) = \phi_0 + \sum_{j=1}^{M} \phi_0 Z_j^1 \qquad 3$$

Where G is the explanatory model, $Z1 \epsilon \{0,1\}^M$ is the coalition vector, M is the maximum size of a coalition and $\phi_j \epsilon \mathbb{R}$ represents a feature's distribution.

IV. RESULT AND DISCUSSION

We developed RF-based classifiers and visualized local and global predictions of model using LIME and SHAP XAI approaches. This section discusses visual explanations provided by LIME and SHAP interpretability methodologies in assessing the detrimental impact of greenhouse gas emissions on human health.

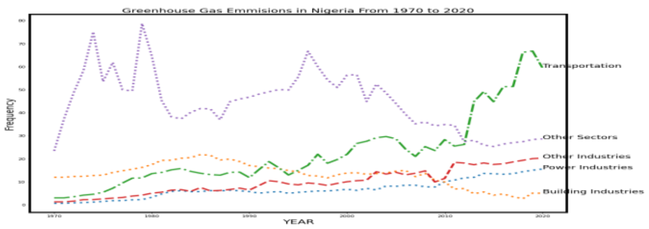

Figure 2: The Chart of Greenhouse Gas Emission in Nigeria

Figure 2 illustrates the greenhouse gas emission line plots for transportation, power, building, and other sectors and industries.

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Other sectors' greenhouse gas emission rate increased dramatically between 1970 and 2000 when compared to power, building, and transportation industries, with transportation industries having the highest rate between 2000 and 2020.

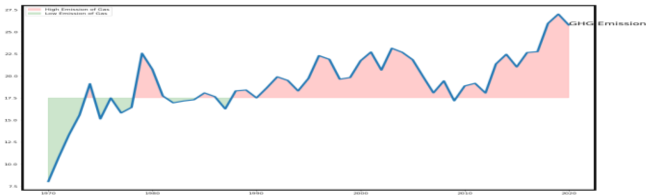

Figure 3: Greenhouse Gas Emission Anomalies

The average line plot of greenhouse gas emissions by building industries, transportation industries, power, other sectors, and industries is shown in figure 3. The rate of rise in gas emissions has been consistent over the years 1970, 1980, 1090, 2000, 2010 and 2020.

It depicts a normal distribution with mean and standard deviation from a dataset with high and significantly low gas emission anomalies.

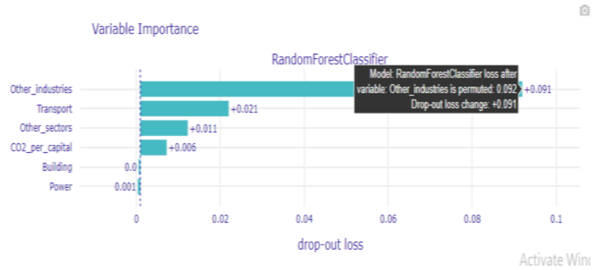

Figure 4: The RF Feature Importance Interactive Interface

The RF model provides a comparable interpretation, with the other sectors contributing the most to model prediction, followed by the transportation as shown in figure 4. The RF classifier loss after other sector was permuted to be 0.091 with variable importance resulted in +0.091 and drop-out loss change value recorded +0.091. The comparison of each component is further aided by relative relevance. Building, for example, is less significant than other sector but far more important than other features.

A. Explainable AI

This section demonstrates how an explanation might appear at the local and global levels utilizing LIME and SHAP XAI techniques. It is presented with graphs that show which parameters influence model prediction and which parameters indicate high or low classification of GHG emissions.

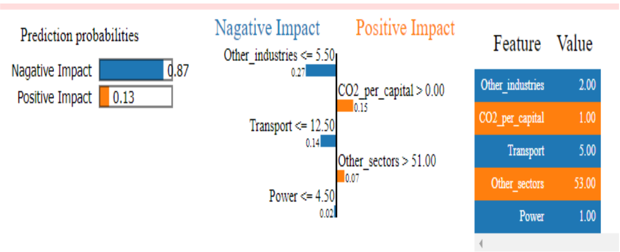

Figure 5: Lime Local Interpretability Prediction

Figure 5 demonstrates how each feature affects the individual predictions. The colors orange and blue represent the positive and negative effects of the feature on the target, respectively. This suggests that while building and other industries had a tolerably low impact on individuals and the environment, other industries and power had a negative influence.

B. Global Explanations of Lime

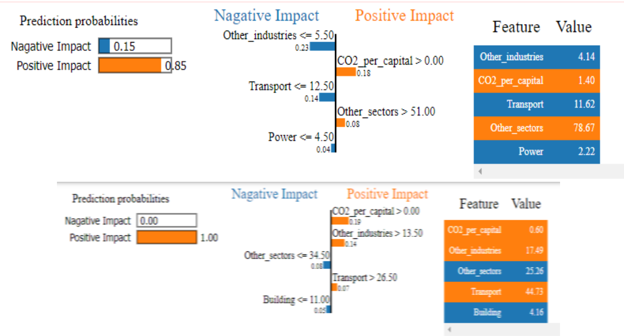

Figure 6: Lime Global Explanations

Figure 7: The Individual Explanations of SHAP for Test Set

Figure 7 shows a force plot visualizing SHAPELY values for the features. The feature values in pick cause to increase the model prediction. Size of the bar shows the magnitude of the feature's effect. Feature values in blue cause to decrease the model prediction.

