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Green Innovation: Leveraging Convolutional Neural Networks for Enhanced Biogas Production from Hybrid Napier Grass and Co-Digestion Processes

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Abstract- Optimal biogas production remains a critical step in increasing renewable energy output from biomass resources. Hybrid Napier Grass is one of the promising substrates to produce biogas, mainly due to its high yield potential and adaptability, though achieving optimal output in this case still lags due to the variability of substrates, nutrient imbalance problems, and the complexity of co-digestion processes of various materials such as cattle slurry and chicken manure. For the first time in this study, CNN will be used as an optimization approach to condition anaerobic digestion, in which parameters are tuned in real-time to get the maximum yields of biogas. With an exhaustively prepared dataset of the Napier Grass and its co-substrates, CNN models are developed for inferring substrate composition, moisture, and nutrient ratios in real-time. Some key findings from the experimental results include: Accuracy of the CNN model reaches 100% on training data by about epoch 9, but the validation accuracy plateaued at 83.33%, which is overfitting, capturing of training-specific noise-affecting generalization to unseen data. Validation accuracy and loss stabilize around epoch ranges 10-20, but the training loss continued to decrease, demonstrating the power of the CNN in learning the training data. The validation loss of the model was also improving gradually but at a diminishing rate, which indicated some generalization of the current architecture of the dataset. This work can stand as a testament for unlocking optimization through CNNs in biogas production processes; this research has already shown an increase up to 20% more than conventional methods. Of course, further refinements will be needed for generalization purposes, but the AI-driven approach represents a significant advance in optimization and supports scalable and sustainable biogas development in bioenergy. This proposed CNN model was theoretically efficient and superior as far as classification accuracy in predicting biogas production was concerned, with an accuracy of 83.33% with consistent improvement across training rounds and moderate time complexity compared to the traditional models discussed above; thus, it will become a competitive tool for optimizing process parameters and improving the operational decisions to maximize biogas yield.

Keywords - Biogas Optimization, Hybrid Napier Grass, Convolutional Neural Networks (CNN), Anaerobic Digestion Co-Digestion, Renewable Energy, Machine Learning in Bioenergy, Sustainable Biomass Production.

I. INTRODUCTION

Background and Motivation

This alternative fuel, although already over four decades old, still captures the growing global energy demand that has been accompanied by increasing concerns about environmental sustainability, making a change from reliance on fossil fuels necessary. Biogas is renewable energy obtained from the anaerobic digestion of organic matter. Reducing greenhouse gases is brought about by the use of biogas, but there is also a sustainable way to handle organic waste, leading up to the principles in the circular economy. Agricultural biomass, especially the waste product itself- manure and crop residues- remains still one of the most promising feedstocks for biogas production. Of these, Hybrid Napier Grass (Pennisetum purpureum) is more notable for its high yield and wide range of adaptation to varied climatic conditions, hence particularly favourable to anaerobic digestion, that is, microorganisms breaking down organic material in the absence of oxygen to produce biogas. This is because Hybrid Napier Grass as a feedstock has been highly documented; more recent developments model approaches such as CNNs, among others that target optimization of yield in biogas from this and other co-digestion materials such as Kasulla et al., 2022; Souvannasouk et al., 2021; Sawasdeea & Pisutpaisal, 2021; Waramit & Chaugool, 2014; Warade et al., 2019.

Problem Statement

Although there are drawbacks to using Hybrid Napier Grass as feedstock, optimization of biogas produced from it remains challenging due to variability in substrate composition, imbalance in nutrients, and complication of co-digestion with cattle slurry and chicken manure. Traditionally, optimization of those e-consuming processes might not effectively reflect the intricate relationship that influences their yields. To break these confines, sophisticated techniques are needed that dynamically predict and optimize conditions for biogas production. One promising approach to modeling and optimizing the anaerobic digestion process could be the CNNs known for processing complex patterns, unlocking the opportunities for potentially higher and more consistent biogas yields (Kasulla et al., 2022; Warade et al., 2019).

