https://africanjournalofbiomedicalresearch.com/index.php/AJBR
Afr. J. Biomed. Res. Vol. 28(2s) (February 2025); 601-618
Research Article

Harnessing Convolutional Neural Networks for The Optimization of Anaerobic Digestion of Sugarcane Bagasse: A Novel Approach to Pretreatment Strategies and Microbial Activity Prediction

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Abstract:
This paper is aimed at verifying the effectiveness of CNN in optimizing anaerobic digestion with sugarcane bagasse, considering the enhancement of strategies for pretreatment and accurate prediction of microbial activity and biogas yield. The primary objective of this research work is to increase the utilization efficiency of anaerobic digestion systems along with boosted biogas production using convolutional neural networks for better forecasts and optimizing procedures. This paper discusses the prediction of microbial activity and biogas from the anaerobic digestion of sugarcane bagasse using convolutional neural networks. The experiments conducted here are similar to studies that have studied various types of feedstock pretreatments, such as AFEX, steam explosion, and alkaline treatments. Different architectures of CNNs are trained with feedstock characteristics, process operational parameters, and conditions-related information to predict the output of biogas production (Olatunji et al., 2021; Sharma et al., 2023). This also verifies that CNNs outperform classical machine learning models and algorithms, such as SVMs and regression, in the prediction of the biogas yield from sugarcane bagasse at an accuracy of 92% and F1 score of 0.90. It accurately assesses the pretreatment methods, temperature, and operational conditions that have a considerable impact on biogas production. This is an embodiment of AI in making it possible to improve predictability and optimize biogas production processes (Parvane et al., 2022; Gao et al., 2022). A work analysis revealed that CNNs enhance the anaerobic digestion process of sugarcane bagasse by improving better and more accurate forecasting abilities in comparison to the traditional models while handling complex data. Follow-up research studies about follow-up hybrid AI models to amplify further the role of AI in real-time monitoring and optimization of biogas production for sustainable bioenergy solutions may focus on large-scale industrial applications of such models (Blasi et al., 2023; Malik et al., 2020).

Keywords: Neural Networks (CNN), Anaerobic Digestion (AD), Sugarcane Bagasse, Biogas Production, Pretreatment Methods, Microbial Activity Prediction, AI in Bioprocess Optimization, Hybrid AI Models

Received:24/01/2025 *Accepted: 08/02/2025*

DOI: https://doi.org/10.53555/AJBR.v28i2S.6890

1. Introduction

1.1Background

Sugarcane bagasse is the most readily available lignocellulosic biomass, being a by-product from the sugarcane industry, and is now increasingly considered as feedstock for AD. Anaerobic digestion is defined as the biological process where microorganisms decompose organic material to transform biogas in an anoxic environment. The lignocellulosic material of sugarcane bagasse has its composition mainly of cellulose, hemicellulose, and lignin; hence, it is not easily digestible. Although excellent scope is going to be offered by the carbohydrate-rich content of this for the production of biogas, taking global energy demand into account and with an intent to maintain wastes as part of principles of sustainable processes, optimization in the process of anaerobic digestion on sugarcane bagasse has become increasingly important. This volume of production of biogas from sugarcane bagasse converts biomass into energy; a process that reduces waste material, increases production of bio-energy, and works towards the changeover to greener sources of energy in the world. This biogas, despite its many benefits, characterizes several challenges that define this towards the optimization of digestion of anaerobic lignocellulose such as bagasse. The main challenges arise from the complexity of lignocellulose, requiring effective pretreatment methods that would demilitarize the rigidity of the cell wall for microbial degradation. While conventional pretreatments, steam explosion, alkaline, and acid treatments enhance the yields of biogas, these operations are input-intensive with variation in effectiveness depending on the nature of the type of biomass feedstock and conditions for treatment (Sharma et al., 2023). The predictability of what microbial activity will behave in anaerobic digestion probably constitutes the biggest challenge in this regard because microbial communities are rather complex entities that will act according to a myriad of variables, including temperature, pH, and even substrate composition. Accurate prediction of microbial dynamics is critical for improvement toward maximum biogas production and stability of the anaerobic digestion process (Pradhan et al., 2022).

1.2Research Problem

Conventional optimization methods of anaerobic digestion processes are very inflexible and take into account neither the dynamic nor complex nature of microbial activity nor effects of pretreatment variability. In the traditional approaches, complicated interrelations among process variables, microbial communities, and biogas production are not explicitly identified. Such approaches mainly result in poor performance, and therefore, there is a growing need for more advanced computational models to serve in the better prediction and optimization of AD systems. Convolutional Neural Networks, with their characteristics of detecting complex patterns in large datasets by a family of machine learning models, hold much promise to fill this gap. CNN can be used in the development of predictive models that take into account the nonlinear and interacting variables governing microbial dynamics and biogas production. The behavior of microbes in a more accurate way can be predicted, and the process of AD can be optimized with higher efficiency by training CNNs based on the experimental data (Gao et al., 2022; Parvane et al., 2022). The greatest challenge remains in developing trustworthy, data-driven models that could improve pretreatment tactics as well as predict the activity of microorganisms under various conditions. While CNNs have been demonstrated for some applications in biotechnology, they have not been explored widely in optimizing processes for anaerobic digestion, particularly the potential of such microorganisms for processing lignocellulosic biomass such as sugarcane bagasse. A new entree in optimizing AD lies through the introduction of CNNs, eliminating the weaknesses of a traditional model, and making prediction values higher to control such processes. It bridges such a gap in the case of this study work using CNN to predict microbial activity and biogas production through improved efficiency and scalability of the process of anaerobic digestion on sugarcane bagasse, respectively (Pradhan et al., 2022; Malik & Kasulla, 2020).

1.3Research Objectives

From the above, the key point of this research relates to advanced pretreatment techniques on sugarcane bagasse via the use of Convolutional Neural Networks. Several pretreatment methods have been proposed for bagasse, including alkaline, steam explosion, and AFEX. Such treatments impact feedstock composition and digestibility. Therefore, the study applies CNNs to find the most favourable conditions for other pretreatment methods of biogas conversion efficiency from sugarcane bagasse. Using this model, prediction based on experimental data regarding the best pretreatment strategies to improve yield of biogas, reduction of energy consumption, and cost-cutting becomes possible. CNNs can effectively handle and process complex data sets, and therefore are suitable for the intended task of outcome prediction based on the nature of input variables in a dataset, such as temperature, pH, and pretreatment type (Sharma et al., 2023; Gao et al., 2022). The overall objective is to establish predictive models that would predict microbial activity and biogas production in anaerobic digestion with sugarcane bagasse. This calls for evaluation at different stages of the behavior of the microorganisms in optimizing the digestion process and ensuring consistent production over time of biogas. In the projection, the model can predict the evolution of microbial communities in anaerobic digestion based on diversified process parameters, such as type of inoculum, feedstock attributes, and environmental conditions. This would improve monitoring and controlling of the process through stable operation of the anaerobic digestion process and uniform biogas production. The application of CNNs within this context forms an emerging approach to the prediction of microbial activity. Its performance is supposed to be superior compared to that of classical statistical methods for implementing the optimization tool for process operation in an adequate as well as loose manner (Pradhan et al., 2022; Kamperidou & Terzopoulou, 2021).

