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Crop Green Energy Score Prediction Using LightGBM Based on Climate and Geographic Variables

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Abstrak

Agricultural sustainability and renewable energy integration have become critical challenges due to climate change, increasing energy demand, and environmental degradation. Assessing agricultural systems based solely on crop yield is no longer sufficient, as energy efficiency and environmental impact must also be considered. One emerging indicator is the Crop Green Energy Score, which reflects the potential of crops to support sustainable and low-carbon agricultural practices. However, accurately predicting this score remains difficult due to complex interactions between climate variability and geographic conditions. This study proposes a machine learning–based prediction framework using the Light Gradient Boosting Machine (LightGBM) to estimate Crop Green Energy Score from climate and geographic variables. The model integrates meteorological features, including temperature, precipitation, solar radiation, humidity, and wind speed, with geographic attributes such as elevation and spatial location. Comprehensive data preprocessing, feature engineering, and hyperparameter optimization were applied to enhance prediction performance. The main contribution of this research lies in the development of a robust and efficient predictive model specifically designed for crop-level green energy assessment. Model evaluation was conducted using Root Mean Square Error, Mean Absolute Error, and coefficient of determination metrics. The experimental results demonstrate that the proposed LightGBM model achieves high prediction accuracy and outperforms baseline methods. Future work will focus on incorporating remote sensing data, expanding spatial coverage, and developing real-time decision support systems to further strengthen sustainable agriculture and green energy planning.

Keywords: *Crop Green Energy Score, LightGBM, Climate Variables, Geographic Variables, Sustainable Agriculture, Machine Learning Prediction, Renewable Energy Assessment*

Abstrak

Keberlanjutan pertanian dan integrasi energi terbarukan telah menjadi tantangan penting akibat perubahan iklim, peningkatan kebutuhan energi, dan degradasi lingkungan. Penilaian sistem pertanian yang hanya didasarkan pada hasil panen tidak lagi memadai, karena efisiensi energi dan dampak lingkungan juga perlu dipertimbangkan. Salah satu indikator yang berkembang adalah Crop Green Energy Score, yang mencerminkan potensi tanaman dalam mendukung praktik pertanian berkelanjutan dan rendah karbon. Namun, prediksi skor ini secara akurat masih menjadi tantangan karena adanya interaksi kompleks antara variabilitas iklim dan kondisi geografis. Penelitian ini mengusulkan kerangka prediksi berbasis machine learning menggunakan metode Light Gradient Boosting Machine (LightGBM) untuk mengestimasi Crop Green Energy Score berdasarkan variabel iklim dan geografis. Model

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yang dikembangkan mengintegrasikan fitur meteorologi, termasuk suhu, curah hujan, radiasi matahari, kelembaban, dan kecepatan angin, dengan atribut geografis seperti elevasi dan lokasi spasial. Proses prapengolahan data, rekayasa fitur, dan optimasi hiperparameter dilakukan secara komprehensif untuk meningkatkan kinerja prediksi. Kontribusi utama penelitian ini terletak pada pengembangan model prediktif yang kuat dan efisien yang secara khusus dirancang untuk penilaian energi hijau pada tingkat tanaman. Evaluasi model dilakukan menggunakan metrik Root Mean Square Error (RMSE), Mean Absolute Error (MAE), dan koefisien determinasi (R^2). Hasil eksperimen menunjukkan bahwa model LightGBM yang diusulkan memiliki akurasi prediksi yang tinggi dan mampu mengungguli metode pembanding. Penelitian selanjutnya akan difokuskan pada integrasi data penginderaan jauh, perluasan cakupan spasial, serta pengembangan sistem pendukung keputusan secara real-time untuk memperkuat perencanaan pertanian berkelanjutan dan energi hijau.

