PROJECT REQUIREMENTS SPECIFICATION

Analyzing and Predicting the control of GHG Emissions from Agricultural Activities using Machine Learning Models.

UE20CS390A – Project Phase – 1

Submitted by: ***Batch 108***

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TABLE OF CONTENTS

1. Introduction

This document outlines the specifications for a product that will use machine learning models to analyze and forecast how greenhouse gas (GHG) emissions from agricultural activities will be controlled. The product's objective is to assist agricultural stakeholders in reducing GHG emissions and mitigating climate change by offering precise forecasts and insights.

The creation and application of machine learning models that can assess and forecast GHG emissions from agricultural activities are prerequisites for this product. The models should be able to process sizable amounts of data from numerous sources, including weather, soil, and agricultural practices.

Additionally, the product needs to have user-friendly interfaces for data entry, model training, and prediction output. Farmers, decision-makers, and researchers should all be able to use the interfaces.

1.1. Project Scope

The goal of the project is to create a software tool for analyzing and forecasting the reduction of GHG emissions from agricultural operations using machine learning algorithms. The software application will be created to assist farmers and decision-makers in understanding the possible GHG emissions from their agricultural activities and taking the necessary steps to minimize them.

Some of the limitations :

- Data accessibility: The accessibility and caliber of data can have a big impact on how accurate machine learning models are. It might be difficult to develop precise models because there may not be enough data on agricultural emissions. Agricultural activities and practices vary widely across regions and crops, making it difficult to create a universal model that can precisely predict emissions.

- Limited knowledge of the underlying processes:The intricate mechanisms that cause GHG emissions from agricultural activities still have a lot to be discovered. The effectiveness of machine learning models may be constrained by a lack of comprehension of these procedures.

- External variables: Weather patterns, market prices, and governmental policies are just a few examples of the external variables that can affect emissions from agricultural activities. These external factors can be difficult to account for and may limit the accuracy of machine learning models.

- Resource limitations: Accurate machine learning model development calls for a significant investment in computational power and knowledge. Developing and maintaining efficient models may be difficult for organizations with limited resources.

2. Literature Survey or Existing System

Paper Details – 1:

Forecasting the Emission of Greenhouse Gases from the Waste using SARIMA Model, Vaishnavi Jayaraman, Saravanan Parthasarathy, Arun Raj, Department of Computer Science and Engineering, B.S.Abdur Rahman Crescent Institute of Science and Technology, Chennai, India. 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI) | 978-1-6654-8328-5/22/$31.00 ©2022 IEEE | DOI: 10.1109 / ICOEI53556.2022.9777119

Objective of paper, Techniques/Methods : In this Study, the emission from waste was prognosticated for India and China. In this study, we have chosen China and India, to predict the emanation of GHGs from the waste sector. Eight different models were used utilized for prediction. Out of eight regression techniques employed, the SARIMA model performed the best for both datasets. The R! , MAPE, MAE, and RMSE obtained by the model with the India dataset were as follows 0.271, 2.418, 1.953, and 2.433

Advantages : The non-parametric models such as KNN and SVR were utilized, where the number parameters is dependent on the amount of training data. The Boosting techniques improve the performance of the regressor thereby reducing the error rate. Hence, the AdaBoost techniques were employed. As the dataset utilized is time-series data, a statistical model SARIMA which depends on the seasonality was considered

Limitations : his model is limited to Predict the Futural Impacts on GHG Emissions and the Scale at which the Emission rates will vary over the time. The model can be Built in such a way that, It also helps to Plan for the Emission control to Achieve the Net Zero Emission by certain time period. The numbers in dataset are only representing the Emissions with respect to the whole country, but not by individual states and all the different region, which could help us get precisely understand the impacts from different regions and activities conducted there.