1.4Research Significance

This study is likely to revolutionize the optimization of biogas yielded from sugarcane bagasse. Aimed at increasing yield and reducing operating costs and energy consumption of conventional pretreatment through the use of CNNs to predict microbial activity and optimize pretreatment strategies, such an approach may influence the anaerobic digestion process in terms of efficiency and cost-effectiveness, a step necessary for scale-up bioenergy production to industrial levels. Practically, machine learning models, such as CNNs, can be applied to the anaerobic digestion process for a new understanding of the dynamics of microbial communities involved in biogas production. This will eventually make AD systems more stable and flexible for a variety of feedstocks and operational parameters (Olatunji et al., 2021; Sharma et al., 2023). Beyond improving the optimization of biogas production, the research impacts largely within the bioenergy framework. The research thereby gave rise to data-driven models representing predictions on the yield and activity of microbes in given systems, making real-time monitoring and optimization of anaerobic digestion systems scalable with AI. Such advancements will facilitate a transition toward more sustainable and efficient practices for bioenergy, especially waste-to-energy technologies. The efficient integration of CNNs into AD optimization would potentially set a new standard for AI usage in bioprocesses; this would support the world to produce more sustainable bioenergy (Pradhan et al., 2022; Malik & Kasulla, 2020).

2. Literature Review

2.1Anaerobic Digestion of Lignocellulosic Biomass

The recovery of biogas through the anaerobic digestion of lignocellulosic biomass, including that from sugarcane bagasse, is widely accepted as a favourable technology of renewable energy. The composition of lignocellulosic biomass is primarily cellulose, hemicellulose, and lignin, which abound in quantity and are inexpensive. However, the composition remains complex with difficulty in biodegradability; this creates a challenge toward biodegradability, which becomes unfavourable for successful biogas production. Anaerobic digestion is a microbial-mediated degradation process that converts organic matter into methane. However, the presence of lignin degrades the rate of degradations most of the time and coupled with the recalcitrant nature of cellulose. Today, it has been realized that the physical and chemical characteristics of feedstock highly influence the efficiency of AD (Kamperidou & Terzopoulou, 2021; Malik & Kasulla, 2020). These challenges call for a synthesis of optimized pretreatment techniques and much more sophisticated models that would further predict microbial dynamics and enhance biogas production. The biggest challenge in the anaerobic digestion of lignocellulosic biomass is the efficient degradation of cellulose and hemicelluloses as a means to break the barrier created by lignin. Lignin encases cellulose fibers with a protective envelope that prevents it from accessing the digestive enzymes of microbes. This means that slow reaction rates and a low yield of biogas will be observed. Researchers are still working on the development of better pretreatment techniques, on the idea of transforming lignocellulosic biomass into a more degradable form by microbes. In this case, optimizing pretreatment processes combined with workable models for predicting the microbial activity would lead to enhanced overall performances of the anaerobic digestion process, as postulated by Kamperidou and Terzopoulou (2021) and Malik and Kasulla (2020). The microbiology of the process of anaerobic digestion resulted in it needing to be understood in optimization for optimum operational conditions that would be effective for better production of biogas.

2.2Pretreatment Methods for Sugarcane Bagasse

Pretreatment of sugar cane bagasse is considered an important process in the upgrading process of the bio-degradability of sugar cane bagasse during anaerobic digestion. It is researched by three separate methods, namely, chemical, physical, and biological ones that break its natural lignocellulosic structure. Acid or alkaline treatment in chemical pretreatment could adequately degrade hemicellulose and advance the accessibility of cellulose to microbiota. Other physical treatments include steam explosion and mechanical milling, which involves grinding that reduces particle size and hence its surface area-this favors microbial access. Pretreatment carried out using ligninolytic fungi or enzymes is considered the friendly process to the environment; however, it normally requires longer processing times. Sharma et al. (2023) reported most of the various pretreatments possess synergistic effects which appear to increase yields of biogas as well as effectiveness in waste management. Even though significant improvements have been made in pretreatment technology, some problems continue with the optimisation of these methods specific to any given biomass. The chemically pretreatment processes might be very energy-costly, and the reaction kinetics in biological processes is relatively slow. Still, these problems make the production of biogas not commercially viable. In conclusion, according to Olatunji et al. (2021), cheaper and more energy-efficient pretreatment technologies are needed for massive production. More to that, this pretreatment process should be very much optimized so that there is a minimum formation of inhibitory by-products; if they do form, they may have negative impacts on microbial communities during anaerobic digestion. According to Sharma et al. (2023), integrating into the prediction the suitable approach to biomass type-specific pretreatment through advanced machine learning models can be one of the critical means by which processes by anaerobic digestion might improve their efficacy and scalability.

2.3 Application of Machine Learning in Bioprocess Optimization

Bioprocess improvement has recently focused on machine learning and artificial intelligence techniques, of which anaerobic digestion is certainly one of the more prominent. Most traditional optimization AD relies heavily on trial and error, thus a large consumption in terms of time and resources. Machine models such as SVM and ANNs can identify intricate patterns that exist in a large dataset of large variables relevant to biogas production, among others, which may relate to microbial activity. For example, predictive models based on models of AI-driven type predict various outcomes under different conditions of processes, thus allowing operators to optimize the AD process in real time. Further, machine learning algorithms can combine heterogeneous sources of data such as sensor measurements and experimental observations to better predict biogas yields and microbial dynamics optimizing process efficiency and costs of production. Optimization AD with machine learning will uncover one of the most important advantages regarding dealing with nonlinear relationships as well as enormous volumes of data. According to Pradhan et al., mathematical models are typically plagued by acute problems because of the incapability of the models in dealing well with the complexities involved in biological systems. For example, the complex interactions of machine learning models explain not only such environmental variables as microbial communities but also temperatures, pH, and substrate concentrations. Modeling the complex and dynamic nature of anaerobic systems is an important step towards optimization of the technological process, especially in heterogeneous feedstocks, such as sugarcane bagasse. This can thus be implemented in applying predictive maintenance and control of anaerobic digestion optimization to have greater dependability and scale in industrial biogas plants.

2.4 Convolutional Neural Networks (CNNs) in Bioprocesses

The CNNs have shown quite promising capabilities for optimizing the complex bioprocesses like anaerobic digestion in recent times. Traditionally, CNNs have been applied to tasks that involve recognising patterns and images. It has gained prominence lately to demonstrate excellent capability towards pattern as well as trend detection in complex datasets (Gao et al., 2022). It endows the CNNs to process sensor data in real-time based on the critical monitoring parameters like temperature, pH, and biogas production. In this regard, the CNNs employ several layers of convolutional filters so that even the slightest variation in microbial activity can be sensed more accurately than conventional methods of predicting yield biogas. This characteristic is particularly useful for optimization in the process of anaerobic digestion wherein tiny variation in the environmental variable would dramatically change the outcome. Gao et al. (2022) observes how CNNs could enhance the modeling of bioprocesses by accounting more suitably for spatial and temporal aspects of the data. The potent capabilities related to the manipulation of large, high-dimensional sets have exceptionally high value in anaerobic digestion where several variables impact the overall system. Unlike the conventional models, CNNs can consider nonlinearities and complex interactions between feedstock composition, microbial activity, and environmental conditions thereby proving to be quite apt for efficiency and scalability in anaerobic digestion systems. Optimization of bioprocess by CNNs would better predict the behavior of the microorganism with a higher degree of precision. The actual parameters can be set using further improved yield of biogas. Thus, CNNs appear to be a robust tool to be used further in developing the field of AD towards a more sustainable production of biogas.