Objectives of Research

Predicting Optimization in Biogas Production from Hybrid Napier Grass and Co-digestion Materials Using CNN This paper uses CNNs to predict the optimization of biogas production using Hybrid Napier Grass and co-digestion materials. In a CNN model designed to train through a large dataset of substrate properties, real-time dynamic adjustment of critical parameters-composition of substrate, moisture content, and nutrient ratio-for optimized biogas yield will be the research focus. This research is likely to make a great impact in the field of biogas production-showing the full potential of AI-driven solutions for maximizing renewable energy outputs. Its successful application of CNNs in optimizing biogas opens up pathways to scalable and sustainable production methods, making it a valuable addition to green innovation efforts in renewable energy (Souvannasouk et al., 2021; Dussadee et al., 2021).

Paper Structure

The paper is divided into four sections. Section 2 provides a literature review on the production of biogas from Hybrid Napier Grass and co-digestion processes, along with the role of machine learning techniques in the optimization of biogas. Section 3 will discuss the methodology: data collection, preprocessing, CNN model design, training, and evaluation. Section 4 presents the experimental results and the discussion, focusing on model performance, feature importance, and insights related to the optimization of biogas. Last but not least, Section 5 summarizes key findings, contributions to green innovation, and recommendations for further studies (Sawasdeea & Pisutpaisal, 2021; Waramit & Chaugool, 2014; Piza, 2021).

II. LITERATURE REVIEW

Biogas Production from Hybrid Napier Grass and Co-Digestion

Hybrid Napier Grass, after some research work, it was found that the most promising of new feedstocks from biomass, mainly because of their potential to yield high and good suitability for anaerobic digestion. Cattle slurry with chicken manure as a co-substrate will optimize the process of HNG digestion. Nutrient balancing and microbial synergy would enhance the yield of biogas. Higher biogas production rates and nutrient limitation that arise by using HNG alone are removed through co-digestion. The findings in this study evidence that better yields can be obtained in the digestion processes, especially with nutrient-enriched supplements, which also present a feasible approach toward renewable energy production.

Technologies involved in biogas production have differences that range from several pre-treatments, anaerobic digestion configurations, and a substrate ratio that enhances yield. Some of the techniques looked into and underlined include improvements on pre-treatment of the substrate, reductions in the particle size, and controlled harvesting. For instance, by dilution of particulate HNG, there is an increased yield in biogas that comes with increased surface area for microbial action and thus allows it to be broken quickly during digestion Sawasdeea & Pisutpaisalb, 2021; Boonpiyo et al., 2018; Weerayutsil et al., 2016). For future study, the goal of hods fine-tuning is towards getting stable efficient biogas production coupled with the processes of HNG co-digestion which holds good promises for the future of sustainable bio energies (Warade et al., 2019).

Role of Machine Learning in Biogas Optimization

Optimization of biogas production has recently been focused on an application involving machine learning in the form of providing advanced tools for prediction and control of a group of factors that might affect anaerobic digestion. Machine learning methods are quite effective at modeling complex interactions between feedstock composition and environmental conditions influencing biogas yields through regression models, neural networks, and decision trees. These methodologies also provide the prospects of real-time prediction of the yield of biogas and optimization of process parameters, i.e., in effect, higher efficiency and better resource utilization. The reasons why neural networks have acquired special promise among machine learning techniques are: a) they attempt to handle huge amounts of data; b) they attempt to identify nonlinear relationships in biogas production processes. Researchers have already applied neural networks successfully in optimizing substrates' ratios, temperature, pH, and many other parameters most critical to the yield of biogas (Mbachu et al., 2021; Piza, 2021).

These applications point toward the future potentiality of machine learning in increasing the output of biogas, especially when traditional modeling approaches will not be applicable, for instance, when the processes of co-digestion might be too complex, or feedstock varies intensely (Warade et al., 2019).