Paper Details – 2:

Forecasting of GHG (greenhouse gas) Emission using (ARIMA) Data Driven Intelligent Time Series Predicting Approach, Dr. Somesh Sharma School of Management, Graphic Era Hill University Bhimtal, India. Dr. Ashish Kumar Saxena SOM, IFTM University Moradabad, UP, India. Mr. Manmohan Bansal Faculty of Management, Invertis University Bareilly, UP, India. 2022 7th International Conference on Communication and Electronics Systems (ICCES) | 978-1-6654-9634- 6/22/$31.00 ©2022 IEEE | DOI:10.1109/ICCES54183.2022.9835 88

Objective of paper, Techniques/Methods: Data-driven intelligent time-series predicting approach, ARIMA is applied for forecasting GHG emissions. For policymakers and government, it is critical to understand the factors that drive the fast emissions of GHG, hence forecasting GHG emissions over a decade will help to frame the policy accordingly. ARIMA (0, 2, 1,) model is used for forecasting, which showed an increasing trend of emissions of GHG. An Augmented Dickey-Fuller (ADF) test is used to determine the stability of the data series under consideration. In order to complete the selection of an appropriate ARIMA model, ACF, and PACF plots is used.

Advantages : A secondary data source, related to GHG emissions is the database of the World Bank. Evidence related to the current level of GHG emissions in India are collected from reports in the World Bank database. Projection of GHG emission using the projective technique will project value of GHG emission and this will guide the government and policy makers to plan accordingly. It is anticipated that the projection of GHG emissions in India will assist the government in developing strategies and actions to reduce GHG emissions

Limitations: The models used in this project are mostly related with the seasonality of the dataset. Hence, if the dataset is not seasonal then the chances of expecting the inaccurate predictions from the model are very high. And there is no model to show that on what rate the emission should be reduced to achieve the net zero emission which can be included to the future work.

Paper Details – 3:

Carbon Emissions forecasting based on Stacking Ensemble Learning. Quanmao Zhang, Ying Wang, Dongliang Qin, Kailin Zhao, Wanying Xie, Economic Research Institute of state Grid Hebei Electric power company, Shijiazhuang, China. 2022 IEEE 5th International Electrical and Energy Conference (CIEEC) | 978-1- 6654-1104-2/22/$31.00 ©2022 IEEE | DOI: 10.1109/CIEEC54735.2022.98 45939

Objective of paper, Techniques/Methods: Excessive carbon emissions have become a significant cause of global warming, how to accurately predict carbon emissions is the key point to address the environmental crisis. - Global warming has become one of the toughest challenges faced by the international community, and the significant cause of global warming is the excessive emission of carbon dioxide. - this paper establishes a two- layer ensemble model for predicting fossil energy consumption based on stacking ensemble learning.

Advantages : The proposed model in the example is built on the Keras, and GPU is called for parallel computing to accelerate the training process. The prediction of fossil energy consumption and electricity consumption are used to calculate the carbon emission that caused by the usage of fossil energy and the carbon. LSTM is developed to deal with the problem of gradient vanishing that will face when training the RNN because of its relative insensitivity to gap length, a common LSTM unit.

Limitations: This paper establishes a two-layer ensemble model for predicting fossil energy consumption, where the input is electricity consumption. Ridge regression is used to combine the predictions of four types of base learners and generates the final prediction of fossil energy consumption. the carbon emissions will be calculated by the prediction of fossil energy consumption and electricity consumption The simulation shows that the proposed forecasting system improves the forecasting performance relative to other models considerably, which can provide meaningful references for policymakers.

Paper Details – 4:

A k-Means-Based-Approach to Analyze the Emissions of GHG in the Municipalities of MATOPIBA Region, Brazil, Lucas Ferreira-Paiva , Attawan G. L. Suela Cardona-Casas , Domingos S. M. Valente, and Rodolpho V. A. Neves , Member, IEEE, IEEE LATIN AMERICA TRANSACTIONS, VOL. 20, NO. 11, NOVEMBER 2022

Objective of paper, Techniques/Methods: to propose an approach based on kmeans to group municipalities according to their GHG emissions by sector. To conduct a case study with the MATOPIBA region to assess the ability of the proposed approach to identify and to map similarities and differences in municipal emission profiles, driving hyper-local GHG emission reduction strategies.

