Journal of Information Systems and Informatics
**Vol. 6, No. 4, December 2024** e-ISSN: **2656-4882** p-ISSN: **2656-5935**
DOI: 10.51519/journalisi.v6i4.870 Published By DRPM-UBD

# Evaluating the Impact of Agricultural Technology on Greenhouse Gas Emissions Using Machine Learning

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**Abstract**

Agriculture is a significant contributor to global warming, primarily due to the release of greenhouse gases like methane (CH4) and nitrous oxide (N2O). These gases have a much higher global warming potential than carbon dioxide (CO2), necessitating targeted strategies for their reporting and reduction. This study applies machine learning models, specifically XGBoost and Support Vector Machine (SVM), to evaluate how technological advancements in agriculture influence greenhouse gas emissions. The dataset used includes emission data from various crops and farming technologies. Findings reveal that certain crops considerably elevate emissions, and in some cases, new technologies exacerbate the issue. XGBoost achieved 99.6% accuracy in predicting emission mitigation, proving its effectiveness in developing climate change mitigation plans for agriculture. Support Vector Machine also performed well, with an accuracy of 99.5%. This research underscores the need for precise approaches in managing greenhouse gas emissions through technology-driven policies.

**Keywords**: Greenhouse Gas Emissions, Agriculture, XGBoost, Support Vector Machine (SVM), Agricultural Technolo

## 1. INTRODUCTION

Agriculture has a significant impact on greenhouse gas emissions, with a contribution that cannot be overlooked in global climate change [1],[2]. Greenhouse gas emissions coming from the farming industry, primarily stemming from conventional farming, plantations, and livestock farming, are a major concern in climate change mitigation efforts [3],[4],[5]. One of the principal sources of emissions of greenhouse gases from farming is livestock activities. Livestock produces manure, a major source of methane (CH4), one of the most environmentally damaging greenhouse gases. The process of making manure fertilizer from animal waste also contributes to greenhouse gas emissions, particularly nitrous oxide (N2O). In addition, agricultural land management also contributes to greenhouse gas emissions [6],[7].

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Burning agricultural residues, using chemical fertilizers, and applying lime to soil can all result in the emission of carbon dioxide and nitrogen oxides. These processes can increase the atmospheric concentration of greenhouse gasses [8],[9]. Surprisingly, rice cultivation is among the largest those who contribute to emissions of greenhouse gases from the farming sector, mainly utilizing the production of methane from the decay of organic matter in flooded rice fields [10]. In the context of Changes in climate mitigation, yes, it is essential to comprehend the differences amid generated greenhouse gasses by farming, such as Nitrous oxide, carbon dioxide, and methane. Measuring carbon emissions from agriculture and livestock farming is also a key consideration in developing effective environmental policies [11].

Raising awareness of agriculture's impact on climate change, along with efforts to reduce greenhouse gas pollution from this sector, is crucial to achieving global climate change mitigation goals, as outlined in the Paris Agreement. The complexity of emissions of greenhouse gases from the agriculture industry, with an emphasis on the differences between Carbon dioxide (CO2), nitrous oxide (N2O), and methane (CH4), calls for deeper understanding of their individual contributions, as well as a more detailed approach in reporting and mitigating agricultural emissions with the greatest impact on climate change [12],[13].

This study also highlights the importance of considering economic, technical, and social factors in planning reduction of climate change strategies in farming. There is a recognition of the impact of changes in agricultural technology on future greenhouse gas emissions, and analyses using XGBoost and Support Vector Machine (SVM) modeling techniques help to explore the complex interactions of physical, chemical, and biological elements in the agricultural context [14].

The research results show that some field crops have a significant impact on greenhouse gas emissions, while advances in agricultural technology contribute to an overall increase in emissions. These conclusions underscore the importance of accounting for all types of greenhouse gas emissions in the fight against climate change efforts [15]. Previous research has highlighted the need to consider all types of greenhouse gases in the reduction of climate change efforts, especially in the context of the agricultural sector. We plan to refine previous research by incorporating machine learning techniques into our analysis [16],[17],[18].