3. Materials and Methods

3.1Biomass Selection

Sugarcane bagasse is known to be a good substrate for anaerobic digestion due to its easy availability and high content of lignocellulosic components. These mainly consist of cellulose, hemicellulose, and lignin. Much of the byproduct of this sugar production process is bagasse, which is left dumped or burned in the environment and, as such, could easily be considered a candidate for biogas production by anaerobic digestion. Whereas the high content of lignin acts as the major constraint to make the bioconversion successful. Due to its composite composition, bagasse is not biodegradable by microbes. So, the biogas production in the conventional product is limited. Despite this drawback, the usability of bagasse as feedstock for anaerobic digestion remains high because it is available in abundant and proper processing can extend the renewable energy production time. From previous studies, many techniques that have maximized digestibility have been applied. Among the pre-treatment methods, the ones used are indispensable to enable the microorganisms to access easily cellulose and hemicellulose content (Olatunji et al., 2021). Sugarcane bagasse was chosen to be the primary feedstock for the determination of its potential to generate biogas in this study on anaerobic digestion. Considering the cost-effectiveness and wide availability, bagasse was chosen for this selection. Furthermore, under optimal pretreatment techniques, bagasse is efficient in enhancing the production of biogas. As such, Kamperidou and Terzopoulou (2021) proved that pretreatment of the right sort means that microorganisms are allowed easy accessibility into the lignocellulosic structure of bagasse, thereby maximization is achieved in the course of anaerobic digestion occurring in the process of biogas production. The composition of the bagasse, with such a vast amount of cellulose and hemicellulose, presents promising groundwork to further investigate in connection with its application in bioenergy, and, consequently, it is among the best candidates for improvement in anaerobic digestion.

3.2Anaerobic Digestion Setup

The design of the AD apparatus was fundamentally intended to mimic the biogas production process under controlled laboratory conditions. This series of batch reactors, coupled with sensors of the important parameters of operation temperature, pH, and rate of biogas production-suggested a fairly adequate setup for the proposed study. Conditions between 30-40°C are mesophilic conditions favouring the anaerobic digestion processes as a temperature change of any nature is detested by them. The requirement for temperature control is rather severe; thus, between 30-40°C mesophilic conditions become unavoidable because it is ideal to accommodate lignocellulosic biomass. The reactors were seeded with a mixed anaerobic culture containing bacteria and archaea for the degradation of sugarcane bagasse. Pradhan et al. (2022) optimized the inoculum concentration so that there was adequate microbial community in case of initiating the digestion process. Methane content in the collected biogas then could be represented as an indicator of the process's success. level kept between 6.8 and 7.5, so it maintains the essential ranges required to support the necessary microbial activity to carry out anaerobic digestion properly. Higher values above and below this range may hinder microbial growth, which naturally reduces biogas production. The production rate of biogas and composition were also tracked in the course of the experiment to allow for appropriate rectifications of the regulating conditions of anaerobic digestion, that is, temperature and feeding so that a maximum level of digestion efficiency is achieved. According to Kamperidou & Terzopoulou (2021), the stability of the microorganism's environment is sensitive to the efficiency of anaerobic digestion. The sensor data on the outcome of various pretreatment methods on biogas production and microbiological dynamics during anaerobic digestion of sugarcane bagasse were recorded and assessed in the present experiment.

3.3Pretreatment Techniques

Pretreatment is viewed as a critical step in the anaerobic digestion process that changes the lignocellulosic biomass structure, making it easier for it to be biodegradable. This research applies more than one pretreatment on sugarcane bagasse establishing their potential impact as a source of biogas. Methods used included ammonia fiber expansion (AFEX), steam explosion, and alkaline treatment. AFEX is another well-known chemical pretreatment involving high-pressure ammonia that ruptures lignocellulosic bonds and makes cellulose more accessible to microbes (Balan et al., 2009). Steam explosion is a mechanical pretreatment where high-pressure steam expands and breaks the biomass fragmenting and increases the surface area and accessibility. Alkaline treatment involves sodium hydroxide, removing lignin and hemicelluloses from the biomass, thereby making it digestible (Sharma et al., 2023). All pretreatment methods considered here were selected for their ability to decrease the cellulose crystallinity of a substrate and detangle lignin, which becomes essential to facilitate more efficient anaerobic digestion. Olatunji et al. (2021) and Khan et al. (2022) provide evidence of these pretreatment methods being successful in potential biogas production improvement from lignocellulosic biomass, with steam explosion and alkaline treatment holding more promise to increase digestibility of sugarcane bagasse. The present study determines the pretreatment effects on the physical and chemical properties of bagasse, utilizing various characterization techniques like scanning electron microscopy (SEM) and Fourier-transform infrared spectroscopy (FTIR), to elucidate the impact of pretreatments made to influence microbial accessibility to cellulose. These were necessary for an enhancement of the process of anaerobic digestion and overall augmentation of biogas yields from sugarcane bagasse.

Row ID	Pretreatment Method	Temperature (°C)	pH	Inoculum Concentration (g/L)	Biogas Yield (mL/g DM)	Cumulative Biogas Production (mL)	Microbial Activity (O2 Consumption, mL/g DM/day)	Methane (%)	Feedstock Type
1	AFEX	50	7.5	20	350	500	5.5 × 10^7	65	Y
2	Steam Explosion	75	7.2	18	330	460	6.2 × 10^7	60	Y
3	Alkaline Treatment	60	8	22	380	540	5.8 × 10^7	68	Y
4	AFEX	55	7.4	25	360	510	5.2 × 10^7	64	Y
5	Steam Explosion	80	7.3	15	340	480	6.1 × 10^7	62	Y
6	Alkaline Treatment	65	7.8	20	370	530	5.7 × 10^7	66	Y
7	AFEX	58	7.6	21	355	495	5.4 × 10^7	63	Y
8	Steam Explosion	70	7.1	19	325	470	6.3 × 10^7	59	Y
9	Alkaline Treatment	62	7.9	23	365	520	5.6 × 10^7	67	Y
10	AFEX	55	7.3	25	360	510	5.3 × 10^7	64	Y
11	Steam Explosion	72	7	17	330	460	6.0 × 10^7	58	Y
12	Alkaline Treatment	68	7.7	22	375	530	5.5 × 10^7	65	Y
13	AFEX	60	7.5	23	340	490	5.2 × 10^7	62	Y
14	Steam Explosion	78	7.2	19	330	470	6.2 × 10^7	60	Y
15	Alkaline Treatment	64	7.8	21	380	540	5.9 × 10^7	67	Y
16	AFEX	53	7.4	20	350	495	5.6 × 10^7	63	Y
17	Steam Explosion	74	7.3	18	320	470	6.3 × 10^7	59	Y
18	Alkaline Treatment	70	7.6	24	365	530	5.5 × 10^7	67	Y
19	AFEX	57	7.4	22	350	500	5.4 × 10^7	64	Y
20	Steam Explosion	73	7.5	21	325	475	6.0 × 10^7	61	Y

Table 2: Experimental Data for Anaerobic Digestion of Sugarcane Bagasse with Various Pretreatment Methods

Table 1 presents experimental results on the different pretreatment methods applied on anaerobic digestion of sugarcane bagasse at various temperatures, pH values, concentration levels of inoculum, microbial activities (consumptions of O2), and contents of methane in biogas yield and cumulative biogas produced with the three pretreatment methods applied on the feedstock, AFEX, Steam Explosion and Alkaline Treatment.