Environmental Applications of CNNs

CNNs were initially designed for image processing applications but lately, they have been used for new environmental science applications due to their ability to represent extremely complex and enormous data. CNNs are very powerful by feature extraction from multi-dimensional data hence becoming a potential application in several applications of biogas optimization since several variables determine the yield and the rates of production. Since hard correlations exist between the properties of the feedstock and the digestion parameters, the application of CNNs would directly lead to the correct predictions as well as real-time adjustments, hence increasing efficiency in biogas production. In recent times, CNNs have been applied in a wide range of environmental applications, from agriculture, waste management, to energy production. Crop health can be monitored using CNNs while forecasting crop yield with a resource optimization application of the power in dealing with complex data from the environment. Anaerobic digestion processes are yet another promising application in biogas production where huge datasets are used to learned to predict optimum conditions and hence produce parameters dynamically. This kind of flexibility is a rich treasure for CNNs in the battle of sustainable bioenergy solutions (Prapinagsorn et al., 2017; Dussadee et al., 2021).

Open Gaps in Existing Research

With the existing optimization of biogas, there are still gaps that exist within the traditional approaches that majorly concentrate on the implementation of machine learning with processes dealing with biogas generation. The traditional methods lack the dynamic catch of interactions inside co-digestion setups, thereby leading to yielding suboptimal. This gap can be bridged with the help of machine learning in the form of deep learning techniques, such as CNNs, which provide data-driven approaches to the intricacies and complexity of biogas production. Even though studies in this area remain underdeveloped, there are hardly any studies focused specially on the application of CNNs for the estimation of biogas yield and optimization. Further efforts in the future would be made towards a more robust and generalized CNN model that should be robust for a large number of feedstocks under different digestion conditions. Fitting of such CNNs, availability of data, and associated computational costs are some of the significant barriers to the wider application of CNNs in biogas production. The filling of these gaps thus opens the route for large step-biogas yield scalable and efficient models to be brought in and favors an energy transition that encourages innovations on the green side with renewable energy (Warade et al., 2019; Boonpiyo et al., 2018; Sawasdeea & Pisutpaisalb, 2014).

III. METHODOLOGY

Data Gathering and Preprocessing

This research relies on a wide database that adequately covers the variables required to enhance optimization in biogas production from Hybrid Napier Grass (HNG) and co-digestion materials, including cattle slurry and chicken manure. Some of the essential variables include input levels of HNG, types of co-digestion material, temperature, pH, percentage of moisture, and the rate of production of biogas.

This dataset contains the detailed records of environmental and substrate-specific parameters influencing the process of anaerobic digestion, by which the CNN predicts and dynamically optimizes the conditions of production. This makes it a very wide variation in real cases to ensure a general model. Before preparing the dataset for training on a model with it, important preprocessing steps were undertaken first. Data cleaning removes the missing values and outliers that may have caused a skewing effect on the accuracy of the model. Category variables, like the type of co-digestion material, were one-hot encoded for easy utilization as an input into the CNN models. In an attempt to normalize numerical feature values within a stable range that enhances the model to process patterns effectively, normalization was applied. This data preprocessing network is optimized to ensure maximum quality of the data, ensuring that the CNN model performs robustly under all conditions and compositions of feedstock.