By using machine learning techniques, we hope to provide more valuable contributions and produce more comprehensive findings in understanding the impact and patterns of emissions of greenhouse gases from the agriculture industry. These techniques allow us to analyze data more deeply and identify patterns that may not be detected with conventional methods [19]. With a careful approach to planning climate change mitigation strategies in the agricultural sector, we believe that integrating machine learning techniques will help optimize mitigation efforts and achieve more effective results [20].

This research aims to address the challenges posed by greenhouse gas emissions from the agricultural sector, including emissions from gases such as methane (CH4) and nitrous oxide (N2O). By utilizing machine learning techniques such as XGBoost and SVM, this study seeks to better predict and manage these emissions while providing insights into the

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

impact of agricultural technologies on emissions. The study also adds a new dimension by integrating economic, technical, and social factors into the analysis of climate change mitigation in agriculture. With a focus on a careful approach to planning climate change mitigation strategies in the agricultural sector and the use of accurate modeling techniques, this study offers valuable contributions to understanding the complexity of the issue and provides guidance for policymakers in addressing future climate change mitigation challenges.

Based on previous studies, there is a variation in methods and results in predicting specific issues. Jianlan Lu et al. (2024), using the same dataset, "agri-food-co2-emission-dataset," discussed the characterization and monitoring of gas emissions in agricultural waste treatment [21]. Maliha Homaira et al. (2021) applied the Linear Regression method with an accuracy of 85% [22]. Meanwhile, Debasish Saha et al. (2021) implemented Random Forest, achieving an accuracy of 89% [23]. Jude O. Asibor et al. (2023) also used Random Forest and attained an improved accuracy of 98% [24]. In comparison, Nourin Nishat et al. (2024) achieved an accuracy of 92% using the same method [25]. Although Random Forest generally shows better performance than Linear Regression, there are significant variations in the results across studies. The GAP identified from this table is the difference in accuracy levels among the studies using Random Forest, even though the method is the same, indicating potential factors affecting the model's performance.

## 2. METHODS

The procedure used to obtain the predictive analysis findings on the classification of agricultural technology's impact on greenhouse gas emissions is shown in Figure 1.

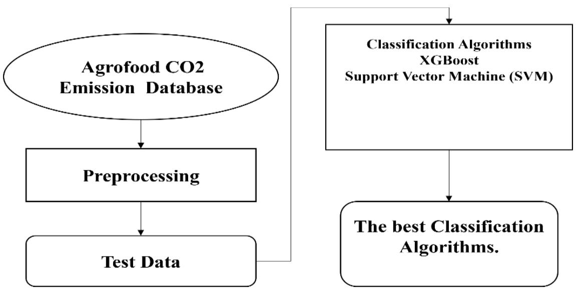

**Figure 1.** Research Methodology

The comprehensive analyses in this study were conducted using Python version 3.9.12. To support the analysis, several essential modules were integrated, including NumPy, Matplotlib, and Scikit-Learn. Python 3.9.12 utilizes NumPy, a library that provides extensive support for multidimensional arrays and matrices. NumPy not only offers efficient representations for numerical data but also provides a variety of high-level mathematical operations that can be applied to these arrays. This advantage is key in data analysis that involves array manipulation and complex mathematical operations. In the context of numerical analysis, Matplotlib serves as an extension of NumPy, specifically dedicated to data visualization and graph creation. As a plotting library for the Python programming language, Matplotlib allows for clear and informative visual representations

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

of analysis results, making data easier to understand and interpret. To support the machine learning aspect of this research, Python 3.9.12 uses Scikit-Learn (previously known as Scikits Learn or sklearn) [26]. Scikit-Learn is a free machine-learning library designed specifically for use with Python. This module provides the necessary algorithms and utility functions for model training, performance evaluation, and the implementation of various machine learning techniques. With the combination of Python 3.9.12 and these modules, comprehensive analysis can be conducted efficiently and effectively. The use of NumPy for numerical data manipulation, Matplotlib for visualization, and Scikit-Learn for machine learning implementation ensures a robust and in-depth approach to data processing and interpretation.