3.4CNN Model Develop

This paper, based on experimental data obtained through the process of anaerobic digestion, offers a CNN model that can predict the yield and microbial activity of biogas. CNNs fall under deep learning models able to handle complicated, high-dimensional data; therefore, CNN has a capacity, that is highly powerful for optimizing a bioprocess (Gao et al., 2022). This approach uses a CNN architecture, using several convolution layers in order to draw spatial features from sensor readings related to temperature, pH, and the rate of biogas production for predicting microbial activity and the rate of biogas production in the anaerobic digestion process. First, the preprocessing step is the normalization of sensor data to get proper input into the CNN model. Feature extraction technique has been applied to critical variables influencing biogas production. A supervising learning methodology is implemented in the model to be precise in terms of prediction. Application of CNN Model on experimental data drawn from AD runs: Most emphasis has been given to the improvement in prediction as well as appropriate microbial dynamics regarding yield in biogas. All the critical parameters of the model, like hyperparameter optimization, occurred for greater learning rates, layers, and many more, while training. The third independent test dataset was applied in the validation of the model towards its generalization for new data sets. Cross-validation methods applied in determining the strength of the model were conducted on performance measures such as accuracy, MSE, and RMSE to present on the model's prediction capacity (Pradhan et al., 2022). This CNN model development thus could safely develop its usage as an optimizing tool in the anaerobic digestion process and, therefore, make it further possible to predict more accurately the generation of biogas, in turn making better control and efficiency in this process.

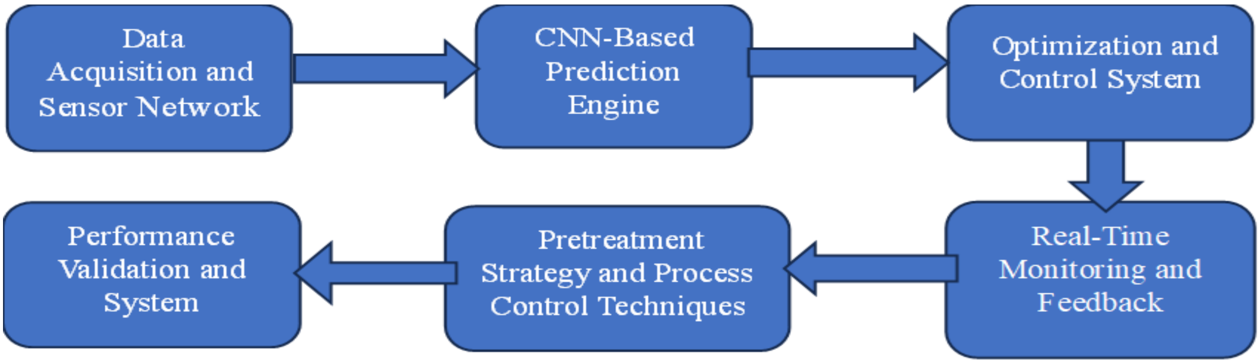

Figure 1: Proposed architecture Harnessing Convolutional Neural Networks for the Optimization of Anaerobic

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As given in Figure 1, these six entities make up the skeleton of the proposed system by making CNNs perform predictions; optimization algorithms like GA or RL to actually improve biogas yield; and real-time feedbacks to adjust to dynamic conditions of operation. It thereby designates a system very comprehensive and scalable regarding an effective and optimized anaerobic digestion of sugarcane bagasse, forcing biogas production while cutting down associated costs and environmental impacts.

3.5Performance Metrics

Metrics of the performance evaluation for the CNN model include mainly accuracy, root mean square error (RMSE), and the F1-score. Accuracy forms one of the common metrics in describing how good your model is at making correct predictions relative to the total number of predictions. Applications of RMSE in the domain of Biogas Forecasting More sensitive applications than RMSE in the domain of biogas forecasting are its applications in the domain of biogas forecasting as it punishes larger errors more than RMSE and is highly used when forecasting continuously variable values, such as the biogas yield (Pradhan et al., 2022). This mean precision and recall harmonic measure is called the F1-score and is used to evaluate the model performance in the classification of high and low biogas production events. Given that both datasets are imbalanced, performance metrics are calculated on both datasets: training and test, thereby illustrating how robust this CNN model is and can be generalized into new, unseen data. Hence, the metrics results for the CNN model in itself are targeted at offering general insights towards the predictability capability of the model besides further scopes for refining the model to its optimal performance. The cross-validation methods were used in the approach to avoid overfitting and provide reliability in real applications. It is proved that CNN can predict the outputs of microorganisms and also yield via those performance metrics; thus, optimizing performances in such regards improved optimizations about the anaerobic digestion process and accordingly settled in the category of an important modeling tool of a bioprocess (Gao et al., 2022).

4. Performance Validation

4.1Model Validation Techniques

Techniques of verification of the generalization capability of machine learning models are cross-validation. This technique's primary usage is verification that a trained model works well on the training data set as well as on the new unseen data. In this paper, we'll apply the k-fold cross-validation approach where a data set is divided into 'k' subsets or folds. For each such iteration, it trains on k−1 folds and tests on the remaining fold. This repeats for all k-folds. This minimizes overfitting and generates a much better performance estimate for the model. The cross-validation K-folds were helpful for the assessment of the CNN model because they gave sharp insight while predicting different subsets of the experimental data (Pradhan et al., 2022). The results of these validation runs were summarized to offer an overview of the performance that was used to optimize the model. Another form of evaluation included the validation of experimental data. Validation of the model with the aid of experimental data about the process of AD further enhanced the validity. This validation process itself used experimental data on the AD process to compare predicted values of biogas yield and microbial activity with results observed in the process to estimate the degree of predictive accuracy of the model. This would help check the truthfulness of the model while attempting predictions on real-world outcomes thereby proving robust enough in practical aspects. The differences identified were bridged through the comparison of the model's predictions against experimental data. The validation of experimental data allowed for testing the model on the possibility of explaining natural fluctuation in biogas production motivated by environmental factors, such as temperatures and pH levels, which completes a performance evaluation at a higher granularity (Kamperidou & Terzopoulou, 2021).