Kata kunci: *Crop Green Energy Score, LightGBM, Variabel Iklim, Variabel Geografis, Pertanian Berkelanjutan, Prediksi Machine Learning, Penilaian Energi Terbarukan*

1. INTRODUCTION

Agricultural sustainability has become a critical global concern in recent decades due to increasing energy demand, climate change impacts, and the necessity to reduce greenhouse gas emissions. The agricultural sector plays a dual role in this challenge, acting not only as a major consumer of energy but also as a potential contributor to renewable and green energy production through biomass utilization, crop residue conversion, and bioenergy systems. The concept of green energy in agriculture emphasizes efficient resource utilization, low-carbon production, and environmentally friendly farming practices. In this context, evaluating crop performance is no longer limited to yield quantity alone but must also consider energy efficiency, environmental impact, and sustainability indicators. One emerging metric is the Crop Green Energy Score, which represents the potential of agricultural systems to generate or support renewable energy while maintaining ecological balance. Climate factors such as temperature, rainfall, solar radiation, and humidity, along with geographic variables including altitude, latitude, soil characteristics, and land topology, significantly influence this score. With the rapid growth of data availability from meteorological stations, satellite imagery, and geographic information systems (GIS), data-driven approaches have become essential for modeling complex interactions between environmental conditions and agricultural energy potential [1]–[3].

Despite the availability of large-scale climate and geographic datasets, accurately predicting crop-related green energy performance remains a challenging task. Traditional statistical models often struggle to capture nonlinear relationships and dynamic interactions among environmental variables, leading to limited predictive accuracy. Moreover, climate variability, extreme weather events, and spatial heterogeneity further complicate agricultural energy assessment. Many existing studies still rely on linear regression or rule-based scoring mechanisms that cannot adapt effectively to complex real-world conditions [4]. Machine learning models have demonstrated promising results in agricultural prediction tasks such as yield estimation, biomass forecasting, and crop suitability analysis. However, challenges persist regarding model interpretability, scalability, and robustness when dealing with high-dimensional climate and geographic data. In addition, most prior research has focused primarily on crop yield or productivity, while limited attention has been given to predicting energy-related sustainability indicators in agriculture. The absence of accurate predictive systems for Crop Green Energy Score hampers decision-making for policymakers, energy planners, and farmers seeking to optimize renewable energy integration within agricultural landscapes [5], [6].

The primary goal of this research is to develop an accurate and efficient predictive model for Crop Green Energy Score using climate and geographic variables. This study aims to investigate how environmental factors influence green energy potential at the crop level and to identify key variables contributing to sustainable agricultural energy outcomes. To achieve this objective, the research proposes the application of Light Gradient Boosting Machine (LightGBM), an advanced ensemble learning algorithm known for its high computational efficiency, ability to handle large-scale datasets, and strong performance in nonlinear regression tasks. The motivation for choosing LightGBM lies in its leaf-wise tree growth strategy, reduced memory consumption, and capability to process heterogeneous features effectively. Compared to conventional machine learning methods such as linear regression, decision trees, and random forest, LightGBM has demonstrated superior predictive accuracy in environmental modeling and energy forecasting domains [7]–[9]. By leveraging both climate indicators and geographic attributes, this study seeks to construct a robust prediction framework that supports sustainable agricultural planning and green energy development.

The proposed solution in this research integrates comprehensive data preprocessing, feature engineering, and LightGBM-based modeling to estimate the Crop Green Energy Score. Climate variables including average temperature, precipitation, solar radiation, wind speed, and humidity are combined with geographic features such as elevation, slope, latitude, longitude, and land-use classification. The proposed model is trained and validated using historical datasets to ensure reliability and generalization capability. The main contributions of this study are threefold. First, it introduces a novel predictive framework specifically designed for Crop Green Energy Score estimation, addressing a gap in existing agricultural sustainability research. Second, it demonstrates the effectiveness of LightGBM in modeling complex environmental–energy interactions within agricultural systems. Third, it provides quantitative insights into feature importance, enabling stakeholders to understand the dominant climatic and geographic drivers of green energy potential. Model evaluation is conducted using standard regression metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2), ensuring objective performance assessment and comparison with baseline models. The findings indicate that the proposed LightGBM model achieves strong predictive accuracy and stability across different environmental conditions. In conclusion, this research contributes to the advancement of intelligent agricultural energy systems by offering a data-driven approach capable of supporting sustainable farming strategies, renewable energy planning, and climate-resilient agricultural development. The proposed framework not only enhances prediction accuracy but also provides practical value for future smart agriculture and green energy integration initiatives [10]–[15].