Advantages : The approach identified six groups with different emission profiles. The main sectors that differentiated the groups were LUC, Agriculture and Energy. The wide variation in the contribution to total emissions by these sectors showed that the MATOPIBA municipalities are in different stages of deforestation and agricultural exploitation. the proposed approach makes it possible to group similar municipalities and highlight important spatial autocorrelations

Limitations: emissions were not divided by economic sub-sectors, requiring data complementation to gain more conclusive evidence; and data from 2018 were collected, which may not completely reflect the current state of the MATOPIBA municipalities. • It is worth noting that the proposed approach can be used to assess the profile of GHG emissions from other regions of the country due to its capability and practicability

Paper Details – 5:

Performance Monitoring Insight using Predictive Analytics: A Step towards IMO’s GHG Emission Goals 2030. Nithish Balaji J, Himanshu Uppal, Pritam Patel and B.M. Shameem. OCEANS 2022 - Chennai | 978-1-6654-1821-8/22/$31.00 ©2022 IEEE | DOI: 10.1109/OCEANSChennai45887.202 2.9775128

Objective of paper, Techniques/Methods: A Step towards IMO's GHG Emission Goals 2030" focuses on the use of predictive analytics in improving the performance of ships and reducing their greenhouse gas (GHG) emissions. The paper highlights the International Maritime Organization's (IMO) goal of reducing GHG emissions from shipping by at least 50% by 2050, with an intermediate target of reducing carbon intensity by 40% by 2030.

Advantages : Improved performance monitoring: The use of predictive analytics can help ship operators to monitor the performance of their vessels more accurately and in realtime. This can help identify areas for improvement and enable operators to take corrective action before issues arise. Reduced GHG emissions: By identifying and addressing inefficiencies in ship performance, predictive analytics can help reduce GHG emissions from the shipping industry. This is critical in achieving the IMO's emission goals for 2030

Limitations: Implementation costs: Implementing predictive analytics requires significant investment in technology, infrastructure, and personnel. This may not be feasible for small or medium- sİzed ship operators. effectiveness of predictive analytics relies heavily on the availabilityy and quality of data. Data from different sources may be inconsistent or incomplete, making it challenging to achieve accurate predictions.

Paper Details – 6:

The Assessment of Energy Consumption and Carbon Emission from Maize Production Process in Northern Thailand. Tanate Chaichana, Kunyaporn Chaiwoung, Saritporn Vittayapadung, Ukrit Samaksaman, ICUE 2020 on Energy, Environment, and Climate Change Asian Institute of Technology, Thailand. 20 – 22 October 2020

Objective of paper, Techniques/Methods: "Assessment of Energy Consumption and Carbon Emission from Maize Production Process in Northern Thailand" aims to investigate the energy consumption and carbon emission associated with maize production in Northern Thailand. The study was conducted in three maize production areas in Northern Thailand

Advantages : The study uses a comprehensive Life Cycle Assessment methodology to evaluate the energy consumption and carbon emission associated with maize production in Northern Thailand. The study identifies opportunities for reducing energy consumption and carbon emissions through the use of hybrid maize varieties and integrated pest management practices.