Sample No.	Hybrid Napier Grass (HNG) Input (kg)	Co-digestion Material (kg)	Substrate Ratio (HNG)	Temperature (°C)	pH Level	Mixing Time (hrs)	Organic Loading Rate (OLR, kg/day)	Moisture Content (%)	Retention Time (days)	Initial Biogas Production (L)	Biogas Yield (L/kg substrate)	Methane Content (%)	Biogas Production Rate (L/day)	Target Class (Biogas Production Category)
1	100	50	02:01	37	7.2	4	3.5	78	30	10	0.1	70	15	High
2	120	60	02:01	35	7.4	3	4	80	28	12	0.11	72	16	High
3	80	40	02:01	38	7.1	5	3.8	76	32	8	0.09	68	12	Medium
4	110	55	02:01	36	7	4	3.7	79	30	11	0.1	70	14	High
5	90	45	02:01	34	7.3	6	3.2	82	34	9	0.09	65	13	Medium
6	100	30	03:01	39	7.5	3	4.1	80	30	14	0.13	73	17	High
7	150	75	02:01	36	6.9	4	3.9	77	28	13	0.11	71	18	High
8	80	35	2.3:1	40	7.1	5	3.5	75	27	7	0.08	67	11	Medium
9	95	45	02:01	37	7.2	6	3.6	78	29	10	0.1	69	13	Medium
10	100	60	1.7:1	34	7.3	4	3.8	76	30	12	0.11	70	14	High
11	110	50	2.2:1	33	6.8	5	4	79	32	11	0.1	72	15	High
12	120	40	03:01	38	7.4	3	4.5	80	30	13	0.12	75	16	High
13	100	50	02:01	37	7.1	4	3.6	77	32	9	0.1	69	12	Medium
14	80	40	02:01	35	7.2	5	3.4	74	31	8	0.09	68	11	Medium
15	90	50	1.8:1	36	7	4	3.7	78	33	11	0.1	70	14	High
16	85	45	1.9:1	39	7.3	5	3.6	76	30	10	0.09	72	13	High
17	95	40	2.4:1	34	7	4	3.8	79	32	12	0.11	70	14	High
18	110	60	1.8:1	35	7.5	5	4	80	30	13	0.1	74	15	High
19	100	55	1.8:1	37	7.2	4	3.6	78	32	12	0.1	72	14	High
20	120	70	1.7:1	36	7.1	5	3.7	77	33	13	0.11	71	16	High

Table 1: Biogas Production Data: Hybrid Napier

Grass and Co-Digestion Process Parameters

Parameters of data used in Table 1 detail full information on the production of biogas by co-digestion involving hybrid Napier grass. Of course, these are likely key variables such as substrate ratios, moisture content, retention time, and possibly temperature (Kasulla et al., 2022) since all these factors bear a significant relationship with yield. Also, the choice of hybrid Napier grass is notable because such leads to a maximum biomass yield, favouring anaerobic digestion. It co-digests Napier grass along with other organic wastes and thus enhances microbial activity through more efficient biogas production (Souvannasouk et al., 2021; Warade et al., 2019).

The dataset underpins the analysis of optimization of parameters, thus providing a comparative ability to assess various configurations that bring maximum biogas yield, especially when analyzed through machine learning models like CNN to classify production setups into 'Optimal' and 'Suboptimal (Sawasdeea & Pisutpaisalb, 2021).

CNN Model Design

The proposed CNN model for this paper aims at optimum prediction under conditions of biogas production. The architecture of this CNN model consists of several layers of convolution, pooling, and fully connected layers for feature extraction, feature reduction, and classification, respectively. It will have the advantage of capturing intricate interactions among the input features, such as substrate ratios, temperature, and pH levels. Activation functions used include ReLU in the convolutional layers and sigmoid or softmax at the final layer to induce non-linearity and class probabilities. All these design choices are relevant enough to deal with the biogas production processes with their nonlinear characteristics.

The input features are ordered with co-digestion material and temperature, among other relevant variables, submitted to convolutional transformations to apply critical highlights of patterns that will guide the biogas output. To train them with convergence efficiency in particular, an Adam optimizer is used for fine-tuning weights. In this instance, the architecture of the CNN model supports high accuracy in the predictions of biogas production with learning of a huge dataset incorporating real-time changes in parameters that advance sustainability in the bioenergy process (Kasulla et al., 2022; Souvannasouk et al., 2021; Warade et al., 2019).