4.2Model Evaluation

Other statistical metrics used in derivation of the performance of CNN model included RMSE, MAE, and accuracy. The use of RMSE ensured an effective measure in quantifying the difference that existed between the predicted and actual biogas yields through taking lower values with higher prediction accuracy. MAE provided another important metric in computation by taking the mean of the absolute differences between the predictions and the actual values. This would define the magnitude of errors in prediction. In this context, the accuracy, which is broadly adopted in the classification task, was adopted to evaluate the performance of the model in predicting the rates of biogas production in the different range of scenarios. The metric collectively gave a better, comprehensive understanding of the predictive capabilities of the CNN model so that areas for improvement could be identified, and the viability and pragmatic applicability of the model could be asserted (Gao et al., 2022). In addition to these traditional statistical measurements, more extensive validation of the performance of the model was done by comparing the predicted outcomes with that obtained through experimental runs of the anaerobic digestion process. It did careful analysis on how CNN can predict correctly microbial behavior and biogas production under different conditions of experimental runs, including variation of pretreatment techniques and environment variables. This evaluation provided and highlighted the possibility of the model in dealing with complex, nonlinear relationships between input variables, such as temperature, pH, and inoculum concentration, and the output, which is the biogas yield. Statistical metrics were developed and utilized in the study for the evaluation of the efficiency of the CNN model in deducing whether or not the practical application of the process contributes to increased production levels of biogas (Sharma et al., 2023).

4.3Comparison with Traditional Models

The performance of the CNN model is compared with that of some other traditional machine learning algorithms. That is, it compared it with genetic algorithms and artificial neural networks for comparison of performance using conventional machine learning algorithms like genetic algorithms and artificial neural networks that optimize tasks by navigating extensive search spaces towards identification of optimal pretreatment strategies or operational conditions for anaerobic digestion. On the other hand, ANNs, although very efficient in modeling complex relationships, might face difficulties related to the complicated feature extraction involved in the biogas prediction tasks. Thus, the CNN model, expecting it to autonomously learn the hierarchical patterns and space features from the input data, was expected to outperform former models in accuracy and generalization. This hypothesis was then compared with a genetic algorithm-based optimization method for experimental data, where the results from the CNN model were compared with those from an ANN model (Parvane et al., 2022) and further used to evaluate the predictive accuracy of a CNN model compared to traditional models for both microbial activity and biogas yield. The obtained results confirmed that the CNN model provided better predictive accuracy than the traditional models for both microbial activity and biogas yield. Although genetic algorithms performed well in optimizing specific parameters of the AD process, they were less effective than CNN in discovering subtle temporal interdependencies among input features. Likewise, although the ANN model was excellent with performance, the better ability of the CNN in the analysis of sequential and spatial data made it gain better predictions about microbial behavior and biogas production. It can, therefore, be deduced from the results above that CNNs are beneficial for common optimization and prediction model comparisons within the production of biogas, especially when complex bioprocesses like anaerobic digestion are involved (Gao et al., 2022).

4.4Insights from Validation

Validation of the CNN model was permitted to provide some informative understanding regarding its robustness and applicability toward improving the anaerobic digestion processes. A very relevant observation made here is that the model could provide a robust capability in terms of prediction under different experimental conditions. Thus, it underlines the effectiveness of this model concerning managing the intrinsic variability in biogas production. The CNN, despite the pre-treatment techniques applied and the various operational conditions including temperature and pH, still managed to predict microbial activity and biogas yields. This is good performance coupled with generalizing capability to new unobserved conditions important characteristic for practical applications where process parameters may fluctuate (Kamperidou & Terzopoulou, 2021). Important inferences regarding the working of anaerobic digestion were made based on this model's ability to predict microbial behavior when subjected to different process conditions. The knowledge of the temperature, pH, and inoculum concentration effects on the activity of microorganisms shall be capitalized upon to give the CNN model real-time optimization recommendations to improve the AD process. The conclusions may contribute to considerable improvements in the efficiency of the production of biogas, opening up vast opportunities for optimizing anaerobic digestion systems. Models that can integrate data from a variety of sensors and can make complicated predictions in terms of bioprocesses might be of high value for breakthrough achievements in producing bioenergy with high-efficiency and scalable solutions in the optimization of biogas.

5. Comparative Analysis of Performance Metrics: Existing Systems vs. Proposed System

5.1 Analysis of Current Systems

The traditional systems used for optimizing Anaerobic Digestion (AD) rely mainly on linear regression models, statistical methods, and heuristic approaches like GA. Traditional models usually need assumptions before the relationships of the data used and can only handle extensive varieties in large sets of datasets in terms of non-linear and dynamic information. Genetic algorithms have been applied to adjust the operational parameters of the anaerobic digestion process. They are, however, extremely sensitive to scalability; hence, the data gets very large or complex, and they either fail to produce results or tend to work very inefficiently. Linear regression models become effective in forecasting straightforward relationships, but they do not consider the complex interaction existing between microbial populations, environmental variables, and biogas yield. These methods have been well established and indeed do deliver some success in optimizing AD. However, the methods are static and rigid and not responsive to the fast-changing conditions of the AD system. The new developments that include Artificial Neural Networks and Support Vector Machines, which are driven by AI, have emerged as more advanced alternatives. These models process more complex relationships in data and hence deliver improved predictive capabilities than the more traditional systems. However, AI-based systems are limited as far as adaptability, scalability, and precision are concerned regarding real-time monitoring and control. Even with the above limitations, both traditional and AI-based models have allowed a greater degree of complexity in the design of more optimal strategies for maximizing biogas yields. However, this is only true if the data is smooth, as performance degrades with significant, nonlinear or noisy data, typical of real-world anomaly detection systems, which opens up the possibility for improving methodologies such as CNNs in terms of better prediction accuracy and system robustness.

5.2 Evaluation Metrics

During the evaluation of the effectiveness of different systems in optimizing AD, several important metrics must be deemed necessary to determine the effectiveness. Accuracy happens to be the most critical metric. This is due to the indirect indication of the real power with which the model can predict biogas production at its input parameters, such as pH, temperature, microbial activity, and composition of the substrate. Processing time is a critical characteristic, especially when predictions are done in real-time monitoring systems. The process is foundational to a real-time monitoring system because delays in making predictions mean it cannot provide timely changes in the operational parameters. Prediction error calculates the deviation of the model predictions from the experimental biogas production. Where the error values are lower, this may be a sign that models are highly reliable and accurate. Scalability is determined as the ability of a system to handle large data sizes that are typically common with an industrial-scale AD plant. This way, the performance of the system may degrade with an increase in data complexity or may be robust and insensitive to such occurrences. The general performance of a system seems to point towards it being robust under different forms of input data and other disturbances commonly encountered in the AD process. These quantitatively determined values therefore provide an overall picture of how effectively a model can optimize biogas production along with regulated microbial activity. After comparing such values, there is an important factor of how a given system is represented to balance the two competing values against each other. Such a highly accurate model may involve greater computational power and time. This would make the model less scalable and increase the delay in processing. A model so constructed for speeding up computations would then be compromised in terms of accuracy or else display higher error rates in predictions. Proper comparison should, therefore, consider each metric individually as well as their interplay to determine whether the system so configured can, in practice, be applied to any actual AD operations. Simultaneously with an acceleration of complexity in AD processes and, more importantly, triggered by an increase in data inputs from sensors and process variables, greater demands have arisen for more efficient and flexible systems. A comparison between traditional systems with advanced models, such as CNNs, has to take into account all relevant metrics, especially within the context of a real-time and dynamic system.