Limitations: The study only focuses on maize production in Northern Thailand, and the results may not be generalizable to other regions or crops. The study does not consider the social and economic aspects of maize production, such as the impact on farmers' livelihoods or the market demand for maize. The study does not include a comparison with alternative crop production systems or practices, which could provide additional insights into the environmental impact of agricultural practices

Paper Details – 7:

Assessment of Emissions with Carbon-smart Farming Practices and Participatory Sensing in Rice, Rushikesh Kulat, Mariappan Sakkan, Prachin Jain, Sanat Sarangi, Srinivasu Pappula TCS Research and Innovation, Mumbai, India. 2022 IEEE Global Humanitarian Technology Conference (GHTC) | 978-1-6654- 5097-3/22/$31.00 ©2022IEEE|DOI:10.1109/GHTC557 12.2022.9910612

Objective of paper, Techniques/Methods: A set of ten selected farmers was split into two groups and asked to follow carbon-smart crop protocols (CSCP) called CSCP-1 and CSCP-2. With the digitally captured record of operations, process modelling was used to simulate the CSCP scenarios followed on the ground, and a classification model was developed to estimate the Nitrogen uptake to improve fertilizer utilization for farmers

Advantages : Improved Accuracy : The model uses participatory sensing to gather data on carbon emissions from rice farming, which can improve the accuracy of emissions estimates. CarbonSmart Farming Practices : The model assesses the impact of carbon-smart farming practices on the emissions reduction. Cost – Effective : The model uses low-cost sensors and mobile technology to gather data Scalability : The model can be scaled up to assess emissions from rice farming across large areas

Limitations: Limited Generalizability: The study focuses on a specific region and type of crop (rice) and the results may not be generalizable to other regions or crops. Data Quality Control: The use of low-cost sensors for data collection may result in inconsistent or unreliable data. Limited Sample Size: The study relies on data collected from a relatively small number of farmers. Methodological Limitations: The model used in the study has several limitations, including the use of simplified emission factors and assumptions about farming practices

Paper Details – 8:

Assessing Impact of Carbon-smart Farming Practices in Rice with Mobile Crowdsensing. Rushikesh Kulat, Mariappan Sakkan, Prachin Jain, Sanat Sarangi, Srinivasu Pappula TCS Research and Innovation, Mumbai, India. 2022 IEEE Region 10 Symposium (TENSYMP) | 978-1-6654-6658- 5/22/$31.00 ©2022 IEEE | DOI: 10.1109/TENSYMP54529.2022.9864 367

Objective of paper, Techniques/Methods: Objective is to explore the use of mobile crowdsensing as a costeffective and efficient tool for assessing the impact of carbonsmart farming practices on rice farms in Vietnam. The paper proposes a methodological framework that combines mobile crowdsensing with machine learning algorithms to collect and analyze data on various carbonsmart farming practices such as AWD, use of organic fertilizers, and reduced tillage. The study aims to assess the impact of these practices on greenhouse gas emissions, soil health.

Advantages : High Accuracy: The hybrid machine learning model achieved an accuracy rate of 90.69%. Robustness: The model is robust and able to handle noisy and incomplete. Flexibility: The model can be easily customized to handle different types of data and variables. Transparency: The model provides a transparent approach to financial distress prediction.

Limitations: Data Requirements: The model requires a large amount of quality data to train effectively Interpretability: While the model provides a transparent approach to financial distress prediction Overfitting: There is a risk of overfitting when using complex machine learning algorithms Implementation: The implementation of the model requires technical expertise and may be time-consuming, particularly when dealing with large datasets.

3. Product Perspective

In Analyzing and Predicting the Control of GHG Emissions from Agricultural Activities using Machine Learning Models, the term "product" refers to a software tool or platform that uses machine learning algorithms to analyze and predict greenhouse gas (GHG) emissions from agricultural activities.

This product's context is rooted in the pressing need to combat climate change and reduce GHG emissions, especially from the agricultural sector, which is accountable for a sizeable portion of global emissions. The product aims to offer a data-driven solution to assist farmers, decision-makers, and other stakeholders in making wise decisions that can reduce GHG emissions and support sustainable agricultural practices. The development of machine learning and other data analytics methods to address environmental problems has sparked an increase in interest, which is where the product's roots can be found. The potential of machine learning models to assess and forecast the effects of various agricultural practices on GHG emissions has been investigated by academics and practitioners in the fields of environmental science and agriculture. This prompted the creation of software tools and platforms that can use machine learning algorithms to offer practical information about GHG emissions from agricultural activities.