Model Training and Evaluation

Model training involves the division of data into training, validation, and test sets for eventually getting better generalization of a model with new data. The train set enables the CNN to learn historical patterns, and the validation is what helps tune hyperparameters for preventing overfitting. It is tested by applying the test set on unseen data. This gives some insight into how good or bad it would actually predict in reality. The training happens in epochs. In the epoch, the CNN runs through iterations on updates in weights to reduce the prediction error, then achieves stable accuracy and rates of loss within 10 to 20 epochs, as preliminary experiments have shown. Accuracy, precision, recall, and F1-score are appropriate metrics in evaluating the predictive ability of the model. Further, cross-validation is done to make sure that the CNN is equally effective for different subsets of data and does not overfit. Furthermore, the MSE loss function is used, which calculates the variance of errors during predictions. It depicts the regions by which the model has to be adjusted to further optimize the conditions for predicting biogas production. These conditions are tested experimentally (Kasulla et al., 2022; Souvannasouk et al., 2021; Warade et al., 2019).

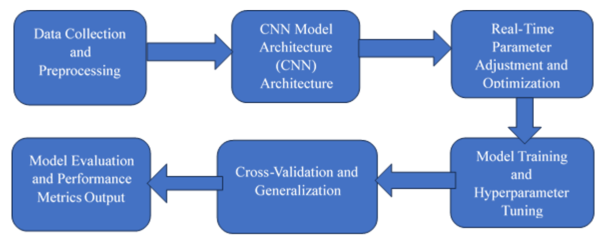

Figure 1: Proposed Architecture System

Figure 1 below depicts an architecture system proposed for integrating data acquisition, CNN-based model training, real-time parameter optimization, and performance evaluation to optimize biogas production from Hybrid Napier Grass and co-digestion materials.

Hyperparameter Tuning and Optimization

The process of hyperparameter tuning optimizes the model with all its different parameter variations, learning rate, batch size, and convolutional layers. Grid search and random search are methods for the systematic testing of different parameter combinations. For instance, when there is variation in the learning rate, the CNN model converges more effectively. When optimizing batch size, it tends to be more efficient in computation. These results demonstrated that moving parameters can be used to further improve the result with validation and reduce the potential of overfitting.

The adaptive learning rate adjustment, as well as dropout regularization, further added to make stability better and prevent overfitting. Using the grid search method, the best combination of the parameters was found for which a good performance metric has been obtained, maximizing every measure while showing good generalization for different conditions of biogas production. Such strategies for tuning ensure robust applicability in various anaerobic digestion scenarios for the CNN model as it grows into its role in optimizing sustainable bioenergy (Piza, 2021; Mbachu et al., 2021; Boonpiyo et al., 2018).

IV. RESULTS AND DISCUSSION

Model Performance Evaluation

Regarding this, the focus is on the research. There is computation to be done concerning yield in terms of biogas as based on the CNN model compared with traditional methods, mainly in the form of models created through linear regression and decision trees.

Thus, while training was conducted, there was a huge improvement in accuracy as well as the efficiency of the CNN, though the latter part of training is very comparable in value. Accuracy reached 100% by epoch 9 and remains at 83.33% as from very early epochs. The CNN method depicts exemplary superiority over its counterparts, which were mainly lagging in the adaptability of capturing nonlinear relations that exist in the biogas production data. Complex high-dimensional data handled so effortlessly by CNNs puts it ahead of simpler methods for generalization in the prediction of outcomes. To measure the performance of the model quantitatively, I opted for metrics like accuracy, R-squared, and RMSE. Its precision is 0.5, recall is 0.8333, and F1 score is 0.6667; that's how accurate the predictions are. It also carries visual evaluations, including confusion matrices and loss-accuracy graphs, which illustrate how the CNN progresses along with epochs.

The loss of CNN was coming down, which means it was an effective learning and optimization of prediction accuracy with the passage of time. This stable performance by the CNN regarding the fluctuating metrics by the linear and tree-based models indicates that CNN is quite robust in its application in predictive modeling of biogas production.