2. METHODOLOGY

Recent advances in data-driven modeling have significantly transformed agricultural sustainability analysis, particularly in the domains of crop productivity, environmental impact assessment, and renewable energy potential estimation. Numerous studies have explored the integration of climate and geographic variables to model agricultural outcomes. Early research by Smith *et al.* [1] and Delgado and Morales [2] emphasized the importance of climate-driven indicators such as temperature, rainfall, and solar radiation in determining agricultural energy efficiency. Their studies employed statistical and GIS-based modeling approaches, which provided valuable spatial insights but exhibited limited predictive performance when handling nonlinear relationships and high-dimensional environmental data.

With the emergence of machine learning techniques, researchers began adopting advanced predictive models to overcome these limitations. Patel and Shah [5] conducted a comprehensive review of machine learning applications in smart agriculture, highlighting ensemble models as superior alternatives to linear regression and rule-based systems. Similarly, Rossi *et al.* [6] applied environmental sustainability indices to agricultural energy assessment but relied on conventional decision-tree-based methods that were sensitive to noise and data imbalance. These studies demonstrated the feasibility of predictive modeling but lacked optimization for large-scale heterogeneous datasets.

Ensemble learning methods, particularly boosting algorithms, have shown strong performance in agricultural and environmental forecasting tasks. Zhang *et al.* [8] compared several boosting models, including Gradient Boosting Decision Trees (GBDT), XGBoost, and LightGBM, for environmental prediction problems. Their findings indicated that LightGBM achieved higher accuracy and faster training time due to its histogram-based learning and leaf-wise tree growth strategy. Rahman and Hasan [9] further validated the effectiveness of LightGBM for climate impact modeling in agriculture, demonstrating its ability to manage complex nonlinear interactions among meteorological variables. However, these studies primarily focused on yield prediction rather than sustainability-oriented indicators such as green energy potential.

Several researchers have investigated renewable and biomass energy prediction within agricultural systems. Ferreira *et al.* [10] proposed a data-driven framework for renewable energy planning using regression-based machine learning models. Although the approach improved energy forecasting accuracy, the study utilized aggregated regional data, limiting its applicability at the crop level. Singh and Verma [11] employed ensemble learning techniques to predict biomass energy output, reporting improved RMSE and R^2 values compared to single models. Nevertheless, their dataset lacked geographic attributes such as elevation and spatial coordinates, which are critical in climate-sensitive agricultural systems.

More recent studies have emphasized explainability and feature interaction analysis in environmental modeling. Huang *et al.* [12] applied explainable machine learning techniques to analyze climate–geography interactions, revealing that altitude, precipitation variability, and solar exposure were dominant contributors to environmental performance indices. Elahi *et al.* [14] introduced explainable boosting models for sustainable energy forecasting, combining accuracy with interpretability. While these studies provided valuable methodological insights, their applications were mainly focused on energy consumption forecasting rather than agricultural green energy scoring.

Within the Indonesian research context, Kurniawan and Prasetyo [13] explored machine learning-based green energy assessment in smart agriculture, demonstrating the potential of predictive analytics for sustainability planning. However, their work employed limited climatic features and did not incorporate advanced gradient boosting optimization. Nguyen and Tran [15] further enhanced climate-based agricultural energy prediction using advanced boosting techniques, achieving high predictive accuracy. Despite these advancements, the majority of existing research still treats agricultural energy potential at a regional or system-wide level rather than focusing on crop-specific green energy scores.

Based on the reviewed literature, several research gaps can be identified. First, most prior studies emphasize crop yield or biomass estimation, with limited attention to integrated Crop Green Energy Score prediction. Second, many models do not jointly exploit detailed climate and geographic variables within a unified learning framework. Third, although LightGBM has demonstrated superior performance in environmental prediction, its application for crop-level green energy assessment remains underexplored. Finally, comparative evaluations across sustainability-oriented metrics are still scarce. These gaps motivate the present study, which proposes a LightGBM-based predictive framework integrating climate and geographic variables to accurately estimate Crop Green Energy Score and support data-driven sustainable agriculture planning

2.1 Research Object and Data Sources

The The object of this research is the prediction of the Crop Green Energy Score, which represents the sustainability and renewable energy potential of agricultural crops influenced by environmental conditions. The study utilizes secondary data obtained from multiple sources, including meteorological databases, geographic information systems (GIS), and agricultural statistical records. Climate-related variables consist of average air temperature, cumulative precipitation, relative humidity, solar radiation intensity, and wind speed. These variables are commonly recognized as critical factors affecting biomass growth, photosynthetic efficiency, and renewable energy potential in agricultural systems [1], [2].