3.1. Product Features

- Data gathering and preprocessing: Information is gathered on the various agricultural practices that increase greenhouse gas emissions, such as the use of fertilizer, tillage techniques, and livestock management. the data is cleaned, complete, and prepared for analysis through preprocessing.

- Engineering Features identifies key characteristics, such as crop type, soil type, and weather conditions, that are important for predicting GHG emissions. extracts information that can be used to make decisions from raw data, such as determining the number of farm animals or the total amount of fertilizer used.

- Modeling using machine learning based on the gathered data and engineered features, trains machine learning models to forecast GHG emissions. uses various metrics, such as mean squared error or R-squared, to assess the performance of the models.

- Analyzes and interprets the trained models to determine what factors are most responsible for GHG emissions. identifies opportunities to reduce emissions by analyzing the predictions, such as by changing tillage procedures or fertilizer application rates. Creating reports and visualizations: Produces these to inform stakeholders, such as farmers, policymakers, and researchers, of the analysis' findings and forecasts. enables users to easily explore the data and outcomes by offering interactive dashboards and visualizations.

- This product's overall goal is to assist users in understanding and managing GHG emissions from agricultural activities by revealing the main causes of emissions and highlighting areas where emissions can be decreased.

The flow of working of the software tool will be:

Data Gathering: The software application will be able to gather information from a variety of sources, including weather, soil quality, crop yield, fertilizer use, and livestock productivity. The developer will provide the necessary data collection and the software tool's capacity to retrieve data from outside sources.

Preprocessing of the Collected Data: Any discrepancies, missing values, and outliers will be eliminated during the preprocessing of the obtained data. Data transformation into a format compatible with machine learning algorithms will also be possible with the software application.

Machine Learning Algorithms: The software application will come with a number of machine learning techniques, including neural networks, decision trees, random forests, and linear regression. Using the preprocessed data, the algorithms will be trained to anticipate GHG emissions from agricultural activities.

Model Evaluation: The software application will have the capability of assessing the effectiveness of the machine learning models. Accuracy, precision, recall, and F1 score are the evaluation criteria.

3.2. User Classes and Characteristics

Users are highly technical and have knowledge of both agriculture and machine learning. They might use the item to carry out investigations or tests into GHG emissions and agricultural practices. They need access to cutting-edge machine learning tools as well as the capacity to alter models and features.

Agricultural Consultants: These users are experts in sustainable agricultural management, though they might not have extensive technical knowledge. They might use the item to offer suggestions to farmers or other agricultural stakeholders on how to lower GHG emissions. They need interfaces that are simple to use, reports that are clear and concise, and the capacity to provide their clients with actionable insights.

Producing Farmers: Farmers and other agricultural stakeholders who regularly oversee agricultural operations are known as agricultural producers. They could use the product to track, manage, and improve their own GHG emissions as well as pinpoint areas for development. They need systems with intuitive user interfaces, real-time data access, and the capacity to produce insights that can be put into practice on the farm.

Government officials or other policymakers : who are in charge of policing agricultural practices and overseeing sustainability initiatives are among these users. They might use the item to help them make informed decisions about agricultural and GHG emission policies. They need reports that are clear and concise, the ability to tailor analysis to meet particular policy objectives, and the capacity to produce insights that can influence public policy.

Teachers or other educators : who are in charge of spreading knowledge about agricultural sustainability to the general public or to students make up this group of users. They might use the product to give case studies or examples pertaining to GHG emissions and agriculture. They demand intuitive user interfaces, succinct and clear reports, and the capacity to produce insights that can be simply shared with the public or students.

Overall, the product must be created to satisfy the various requirements of various user classes, with features and interfaces that can be modified to meet the unique needs and specifications of each class.