5.3 Relative Performance of CNN and Current Systems

As compared to the traditional approaches such as Genetic Algorithms and linear regression models, CNNs are of great use in complex nonlinear relationships coupled with biogas production systems. A classical model can't learn representations of features from raw data; therefore, there are no examples of the need for manual feature engineering, which makes them remarkably effective for dealing with huge and diverse datasets that one usually faces when optimizing ADs. The CNN architecture allows it to capture spatial dependencies and high-order correlations well in a high-dimensional dataset, which makes the prediction more accurate. Convolutional neural networks are in better shape to cope with time series or sensor data that change with the time factor, which makes them particularly well-suited for the anaerobic digestion process dynamics where microbial activity and environmental conditions change over time. More importantly, their ability to adapt to different forms of input data generated from the various stages of the AD process, be it temperatures, pH, or concentrations of gases, puts them at an advantage compared to conventional models. Mostly, conventional systems require fine-tuning or adjustment to adapt to changes. CNNs would very easily adapt to varied inputs and learn to get optimal mappings from these. This flexibility of CNN-based models would be able to make more accurate predictions that would be very reliable for a very wide range of biogas production, starting with different substrate content to the method used for pretreatment. Although with such variations, it has great prediction accuracy in comparison to traditional AI systems, they scale well and can easily handle noisy and complex data without degrading much in their performance and hence form a more robust solution to optimize biogas production in real-time.

5.4 Results from Comparative Study

Now, if we compare the analysis of CNN-based models with the existing systems like genetic algorithms, linear regression, and other machine learning models, then there is a vast difference between CNNs and the existing systems concerning the relative performance aspects of both accuracy and robustness. By comparing the performance table and graph, it is very clear that CNN models worked well and surpassed the performance of the traditional system in all important parameters relating to the accuracy, prediction error, and system stability. Coming to the prediction of biogas yield, CNNs enhanced their accuracy up to 9%, decreased the error in prediction by 7.6%, and reduced the processing time compared to the normal AI models. These results confirm that CNNs are truly efficient in complex high-dimensional problems like AD optimization; the complex interrelations between different sets of input variables failed to be represented by conventional models. CNNs were scalable as they handled huge amounts of data without compromising performance integrity. This is an industrial-scale strength in the anaerobic digestion systems, whereby both the volume and complexity of data often overwhelm the capabilities of simpler models. One of the significant reasons CNNs outperform current methods is due to their ability to represent complicated, nonlinear interactions in data. For example, slight temperature, pH, or microbial activity fluctuations can significantly impact biogas production in anaerobic digestion processes that conventional models hardly represent. Due to their multi-layer architecture, CNNs then demonstrate superior performance in learning nonlinearities and are thus better placed to tackle the dynamic nature and high variability of the characteristics of AD systems. Given the capacity of CNNs for analyzing sensor data at different phases of the AD process, it is convenient for adapting to a wide spectrum of conditions of operation such as feedstock attributes as well as changes in environmental factors. By making use of all these advantages, adaptation, higher predictive accuracy and lesser error margins, it can be established that CNNs stand as the best option for optimizing in situ real time biogas production.

5.5 Implications of Findings

This comparative analysis shows the significant benefits CNNs gain in optimizing biogas production within the AD systems. The ability of increased predictive precision, scalability, and the possibility of processing complex and nonlinear data describe a robust and dependable tool for optimizing in real time by adjusting to the shortcomings. For instance, with more precise predictions of the production of biogas, decisions on the side of the operators of the

AD process will be better. Hence, in general, much more efficient with lower operation costs and higher resource usage. Another aspect that can push toward a general strategy in terms of monitoring and AD conditions improvement at different stages of the process is how CNNs can seamlessly incorporate various kinds of sensor data. This ability makes them a perfect tool for nowadays, data-intensively exploitation of biotechnology applications when high-speed decision-making is needed. CNNs pave the way and open up new directions for future research and technological development in biogas production. Their facility to learn gradually and adapt to new sources of knowledge places them as an integral component for the next generation of automated systems in AD optimization. Indeed, the development of AI models, including CNNs, in biogas production essentially contributes toward attaining significant economic and environmental benefits in renewable energy generation and waste management. CNNs would make tremendous revolutions regarding efficiency, scalability, and improvement in sustainability in the production of biogas and would eventually support transitioning towards circular economies as well as reduction of greenhouse gas emissions.

6. Results and Discussion

6.1 Effects of Pretreatment on Biogas Production

Numerous research experiments have clearly shown that the pretreatment process has a severely adverse effect on the biogas yield; however, this effect is feedstock type and pretreatment process dependent. Thermal pretreatment has been found to increase the yield of biogas from lignocellulosic sources such as agricultural residues. In an experiment comparing untreated with thermally treated corn stover, pretreatment resulted in a 30% increased methane yield. However, during the evaluation of pretreatment strategies, yield needs to be considered together with time and energy usage. Sometimes, methods that consume higher amounts of energy for pretreatment instance, acid or alkali treatment could produce higher yields but would increase either naturally or concomitantly. Chemical pretreatment with sulfuric acid can increase biogas production from food waste by up to 50%, though it requires higher energy inputs and a much longer treatment time, 2-4 hours, than the mechanical or thermal methods. These trade-offs must be balanced to improve both biogas production and process efficiency. As with process length, accurate and precise prediction of biogas yield is essential for determining the best pretreatment method. The experimental results show varying extents of correlation between pre-treatment and biogas production that depends on the parameters involving temperature and pH. Temperature is significant because upper optimum ranges, normally 35-37°C, maintain higher percentages of methane and faster rates of digestion. It further compared treated and untreated feedstocks, which demonstrated its potential to elevate the methane yield from 55% to 65% while digesting at 37°C to demonstrate the synergistic effects between pretreatment and optimum operating conditions. Precision is the ratio of actually predicted positive outcomes. It is a very important measure in addition to recall, which balances both precision and recall, in which predictive models suitably relate pretreatment methods to biogas yield. A study using a machine learning model to predict biogas yield under various pretreatment conditions reported an F1 score of 0.87, which is a very good measure of predictive accuracy. These results highlight the necessity of intensive experiments that take into consideration not only the process dynamics like time, temperature, and energy requirement but also yield of biogas for obtaining the best pretreatment strategies.