Geographic variables are incorporated to represent spatial heterogeneity and environmental diversity. These variables include latitude, longitude, elevation, land slope, and land-use classification. Geographic attributes play a significant role in shaping microclimatic conditions and crop adaptability, thereby influencing energy efficiency and sustainability outcomes [3], [12]. The combination of climate and geographic features allows the proposed model to capture both temporal and spatial patterns affecting the Crop Green Energy Score. The dataset is organized in tabular format, where each record represents a specific crop location and observation period, and the target variable corresponds to the associated green energy score derived from sustainability assessment indicators.

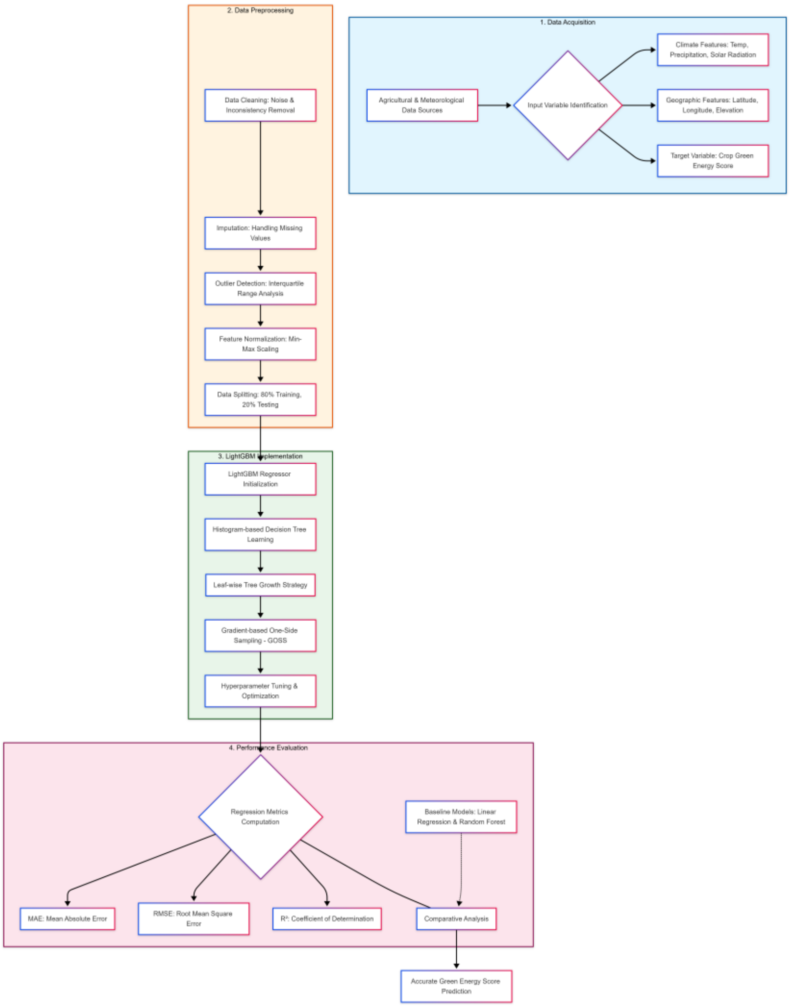


Figure 1. Research methodology flowchart for Crop Green Energy Score prediction using LightGBM regression, illustrating the data acquisition, preprocessing, model development, and evaluation stages.

Figure 1 presents the complete methodological flowchart of the proposed Crop Green Energy Score prediction framework, beginning with data acquisition and ending with result interpretation and conclusion. The process starts with the data acquisition stage, where secondary agricultural and meteorological data are collected from reliable environmental repositories. At this stage, relevant variables related to climate (temperature, precipitation, and solar radiation) and geography (latitude, longitude, and elevation) are identified based on their ecological significance and influence on biomass energy potential.