3.3. Operating Environment

Hardware Requirements

- Pentium IV and above
- RAM 512 mb and above
- Minimum 20 Gb of Disk space

Software Requirements

- Windows, Linux, MacOS or any other OS
- Any Web browser like, Google Chrome, Safari, etc.

3.4. General Constraints, Assumptions and Dependencies

- We are assuming that the user will take necessary precautions to reduce the emission by the estimated rate of decrease.
- The system assumes that the user is any large organization or the policy maker.
- The dataset the model is training on should contain the emission data related to all the different activities of Agriculture.

3.5. Risks

- Collecting the Data and Creating dataset that meets the Project Requirements.
- Building a Decentralized system and integrating federating learning into the project ide

4. Functional Requirements

- A simple User Interface for the user to give their queries describing the symptoms they are experiencing in simple language.
- Prediction of the GHG emission based on the past data values.
- Predicting for Achieving NetZero Emission of GHG

5. External Interface Requirements

5.1. User Interfaces

The interface of Analyzing and Predicting the control of GHG Emissions from Agricultural Activities using Machine Learning Models should have clear and consistent screen formats with GUI standards for styles, providing a user-friendly experience. Simple navigation and standard features like help should be included on the screen layout. An appropriate relative timing for the user's workflow should be used for inputs and outputs. The presence of a programmable function key of some kind could improve user efficiency and experience. In order to help the user fix the problem, error messages should be understandable and offer useful feedback. The interface should also be able to present large amounts of data in an orderly and understandable format, enabling the effective.

Interfaces :

1. A simple interface for the user interaction to take the inputs from the user and give their prediction results and the graphical outputs.
2. An Interface for Predictive system that uses Machine learning models and Displays the Prediction of the Emission rates for the user.
3. An Interface for Analytical model to analyze and display thr results for achieving the NetZero emission of GHG.

5.2. Hardware Requirements

Hardware Requirements

- Pentium IV and above
- RAM 512 mb and above
- Minimum 20 Gb of Disk space

5.3. Software Requirements

Software Requirements

- Windows, Linux, MacOS or any other OS
- Any Web browser like, Google Chrome, Safari, etc.
- Libraries like Pandas, Numpy, Matplot library etc.
- Other ML libraries like Natural Language toolkit, Tensorflow, scikit – learn etc.
- Code editor and IDE's to build the code like Jupyter Notebook, V S code and others.

- Operating System

  An Operating System (OS) is an interface between a computer user and computer hardware. An operating system is a software which performs all the basic tasks like file management, memory management, process management and handling I/O, controlling disk drives and etc.

  Any OS like
  Windows Operating System
  Mac OS
  Linux OS

- Jupyter Notebook

  Jupyter is an open-source project, born out of the IPython Project in 2014 as it evolved to support interactive data science and scientific computing across all the programming languages.

  V6. 5.3 is the latest version available ---- Jupyter notebook

- V S Code

  Visual Studio is a source-code editor made by Microsoft with the Electron Framework, for Windows, and MacOS. Features include support for debugging, syntax highlighting, intelligent code completion, snippets, code refactoring, and embedded Git.

  V 1.75.1 is the latest version available ---- Visual Studio code

- Google Chrome

  Google Chrome is a cross-platform web browser developed by Google. It was first released in 2008 for Microsoft Windows, built with free software components from Apple WebKit and Mozilla Firefox.

Stable Release –

Linux – 101.0.4951.64
Windows – 101.0.4951.67
MacOS – 101.0.4951.64

- Safari

  Safari is a web browser developed by Apple. It is built into Apple's Operating Systems, including MacOS, IOS, and iPadOS. And uses apple's open-source browser engine WebKit, which was derived from KHTML.

5.4. Communication Interfaces

HDMI Cable : for Connecting to External Display
Ethernet Cable : If the Project will be connected to cloud, and needs internet access.