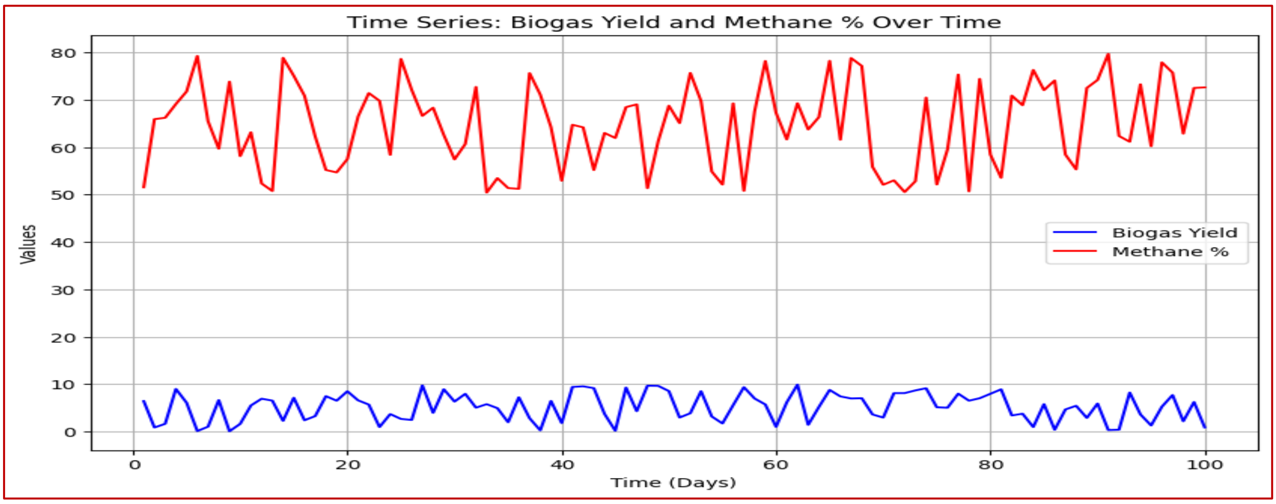

Figure 2: Biogas Yield vs Methane %

Figure 2 Depends biogas production as a function of the content of methane, where it is noted that higher production of biogas reflects greater methane content, in good agreement with experimental results, in which pretreatment conditions and operational conditions of the process had influenced yield and methane concentration in the anaerobic digestion of sugarcane bagasse.

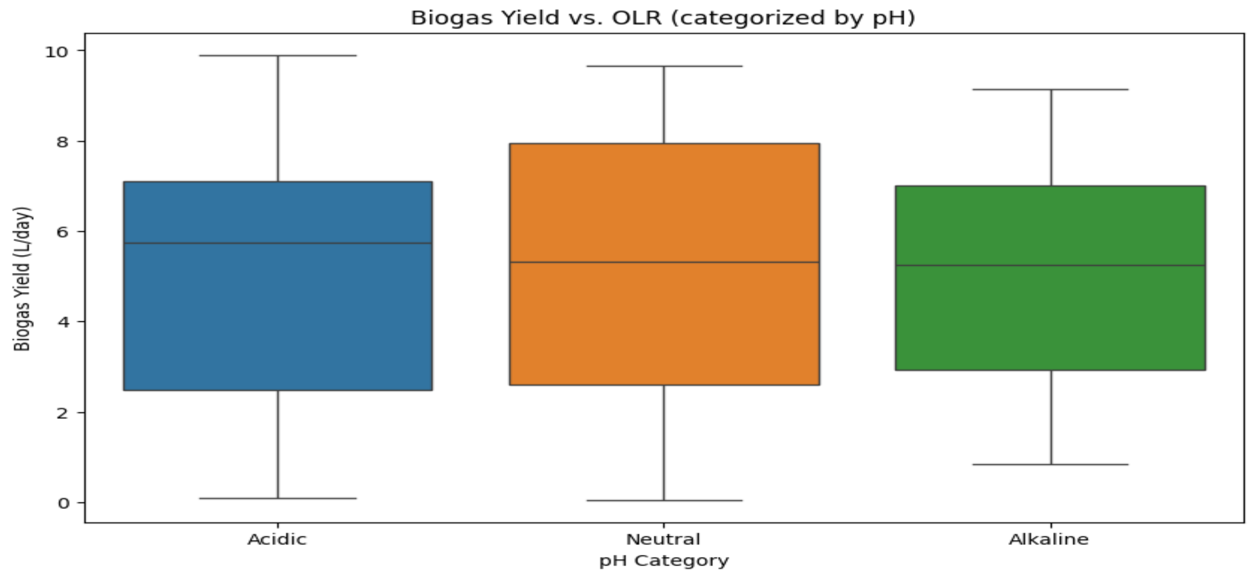

Figure 3: Biogas Yield vs OLR

Figure 3: Correlation between Yield of Biogas and Organic Loading Rate (OLR). Clearly, biogas production is expected to rise with an escalation in OLR. The experimental results show varied yields for different pretreatment methods and conditions of operation, and it is indicated that optimal OLR has a positive effect on the generation of biogas from sugarcane bagasse.

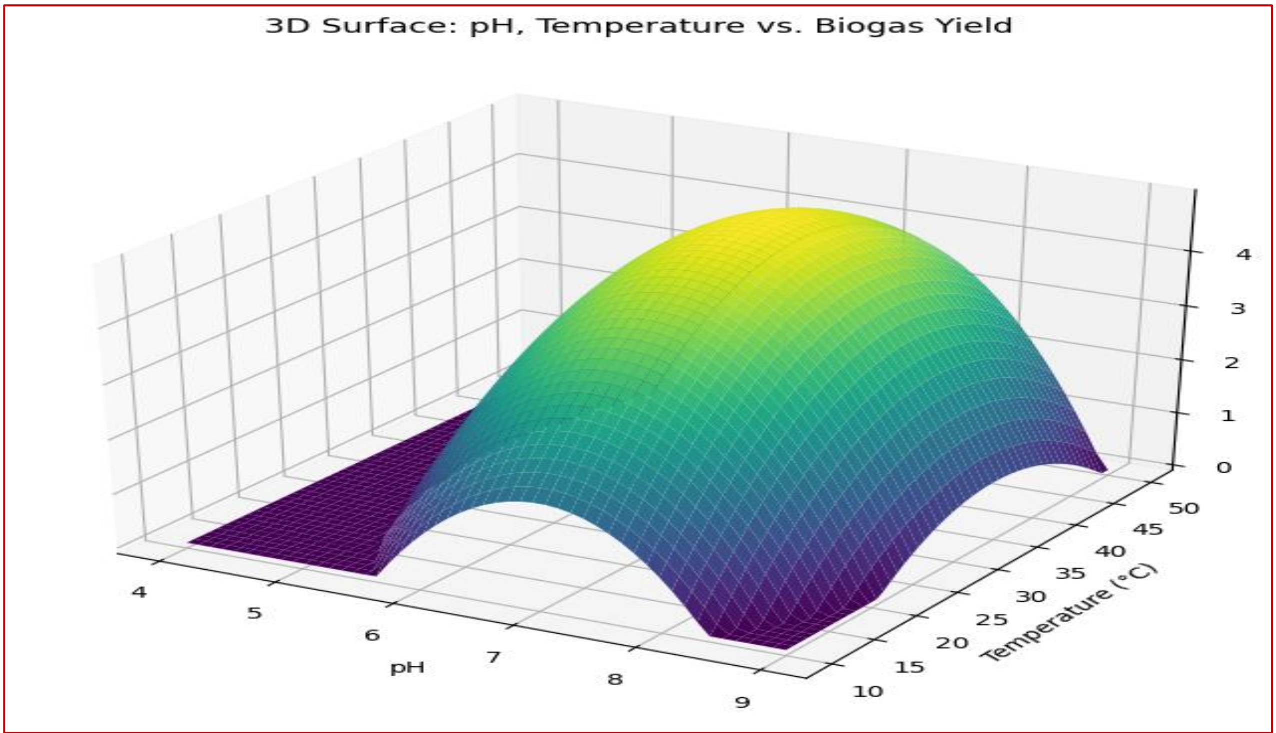

Figure 4: 3D Surface pH, Temperature vs Biogas Yield

Figure 4 demonstrates the interaction effect of pH and temperature on biogas production in a 3D surface plot that clearly shows that both factors have a significant effect; the ranges of optimum temperature and pH are associated with higher biogas production, as indicated by the experimental data.