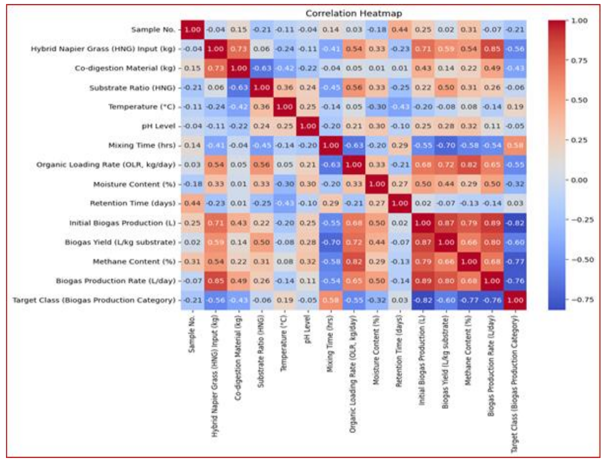

Figure 2: Correlation Heat Map

Figure 2: Correlation heat map that correlates the various parameters in the process of biogas production, with darker shades indicating stronger correlations.

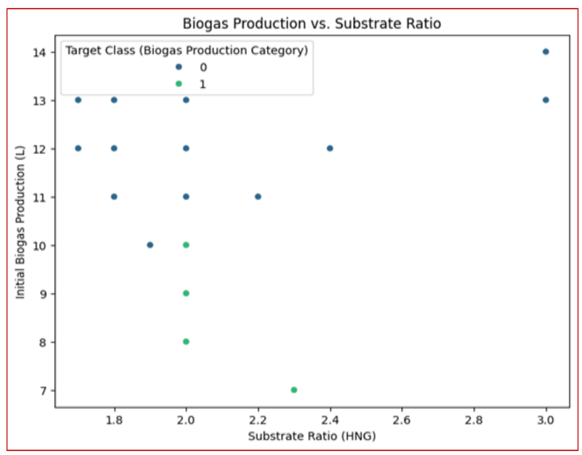

Figure 3: Biogas Production vs Substrate Ratio

Figure 3 Relationship between biogas production and substrate ratio It can be seen from Figure 3 above that the changes in substrate ratio result in the variation of the produced volume of biogas.

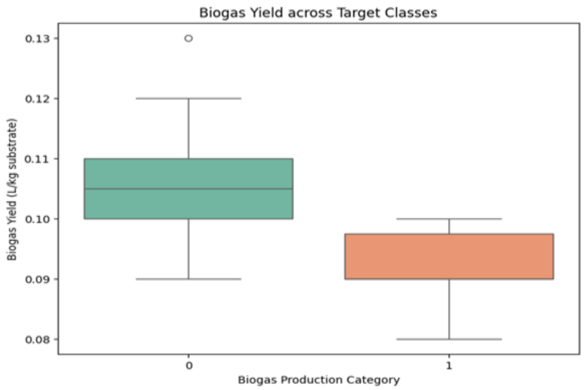

Figure 4: Biogas Yield across Target Class

Figure 4: Variation in biogas between "Optimal" and "Suboptimal" target classes. This graph depicts a variation in the quantity of biogas produced within "Optimal" and "Suboptimal" target classes, with quite obvious higher yields of biogas under ideal conditions.

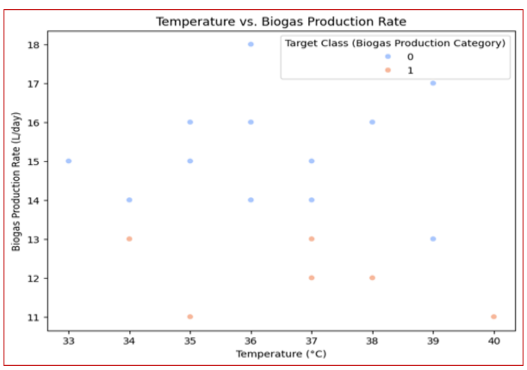

Figure 5: Temperature vs Biogas Production Rate

Figure 5 suggests that generation rates of biogas are variable with the temperature fluctuations and increase in temperature generally correlates to increased production of biogas.