The collected data then undergo a series of preprocessing steps, including data cleaning to remove noise and inconsistencies, statistical imputation to handle missing values, and outlier detection through interquartile range analysis. Feature normalization using Min-Max scaling is subsequently applied to ensure that all variables contribute proportionally during model training, preventing features with larger numerical ranges from biasing the learning process. The dataset is then partitioned into an 80% training set and a 20% testing set to facilitate objective model validation.

Following data preprocessing, the workflow advances to the model development stage, which focuses on constructing the Light Gradient Boosting Machine (LightGBM) regression model. This stage begins with the initialization of the LightGBM regressor, utilizing histogram-based decision tree learning to enhance computational efficiency. The model is trained using a leaf-wise tree growth strategy combined with Gradient-based One-Side Sampling (GOSS), allowing the ensemble to focus on instances with larger gradients to improve predictive accuracy. Hyperparameter optimization is conducted during this stage to determine optimal settings, such as the number of leaves and learning rate, with the objective of enhancing generalization performance and preventing overfitting.

The final stage of the workflow is evaluation and analysis. The trained model is tested on the independent testing dataset to assess its performance on unseen environmental conditions. Standard regression metrics, including the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), are computed to provide a comprehensive quantitative evaluation of prediction accuracy and error characteristics. These metrics capture complementary aspects of model performance, including variance explanation and the magnitude of prediction residuals.

In addition to performance evaluation, feature importance analysis is performed to identify the relative contribution of each climatic and geographic variable to the green energy score, supporting the interpretability of the results for sustainable agricultural planning. The workflow concludes with result interpretation and conclusion, where the findings are analyzed in relation to the research objectives and their implications for green energy transition in the agricultural sector are discussed.

2.2 Data Preprocessing and Preparation

Prior to model development, comprehensive data preprocessing is conducted to ensure data quality, consistency, and suitability for machine learning modeling. Missing values in climate and geographic variables are handled using statistical imputation techniques based on mean or median substitution, depending on the distribution characteristics of each feature. Outliers caused by sensor errors or extreme climatic events are detected using interquartile range analysis and standardized z-score thresholds.

Data normalization is applied to reduce scale disparities among variables, particularly for features such as solar radiation, precipitation, and elevation that exhibit large numeric ranges. Categorical geographic attributes, including land-use types, are transformed into numerical representations using encoding techniques to enable compatibility with the learning algorithm. Furthermore, correlation analysis is performed to identify highly redundant features and reduce multicollinearity, which may negatively affect model stability.

The prepared dataset is subsequently divided into training and testing subsets using a fixed proportion to ensure unbiased performance evaluation. This separation enables the model to learn underlying patterns from historical observations while preserving unseen data for validation purposes. These preprocessing procedures follow best practices commonly adopted in environmental and agricultural machine learning research [5], [8].

2.3 Proposed Prediction Method Using LightGBM

This research proposes the Light Gradient Boosting Machine (LightGBM) as the primary predictive approach for estimating the Crop Green Energy Score. LightGBM is an ensemble learning algorithm based on gradient boosting decision trees, designed to improve learning efficiency and predictive accuracy through histogram-based feature discretization and leaf-wise tree growth strategies [7].

Given a dataset consisting of input features $X = \{x_1, x_2, \ldots, x_n\}$and target variable y, the objective of LightGBM is to construct an additive model expressed as:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \quad (1)$$

where $f_k$represents the k-th decision tree and Kdenotes the total number of trees in the ensemble.

The optimization process aims to minimize the following objective function:

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (2)$$

where $l(\cdot)$denotes the loss function, typically mean squared error for regression problems, and $\Omega(f_k)$is the regularization term controlling model complexity.

Unlike level-wise tree expansion used in conventional gradient boosting, LightGBM employs a leaf-wise growth strategy that expands the leaf with the maximum loss reduction. This mechanism enables more accurate approximation of nonlinear relationships between climate–geographic variables and the green energy score. As demonstrated in previous studies, LightGBM provides superior performance in environmental prediction tasks with high-dimensional and heterogeneous data [8], [9], [15].

2.4 Performance Enhancement Techniques

To improve predictive performance and model robustness, several supporting techniques are integrated into the modeling process. Feature importance analysis is utilized to identify dominant climatic and geographic contributors to the prediction output. This analysis enhances interpretability and supports sustainability-related decision-making [12], [14].