### 2.1. Dataset

The following are the steps that can be reported in research related to the collection and handling of data concerning emissions of greenhouse gases from the agriculture industry. Data Collection: Data was collected through Kaggle ML, the Machine Learning Repository. This dataset contains information about emissions of greenhouse gases from the agriculture industry and is presented in CSV format. Research Focus: The research focuses on the issue of emissions of greenhouse gases from the agriculture industry. The primary objective is to understand the emission patterns from agriculture, as well as the factors that influence these emissions. Handling Class Imbalance: In the dataset, there may be imbalances between the classes, for instance, the number of samples representing high emission levels may be fewer than those representing low levels. To address this issue, oversampling techniques are employed, specifically, SMOTE stands for Synthetic Minority Over-sampling Technique. This method produces artificial samples from the minority group to create equilibrium between the classes. Attributes in the Dataset: The dataset includes various features or variables that are measured or observed for each sample. These features may include characteristics of emissions of greenhouse gases from the agriculture industry (Table 1).

**Table 1.** Attributes and description of emissions of greenhouse gases from the agriculture industry.

| NAME Attribute | Information |
|---|---|
| Area | The area or area may be in certain units such as hectares or square kilometers. |
| Average Temperature (°C) | The average temperature is degrees Celsius in the area in question. |
| Crop Residues | Crop residues after harvest are a possible source of emissions of greenhouse gases. |
| Drained organic soils (CO2) | The amount of carbon dioxide released from drained soil with organic matter, possibly as a result of agriculture or land use change. |
| Fertilizers Manufacturing | Emissions associated with the manufacture of chemical fertilizers. |
| Fires in humid tropical forests | Emissions resulting from forest fires in humid tropical areas. |

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| | |
|---|---|
| Food Household Consumption | Emissions originating from food consumption in households. |
| Food Packaging | Emissions associated with food packaging manufacturing. |
| Food Processing | Emissions from food processing. |
| Food Retail | Emissions related to the food distribution chain until it reaches the final consumer. |
| Food Transport | Emissions from transporting food from production to consumption. |
| Forest fires | Emissions resulting from forest fires. |
| Forestland | Forest land area. |
| IPPU | emissions resulting from industrial operations and human-produced products. |
| Manure applied to Soils | Application-related emissions organic fertilizer to the farming land. |
| Manure left on Pasture | Outputs associated with the management of livestock manure left on pastures. |
| Manure Management | Emissions from livestock manure management, including decomposition. |
| Net Forest conversion | Changes in net forest conversion may result in carbon emissions or sequestration. |
| On-farm Electricity Use | Electricity use in agriculture. |
| On-farm energy use | Energy use in agriculture. |
| Pesticides Manufacturing | Emissions from pesticide manufacture. |
| Rice Cultivation | Emissions associated with rice farming. |
| Rural population | Number of residents in rural areas. |
| Savanna fires | Emissions resulting from savanna fires. |
| Total_emission | Total greenhouse gas emissions or other emissions measured in one particular unit, perhaps in tons of CO2 equivalent. |
| Total Population - Male | The total number of male population |
| Year | Year of the data presented. |

### 2.2. Preprocessing

The check for missing data was conducted by examining whether there were any null values in the Agrofood CO2 Emission dataset. Missing values were filled using the imputation method, specifically by using the mean value of each feature with missing data. This approach was taken to maintain data consistency and avoid deleting data, which could result in the loss of important information [27]. After addressing the missing data, a check for duplicate data was performed. Data duplication can affect model accuracy and introduce bias during training. Therefore, duplicate entries were removed to ensure better data quality. The check was done by comparing all data rows and deleting any rows that were entirely identical. Categorical features, such as region names or other categories, were

Journal of Information Systems and Informatics
Vol. 6, No. 4, December 2024
p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

converted into numerical formats. This technique is essential to ensure that the machine learning algorithms used can correctly process categorical data. The conversion was done using label encoding.

To prevent certain features with large scales from dominating the data, the features were normalized using Min-Max normalization. This approach rescaled each feature to fall within the range of 0 to 1. Normalization is important as it prevents features with larger value ranges from dominating the model's learning process [28]. After the preprocessing was complete, the data was split into training data and testing data, with an 80% training and 20% testing split. This split was done randomly using a method from the sklearn module. This step is crucial to ensure that the model is trained on a portion of the data, while its performance is measured on data it has not seen before, to avoid overfitting.