6. Non-Functional Requirements

6.1. Performance Requirement

- Accuracy: The machine learning models must be highly accurate in predicting GHG emissions from agricultural activities. The accuracy of the models must be tested against actual data to ensure that the models provide accurate predictions.

- Reliability: The system must be reliable and consistent in its performance. The machine learning models must be tested under various scenarios to ensure that they are reliable and produce consistent results.

- Robustness: The system must be robust enough to handle large amounts of data and various input parameters. The machine learning models must be able to handle changes in input data and still provide accurate predictions.

6.2. Safety Requirements

Data Security: The data used in the machine learning models must be stored and transmitted securely to prevent unauthorized access and data breaches. The data must be accessible only to authorized personnel. This can be achieved by introducing login with password feature.

Ethical Considerations: The machine learning models must be developed and used in an ethical manner. The models must not be used to discriminate against individuals or groups based on race, gender, age, or other protected characteristics.

6.3. Security Requirements

Authentication requirements, the product should implement a strong password policy, such as requiring complex passwords that are changed regularly.

7. Other Requirements

[Define any other requirements based on your project like Scalability, Maintainability, Portability,etc.]

Appendix A: Definitions, Acronyms and Abbreviations

GHG : Any gas, such as carbon dioxide and methane, that contributes to the greenhouse effect and results in climate change is referred to as a greenhouse gas.

ARMA: Autoregressive + Moving Average. ARIMA: Autoregressive + Moving Average + Trend Differencing.

SARIMA: Autoregressive + Moving Average + Trend Differencing + Seasonal Differencing.

SVM Support Vector Machines

kNN k-Nearest Neighbor

Appendix B: References

[1] Forecasting the Emission of Greenhouse Gases from the Waste using SARIMA Model, Vaishnavi Jayaraman, Saravanan Parthasarathy, Arun Raj Lakshminarayanan, Department of Computer Science and Engineering, B.S.Abdur Rahman Crescent Institute of Science and Technology, Chennai, India. 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI) | 978-1-6654-8328-5/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICOEI53556.2022.9777119

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[3] Carbon Emissions forecasting based on Stacking Ensemble Learning. Quanmao Zhang, Ying Wang, Dongliang Qin, Kailin Zhao, Wanying Xie, Economic Research Institute of state Grid Hebei Electric power company, Shijiazhuang, China. 2022 IEEE 5th International Electrical and Energy Conference (CIEEC) | 978-1-6654-1104-2/22/$31.00 ©2022 IEEE | DOI: 10.1109/CIEEC54735.2022.9845939.

[4] A k-Means-Based-Approach to Analyze the Emissions of GHG in the Municipalities of MATOPIBA Region, Brazil, Lucas Ferreira-Paiva , Attawan G. L. Suela Cardona-Casas , Domingos S. M. Valente, and Rodolpho V. A. Neves , Member, IEEE, IEEE LATIN AMERICA TRANSACTIONS, VOL. 20, NO. 11, NOVEMBER 2022. References

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[7] Assessment of Emissions with Carbon-smart Farming Practices and Participatory Sensing in Rice, Rushikesh Kulat, Mariappan Sakkan, Prachin Jain, Sanat Sarangi, Srinivasu Pappula TCS Research and Innovation, Mumbai, India. 2022 IEEE Global Humanitarian Technology Conference (GHTC) | 978-1-665450973/22/$31.00©2022IEEE|DOI:10.1109/GHTC55712.2022.9910612

[8] Assessing Impact of Carbon-smart Farming Practices in Rice with Mobile Crowdsensing, Rushikesh Kulat, Mariappan Sakkan, Prachin Jain, Sanat Sarangi, Srinivasu Pappula TCS Research and Innovation, Mumbai, India. 2022 IEEE Region 10 Symposium (TENSYMP) | 978-1-665466585/22/$31.00©2022IEEE|DOI:10.1109/TENSYMP54529.2022.9864367