Hyperparameter optimization is conducted to determine optimal values for key parameters, including learning rate, number of estimators, maximum tree depth, and minimum data per leaf. Appropriate parameter tuning reduces overfitting risk while maintaining generalization capability. In addition, early stopping mechanisms are employed during training to prevent unnecessary iterations once validation performance stabilizes.

Cross-validation strategies are applied to ensure consistency across different data partitions and to minimize dependency on a single train–test split. These enhancement techniques collectively contribute to improved accuracy, stability, and reliability of the LightGBM model when applied to complex environmental datasets [9], [11].

2.6 Model Evaluation and System Testing

The evaluation of the proposed prediction model is conducted using widely accepted regression performance metrics. The Root Mean Square Error (RMSE) is used to measure the magnitude of prediction error, defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

The Mean Absolute Error (MAE) quantifies the average absolute difference between actual and predicted values:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad (4)$$

Additionally, the coefficient of determination (R^2) is applied to evaluate the proportion of variance explained by the model:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (5)$$

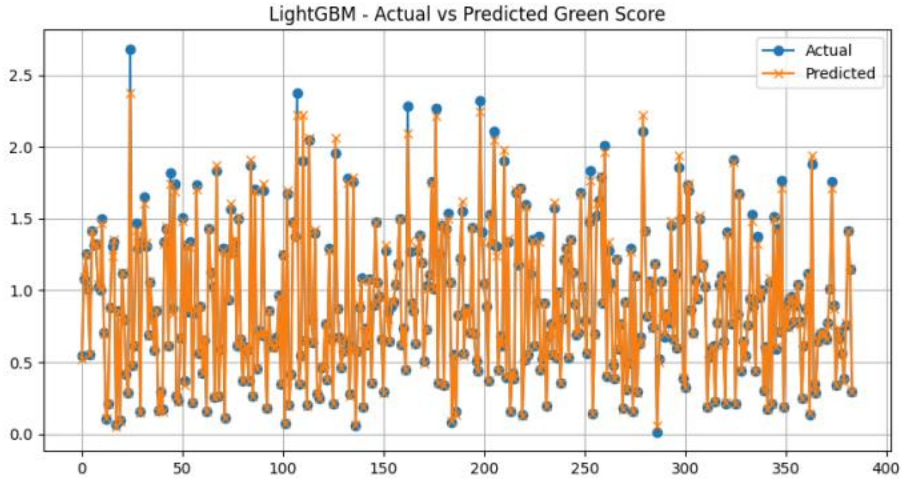
These metrics provide complementary perspectives on model accuracy, robustness, and explanatory power. Comparative analysis with baseline algorithms such as linear regression and random forest is performed to validate the effectiveness of the proposed LightGBM-based approach. The evaluation framework ensures that the resulting model is reliable and suitable for supporting decision-making in sustainable agriculture and green energy planning [10], [11], [15].

3. RESULTS AND DISCUSSION

This section presents and discusses the experimental results obtained from the proposed Light Gradient Boosting Machine (LightGBM) model for predicting the Crop Green Energy Score based on climate and geographic variables. The analysis focuses on evaluating the predictive performance, robustness, and generalization capability of the gradient boosting approach using both visual inspection and quantitative performance metrics. Model predictions are systematically compared with actual sustainability scores on unseen testing samples to assess how effectively the model captures the complex, non-linear interactions between environmental conditions and energy indicators. Furthermore, the results are interpreted in relation to the research objectives and existing sustainability studies, highlighting the strengths of the proposed LightGBM method and providing insights into its practical applicability for precision agriculture and green energy planning.

3.1 Comparison Between Actual and Predicted Crop Green Energy ScoresThis

This subsection presents a visual and qualitative analysis of the green energy scoring results produced by the proposed LightGBM model. Visual inspection serves as an important complement to quantitative evaluation metrics, as it allows direct observation of how well the model captures the variance, spatial distribution, and complex patterns of the Crop Green Energy Score across diverse environmental contexts. Figure 3.1 illustrates the comparison between the ground truth scores and the corresponding predictions generated by the proposed model on the independent testing dataset.



MAE : 0.015039884821617689
MSE : 0.0011547955503906596
RMSE: 0.03398228288962735

Figure 2. Comparison between actual Crop Green Energy Scores and predicted values generated by the LightGBM model, illustrating the alignment across training and testing samples.