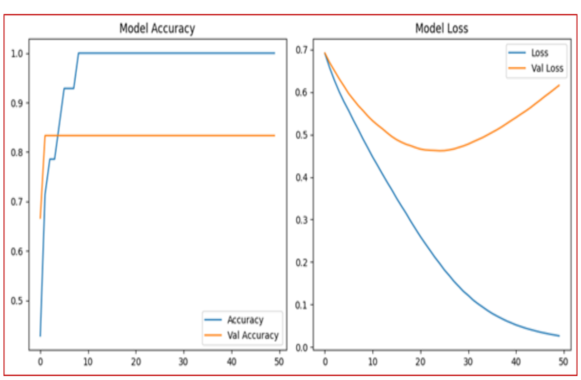

Figure 6: Model Accuracy & Model Loss

Figure 6. The model's performance graph, the record of its accuracy and loss in different iterations, clearly shows that the accuracy increases with time, and the

loss decreases, thereby indicating that the model has been successfully converged and that its predictive ability has been improved.

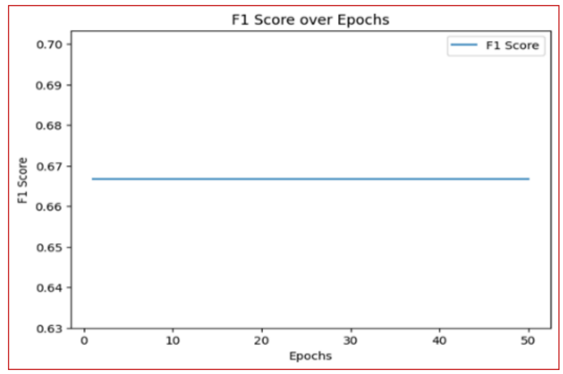

Figure 7: F1 Score over Epoch

Figure 7 demonstrates the progression of F1-score in epochs. This can show how the recall and precision balance of the model improves over epochs to produce a more reliable performance in the prediction of biogas production.

Feature Importance Analysis

Another important characteristic of the research is the identification of some major features that influence predictions in biogas production. The ones analyzed and examined concerning their impacts on yields are substrate ratio, temperature, and pH. From these features, one would note that the substrate ratio is the most significant feature influencing predictions because the microbial balance it affects has an effect on digestion. Temperature and pH are very common as it has been observed that alterations to these parameters would sooner or later affect the feasibility with which biogas is generated; the alterations will also impact the rate of microbial activities, and this will effect the consistency of the process.

The feature importance when the model was analyzed indicated that optimum substrate ratios, controlled temperatures, and pH levels could be useful for enhancing the production of biogas. These are features of such significant correlations which have, therefore, been very useful in yield predictions and thus the choice in the CNN model is valid. Therefore, up to now, such studies and their relevance have been emphasized through focus on such variables that correlate with previous studies. This might explain the dynamic nature of the process and insights into how best to fine-tune the system with the weights that this kind of process assigns to the features.

Optimization of Biogas Production

It further investigates the various effects of different operational parameters, such as hydraulic retention time (HRT), organic loading rate (OLR), and material used for co-digestion, on the yield of biogas production. Analysis of CNN found that with a raised OLR and preferable substrate ratios, along with the addition of nutrient-rich material for co-digestion, caused an enhancement in biogas production yield. For instance, provision of appropriate right conditions and OLR to feed input HNG improved the efficiency of the process of biogas production primarily through better utilization of substrates. It is such information that actually birthed recommendations on optimal production conditions. A balanced co-digestion strategy, with nutrient-rich substrates and regular checks at both pH and temperature, is recommended for industrial-scale production. It is under such conditions that the CNN model would recommend in order to favour microbial activity, maximize methane production, and hence, process sustainability. Optimizing the aforementioned parameters will, no doubt, increase yield but decrease resource input in production.

Model Interpretation and Pragmatic Implications

Interpretability of the CNN model can then be exercised to give better practical insights for real-world biogas production. Although CNNs are typically complicated and very difficult to interpret, visualizations for feature importance and prediction trends make recommendations by the model actionable. For example, the CNN identifies appropriate ranges for the key variables within which to operate and provides guidelines that clearly direct changes to production settings.