Since the Agrofood CO2 Emission dataset has a class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied. SMOTE generates synthetic samples of the minority class to balance the class distribution. By using SMOTE, the machine learning model becomes more capable of recognizing patterns in the minority class, which is often overlooked in imbalanced datasets [29]. After all the preprocessing stages were completed, the dataset was ready for machine learning modeling. The processed data was saved in CSV format and can be used by the model. The model will then be trained using the training data, and its performance will be tested using the testing data. By going through all these stages, the data becomes cleaner, more structured, and ready to be processed by machine learning algorithms to produce accurate predictions related to greenhouse gas emissions from the agricultural sector. Feature Correlation Heatmap Figure 2.

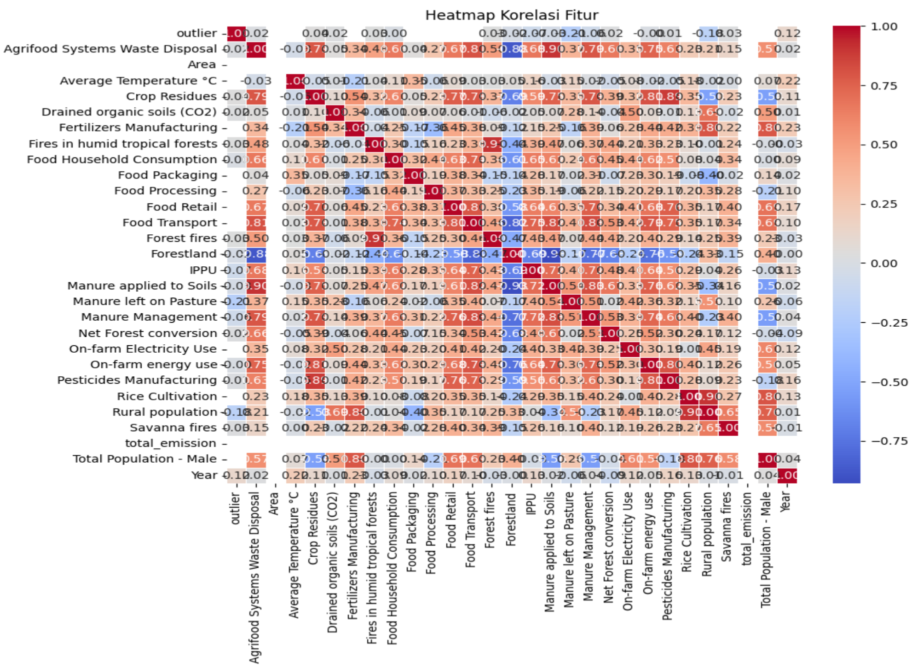


**Figure 2.** Feature Correlation Heatmap of Agrofood CO2 Emission.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

### 2.3. Test Data

After completing the final preprocessing stage, the data was saved in CSV (Comma-Separated Values) format and used as input for the classification stage. Before classification, the data was split for two models: XGBoost and SVM. Using the training and testing sets, the data was separated using the sklearn (sci-kit-learn) module in Python 3.9.12. The data was divided into 20% for testing and 80% for training. This proportion was randomly selected as it is a simple technique and suitable for large datasets.

### 2.5. Metode Machine learning classification

As detailed in the following subsection, we employed a number of popular machine learning techniques.

#### 2.5.1. Support Vector Machine (SVM)

Support Vector Machines, or SVMs, are designed in order to locate a hyperplane in an N-dimensional space, where N is the number of features that effectively classify the information points. This hyperplane is derived from support vectors and aims to achieve the maximum margin of separation in a two-class classification scenario. Despite its primary application as a binary classification method, SVM can adeptly handle multicategory problems by transforming them into binary classification tasks [30].

$$H: wT(x) + b = 0 \tag{1}$$

b = The point where the hyperplane equation crosses the hyperplane and a bias term is consistently formatted as a D-1 operator in space with dimensions of D. For example, a linear line in 2-D space is called a hyperplane (1-D).

#### 2.5.2. XGBoost.

XGBoost is an implementation of the decision tree-based gradient-boosting approach. The basic steps and formulas used are as follows: XGBoost minimizes an objective function made up of the regularization term and the loss function [31].

$$Obj(\theta)= \sum_{i=1}^{n} L(yi, y\hat{}i) + \sum_{k=1}^{k} \Omega(fk) \tag{2}$$

L(yi,y^i) = what the loss function is.
Ω(fk) = the phrase for regularization that controls model complexity to avoid overfitting.