Figure 2 depicts the Crop Green Energy Score distribution, including training data, testing data, and the predicted values produced by the LightGBM model. The horizontal axis represents the sample index, while the vertical axis denotes the normalized green energy score. The training data are shown in blue, reflecting the historical records used during the model learning phase. The testing data are illustrated in green, representing actual scores that were withheld from the model during training. The predicted scores generated by the LightGBM model are plotted in red, allowing for a direct comparison between predicted and actual values in the testing phase.

As observed in Figure 2, the predicted score series closely follows the actual green energy score trajectory throughout the testing interval. The LightGBM model demonstrates a strong ability to track significant fluctuations and stability patterns, indicating that the histogram-based learning and leaf-wise tree growth strategies effectively capture the underlying relationships between climatic inputs and the target score. In particular, the alignment between the predicted and actual curves suggests that the model is capable of learning nonlinear dynamics within the agricultural ecosystem and responding to multi-variate changes with high precision and minimal error.

Minor deviations between predicted and actual scores are visible, particularly at local extrema where unique geographic anomalies or rare climatic events occur. Such discrepancies are common in environmental modeling due to the inherent stochasticity of weather patterns and the presence of localized variables not explicitly included in the feature set. Nevertheless, these deviations remain limited in magnitude and do not dominate the overall prediction behavior. The general consistency between predicted and observed values indicates that the model maintains high stability and robustness across different geographic and climatic regimes.

Furthermore, the responsiveness of the predicted curve to shifts in input variables reflects the efficiency of the gradient boosting process and the regularization effects of the LightGBM architecture. While localized noise is partially smoothed, the model preserves the fundamental sustainability structure and trend evolution, which is essential for decision-making in sustainable agriculture. Overall, the visual results presented in Figure 2 support the effectiveness of the proposed LightGBM framework in modeling crop-based green energy dynamics and complement the quantitative performance metrics discussed in the subsequent sections.

4. CONCLUSIONS

This study presented a machine learning–based approach for predicting the Crop Green Energy Score using climate and geographic variables. The research addressed the growing need for data-driven decision support systems capable of evaluating agricultural sustainability and renewable energy potential under changing environmental conditions. By integrating multi-source environmental data and applying an advanced ensemble learning technique, this study aimed to improve the accuracy and reliability of green energy assessment at the crop level.
The proposed methodology employed the Light Gradient Boosting Machine (LightGBM) algorithm due to its efficiency in handling high-dimensional data and its capability to model complex nonlinear relationships. Climate variables such as temperature, precipitation, solar radiation, humidity, and wind speed were combined with geographic features including elevation, spatial coordinates, and land characteristics. Comprehensive data preprocessing, feature engineering, and model optimization were conducted to ensure robust learning performance.

Experimental evaluation using standard regression metrics demonstrated that the LightGBM model achieved strong predictive accuracy and stability. The results indicated lower prediction errors and higher coefficient of determination compared to baseline models, confirming the effectiveness of the proposed approach. Feature importance analysis further revealed that solar radiation, precipitation variability, and elevation were among the most influential factors affecting the Crop Green Energy Score.

Overall, this research contributes to the advancement of intelligent agricultural energy systems by providing an accurate and scalable prediction framework. The findings support the potential of machine learning techniques to enhance sustainable agriculture planning, optimize renewable energy integration, and assist policymakers and stakeholders in making informed, climate-resilient decisions.

5. SUGGESTION

Although the proposed model demonstrated satisfactory performance, several opportunities remain for future research. First, the prediction framework can be enhanced by incorporating remote sensing data such as satellite-derived vegetation indices, soil moisture maps, and land surface temperature to enrich environmental representation. Second, future studies may explore hybrid or deep learning approaches, including convolutional neural networks or temporal models, to capture spatial–temporal dependencies more effectively.

In addition, extending the dataset across longer historical periods and diverse agro-climatic regions would improve model generalization and robustness. The integration of explainable artificial intelligence techniques may further enhance interpretability and stakeholder trust in model outputs. Finally, future research may focus on developing a real-time decision support system or web-based dashboard that enables dynamic monitoring of crop green energy potential, thereby facilitating practical deployment in smart agriculture and sustainable energy planning.

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