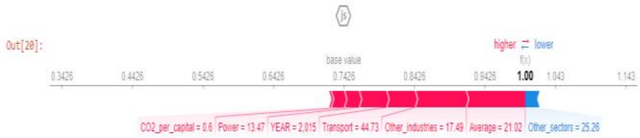

Figure 8: The Individual Explanations of Shap or Test Data

Figure 8 depicts number of correctly predicted greenhouse gas emissions in power, transportation, industries, and other sectors recorded high rate in 2015, but the base model estimate is 0.7426 and predicted value 1.00. Other sectors produced low impact and values, but power, transportation industries, and other sectors have high values in 2015. Other sectors recorded low values, but power, transportation industries, and other sectors gave high values in 2015.

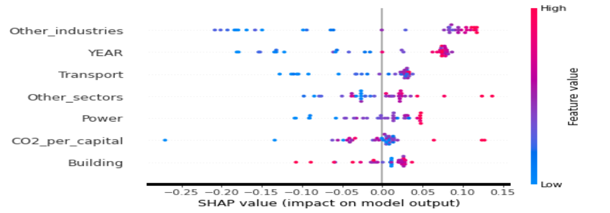

Figure 9: Summary Plot Showing the Global Picture RF Model

Figure 9 is comprised of different points, each of which has three attributes:

The Vertical position indicates which feature is being depicted, and the Color indicates if that feature was either high or low for just that row of such dataset.

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The horizontal placement indicates if the value had such a high(positive) or low(negative) impact on the prediction.

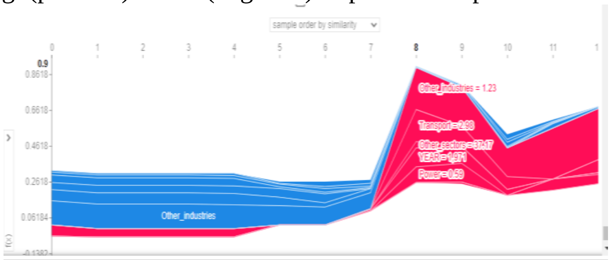

Figure 10: Shap Explanations for Sample Order Forced Plotted y Similarly

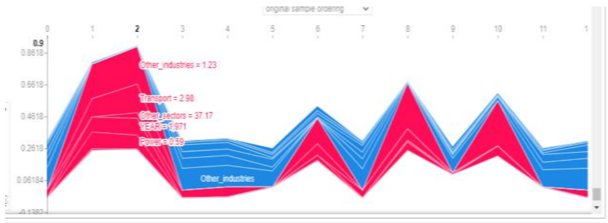

Figure 11: Shap Explanations for Original Sample Ordering

Figures 10 and 11 show the interactive visual explanations created by SHAP on sample order forced plots and original sample ordering of GHGs. The SHAP explanations can assist users to interactively explain and see specifics of values in the output. The force plot is used here to visualize the RF model's predicted results. SHAP allows users to view the force plot and understand the impact of each attribute on the model's prediction, even for a specific instance of data. The Force plot depicts the influence of each attribute on the current prediction, with blue values indicating a positive influence on the prediction and red values indicating a negative influence on the prediction. The SHAP forced plot results are shown in an ML interface, generating interactive visual explanations.

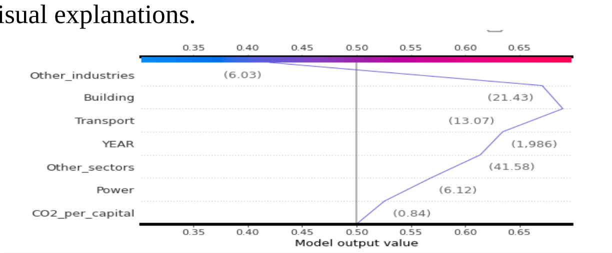

Figure 12: The Decision Layout of Shap

Figure 12 is a little more noticeable in the decision plot. There are several features, such as other sectors, that drive prediction models, but substantially influences from building, transportation, other sectors, power and co2 per capital which brought the needle all the way to 0.65.

V. CONCLUSION

XAI techniques such as LIME and SHAP were utilized to determine which sectors' GHG emissions had the greatest impact on human health and the immediate environment. With the LIME technique, other sectors had the most significant emission rates with favorable impacts on individuals as well as the environment, while other industries, such as the power, building, and transportation sectors, had the lowest emission rates with adverse consequences. Power, transportation, and other sectors provided high values while other sectors reported low values using the SHAP approach. LIME explanations exceeded SHAP in terms of understandability, sufficiency, and satisfaction. SHAP fared better than LIME in terms of trustworthiness. The LIME explanations were more understandable and faithful to user groups as compared to SHAP in terms of measuring the positive and negative impacts of emissions on human health. The LIME explanations were more favorable to user groups than the SHAP explanations in evaluating both positive and impact impacts of GHG emissions on human health.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been sponsored or funded by any organization or agency. The independence of this research is a crucial factor in affirming its impartiality, as it has been conducted without any external sway.
- **Ethical Approval and Consent to Participate:** The data provided in this article is exempt from the requirement for ethical approval or participant consent.
- **Data Access Statement and Material Availability:** The dataset comprising GHG emissions and the source is provided above.: https://catalog.data.gov/dataset/?organization=epa-gov&res_format=EXCEL
- **Authors Contributions:** The authorship of this article is contributed equally to all participating individuals.

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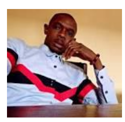

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