## 3. RESULTS AND DISCUSSION

### 3.1. Performance Evaluation

The objective of this project is to apply machine learning to develop a model for greenhouse gas emissions originating from the agriculture industry. The research steps include data processing, model creation utilizing three machine learning techniques, and

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

assessing the performance of the model using a range of measures, such as recall, accuracy, precision, and F-1 score. The conclusions show that XGBoost achieved an accuracy of 99.6%, while Support Vector Machine (SVM) demonstrated a high accuracy of 99.5%. To further enhance model performance, an automatic algorithm selection procedure was also applied. By utilizing an effective method for detecting greenhouse gas emissions from the agricultural sector, this research has significant practical implications, particularly for communities in agricultural areas. The results highlight advancements and the superiority of the proposed paradigm compared to previous studies. Although further verification is still needed, this research provides a strong foundation for future progress in identifying and addressing greenhouse gas emissions from the agricultural sector. A comparison of the way in which machine learning techniques are presented in Table 2.

**Table 2.** Values of various methods.

| Algorithm | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| XGBoost | 0.996 | 0.990 | 0.99 | 0.997 |
| Support Vector Machine | 0.995 | 0.995 | 1.0 | 0.997 |

The ROC Curve, short for Receiver Operating Characteristic Curve, illustrates how well the performance of a classification model is variable over threshold settings. It illustrates how the True Positive Rate (TPR) and False Positive Rate (FPR) are related at different thresholds. TPR, also called Sensitivity or Recall, gauges the capacity of the model to identify positive cases. It's calculated as TP / (TP + FN), where TP represents True Positives and FN represents False Negatives. On the other hand, FPR quantifies how frequently the model incorrectly labels negative cases as positive, computed as FP / (FP + TN) represents False Positives and True Negatives, respectively. When discussing the AUC (Area Under the Curve) value of 0.93, it indicates strong discrimination between positive cases (greenhouse gas emissions from agriculture) and negative cases (non-greenhouse gas emissions from agriculture). Such a high AUC suggests that the classification model effectively distinguishes between those with agricultural greenhouse gas emissions and those without. Therefore, a high AUC, like 0.93, signifies excellent model performance in identifying agricultural greenhouse gas emissions Figure 3.

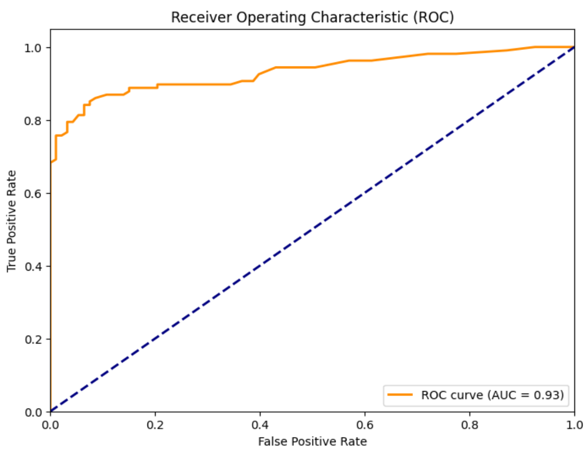


**Figure 3.** ROC Curve

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### 3.2. Evaluation Metrics

Evaluation Metrics present a comparison between the results of this study and several previous studies, highlighting the highest accuracy achieved in this research (XGBoost: 99.6%). It also includes the calculation of accuracy differences between each of these studies and the current results. Highest Accuracy: This research, using XGBoost, achieved the highest accuracy of 99.6%, followed by SVM at 99.5%. Compared to the studies by Jude O. Asibor (98%) and Debasish Saha (89%), this model shows significantly better performance, with differences of 1.6% and 10.6%, respectively.