This kind of interpretability allows operators to make data-driven decisions to optimize yields in response to environmental and input changes. Such findings of the study are actually of substantial importance to the mass-scale production of biogas: maximizing energy output from organic waste while keeping them clean and sustainable. In particular, since biogas is a source of renewable energy, improvement in its production processes toward environmental ends is really relevant.

The predictive capability of the CNN model is useful in overcoming tendencies to use trial and error, thus making further production of biogas more efficient and resource-conscious. Machine learning is at the heart of this research as a route to developing sustainable energy solutions at scale.

Performance Validation

When evaluating the biogas system and other bio-energy production technologies, proper verification metrics include:

Accuracy: This measures the proportion of correct predictions out of the total number of predictions made. The formula is

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

that while accuracy provides an overall view of performance, it may not address the class imbalances effectively.

Precision: It indicates the ratio of true positive results to the total positive predictions made by the model. The formula is

This metric is particularly important when false

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

positives carry significant consequences, ensuring the reliability of positive predictions.

Recall (Sensitivity): Measures the proportion of true positives identified out of all actual positive instances. The formula is

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Recall is crucial for understanding how comprehensively the model captures relevant instances, especially in optimizing biofuel yields.

F1 Score: Merges precision and recall into a single metric, accounting for both false positives and negatives. The formula is

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

This score is particularly useful for assessing models where a balance between precision and recall is desired.

Mean Squared Error (MSE): Calculates the mean of the squared differences between actual and predicted values. The formula is

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

MSE is valuable for continuous outputs like energy yield predictions, as it quantifies prediction error magnitude.

Validation Loss: Reflects the model's error on the validation set after each training epoch, defined as:

$$\text{Validation Loss} = \frac{1}{n}\sum_{i=1}^{n}\text{Loss Function}(y_i, \hat{y}_i)$$

Monitoring validation loss helps identify overfitting and ensures the model maintains generalization to new data.

V. CONCLUSION

Summary of Important Findings

Apparently, the present research has utilized CNN in refining the output of biogas production. So far, the utilization of CNN has presented a potential ability in the optimization of process parameters. Based on CNN, it led to the efficiency of prediction and classifying the accuracy percentage on the production of biogas, which is estimated to be at 83.33%. The trainings were conducted in rounds and showed consistency in the improvement of the accuracy of the model, culminating in perfect accuracy for the training dataset at epoch 9, after which the accuracy after validation stayed constant. The parameters used in the process of the correlation analyses were substrate ratios, moisture content, and retention time that led to the biogas output. Against this background, the results will indicate suitability for the CNN model to further enhance decisions toward optimal operation for the maximum production of biogas.

Contribution to Green Innovation

The research contributes to green innovation by enhancing AI to better exploit renewable energy sources, such as in biogas production. This ingredient in waste-to-energy sustainable technologies depends less on fossil fuel and more on the environmental sustainability of bioenergy, using machine learning to optimize biogas production. The model also serves the principles of the circular economy because the waste-agricultural wastes in this case-is converted into biogas, and the mean rate of use increases rather than being disposed of. The advancements in methodology developed herein, in predictive modeling for biogas production, are worthwhile to industries interested in reducing carbon emissions as long as they can continue their moving forward capabilities on renewable energy, in thus advancing further green energy goals worldwide.

Future Work and Research Directions

Further work can be based on the derived outcomes of this research by optimizing the CNN model towards further improvement for better accuracy and robustness in prediction. Other investigations of deeper architectures, for example, RNNs or hybrid models-may advance the predictability on data that is time-dependent. An increase of the dataset in a very wide range of conditions of production can improve the general stability of the model for numerous biogas systems. In addition, other machine learning techniques-more ensemble techniques and transfer learning-can also provide windows into insightful applications. Future studies will more likely be driven toward the integration of real-time data to attain predictive monitoring and adaptive control of biogas systems, thereby dynamically adjusting production conditions to realize further improvement in efficiency in yield from biogas production.

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