Performance of Linear Regression: A study by Maliha Homaira using Linear Regression only achieved 85% accuracy, which is 14.6% lower than the accuracy reached by XGBoost in this research. This highlights that simpler algorithms may not perform as well in complex tasks like CO2 emission prediction. Random Forest: Several studies, including those by Debasish Saha and Jude O. Asibor, demonstrated that Random Forest is a strong algorithm, though its achieved accuracy (89%-98%) remains lower than XGBoost in this study, with differences ranging from 1.6% to 10.6%. SVM vs XGBoost: Although SVM comes close to XGBoost with a very small accuracy difference of 0.1%, SVM has a recall of 100%, indicating that the model successfully identified all positive instances in the dataset. This makes SVM a highly reliable model, particularly for applications that prioritize recall over other metrics. This evaluation underscores the superior performance of these models compared to existing research, while also highlighting the advantages of using XGBoost and SVM in predicting CO2 emissions in the agricultural sector.

The implications of this comparison show that more advanced machine learning models like XGBoost and SVM provide significant improvements in accuracy, especially when dealing with complex datasets such as CO2 emissions in the agricultural sector. Simpler algorithms like Linear Regression are less efficient in predicting dynamic emission patterns, which may be influenced by factors like weather conditions, fertilizer use, crop types, and agricultural technologies.

### 3.3. Discussion

Technological advancements in the agricultural sector can be a double-edged sword. On one hand, the use of modern technologies such as tractors, automated irrigation systems, and precise application of chemical fertilizers can enhance crop productivity and reduce unnecessary inputs. On the other hand, the use of heavy machinery and the intensive application of chemical fertilizers can lead to increased CO2 emissions, particularly from the production and combustion of fossil fuels used by such agricultural equipment. Findings from this research show that despite efforts to reduce emissions by improving technological efficiency, the cumulative effects of agricultural intensification may actually contribute to higher CO2 emissions. Therefore, it is crucial to adopt sustainable approaches to agricultural technology that balance productivity with environmental impact.

This research could take a more critical approach by examining the contributions of various crop types to CO2 emission levels. Some crops have higher carbon intensities than others, depending on agricultural practices and the inputs required for their growth. For example, rice tends to produce more greenhouse gases due to anaerobic fermentation in

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paddies, which releases methane. In contrast, legumes can fix nitrogen in the soil, reducing the need for synthetic nitrogen fertilizers that generate CO2 during their production. A more in-depth analysis of crop types in the dataset would provide additional insights into how specific crops contribute more or less to CO2 emissions. This could also aid in designing targeted mitigation strategies for specific crops, such as reducing fertilizer intensity on high-emission crops or implementing more environmentally friendly agricultural practices like agroforestry. This comparative analysis highlights that while technological advancements can boost agricultural productivity, they can also contribute to increased CO2 emissions if not balanced with sustainable practices. It is important to continue developing robust predictive models to understand CO2 emission patterns in the agricultural sector, while also considering specific factors such as the contributions of crop types and the impact of the technologies used.

## 4. CONCLUSION

This research highlights the superior performance of machine learning models, particularly the XGBoost and Support Vector Machine (SVM) algorithms, in predicting greenhouse gas emissions from the agricultural sector. The findings indicate that these models achieved very high accuracy rates, with XGBoost reaching 99.6% accuracy, closely followed by SVM at 99.5%. The integration of statistical feature engineering using both classification algorithms on the "Agrofood CO2 Emission" dataset yielded satisfactory results and significantly enhanced the prediction performance for greenhouse gas emissions. These models not only offer high predictive capabilities but also provide deeper insights into the factors influencing CO2 emissions in agriculture, such as crop types, land management methods, and the use of agricultural technology. The results of this research have important practical implications, particularly for policymakers and agricultural industry stakeholders. With their high accuracy, these models can aid in designing more effective CO2 reduction strategies, enabling the identification of low-emission agricultural practices and more efficient eco-friendly technologies. This research also supports the development of data-driven policies to enhance sustainable farming practices, with a focus on optimizing greenhouse gas emissions. To broaden the impact of this research, further studies are needed to test the models on more diverse datasets, including different geographic regions and crop types. Additionally, exploring other machine learning algorithms, such as Neural Networks or Deep Learning, could improve prediction accuracy and provide deeper insights into the complex interactions between variables affecting emissions. This extended research is expected to offer more holistic and specific solutions for reducing greenhouse gas emissions, particularly in agriculture, and ultimately support global efforts to combat climate change.

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