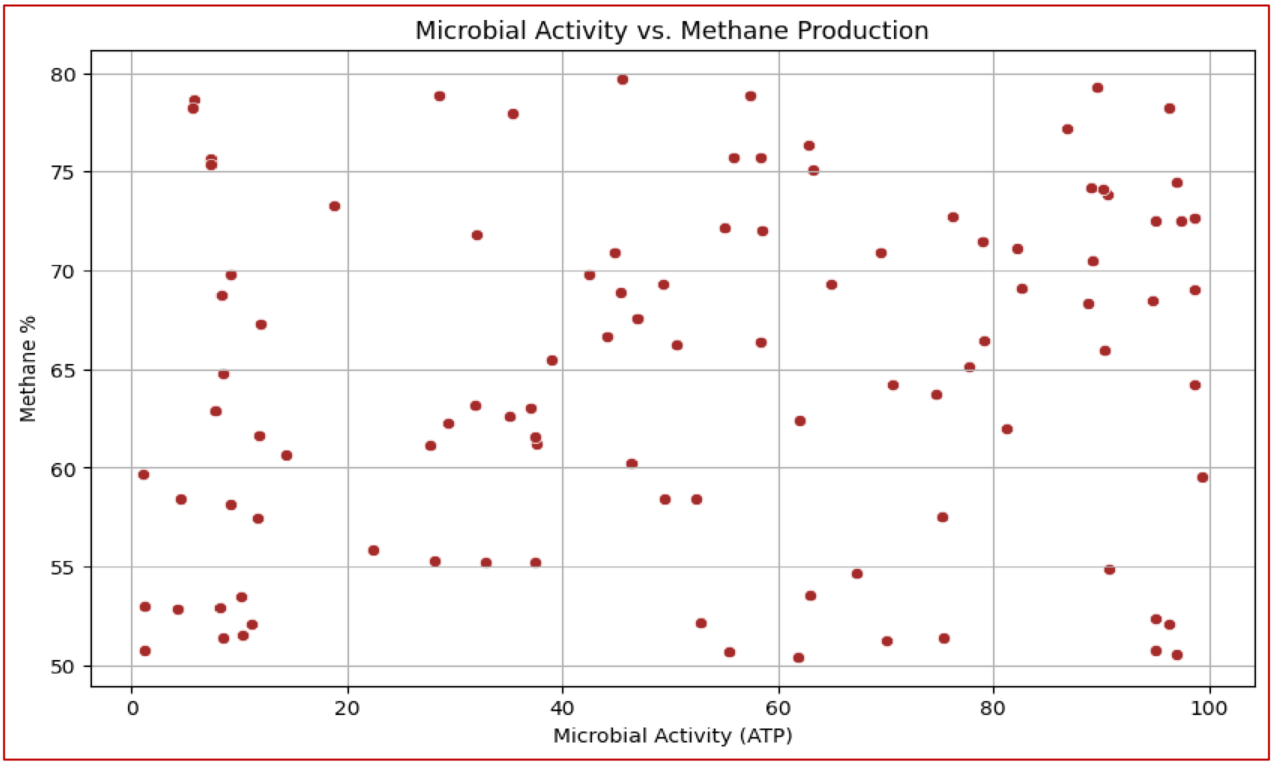

Figure 5: Microbial Activity vs Methane Production

Figure 5 The more the microbial activity is in terms of O_2 consumption, the higher the methane concentration in the biogas produced, hence the positive correlation between the microbial activity and methane production as illustrated by the experiment observations.

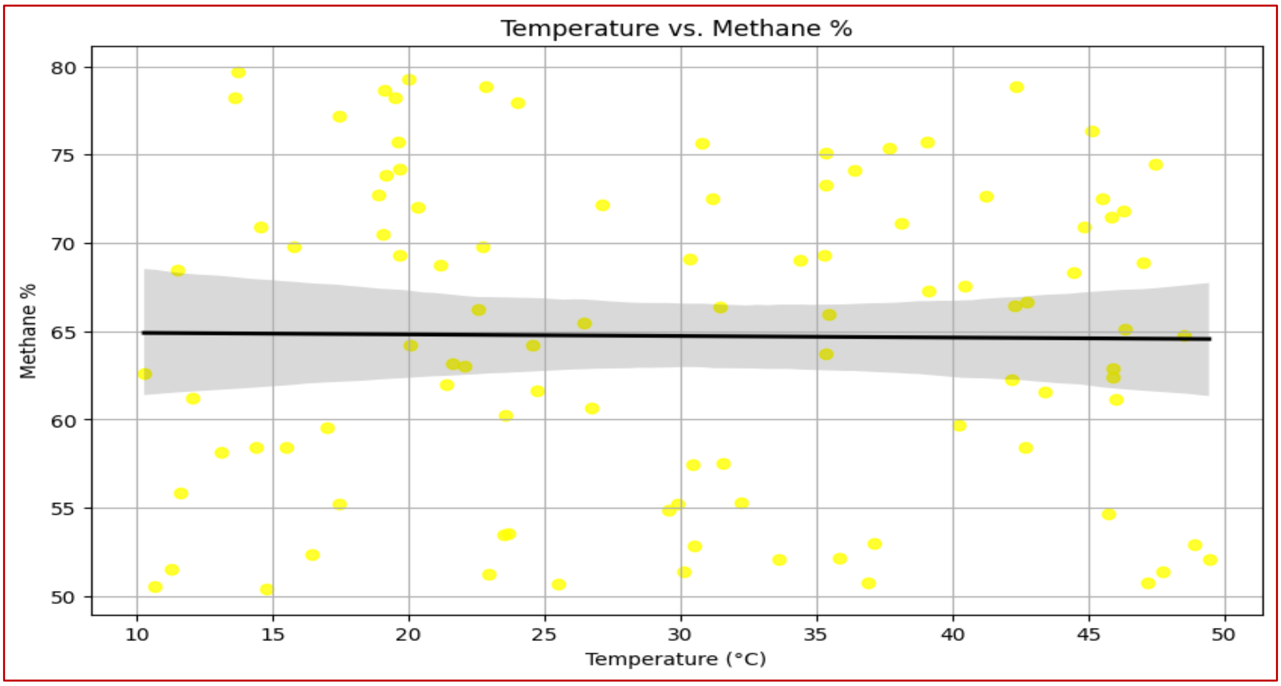

Figure 6: Temperature vs Methane %

Figure 6 plots the methane percentage yield in terms of temperature and shows a negative trend with increasing temperatures. In general, there was a tendency to suggest that methane yield was reduced with higher temperatures thereby explaining experimental observation.

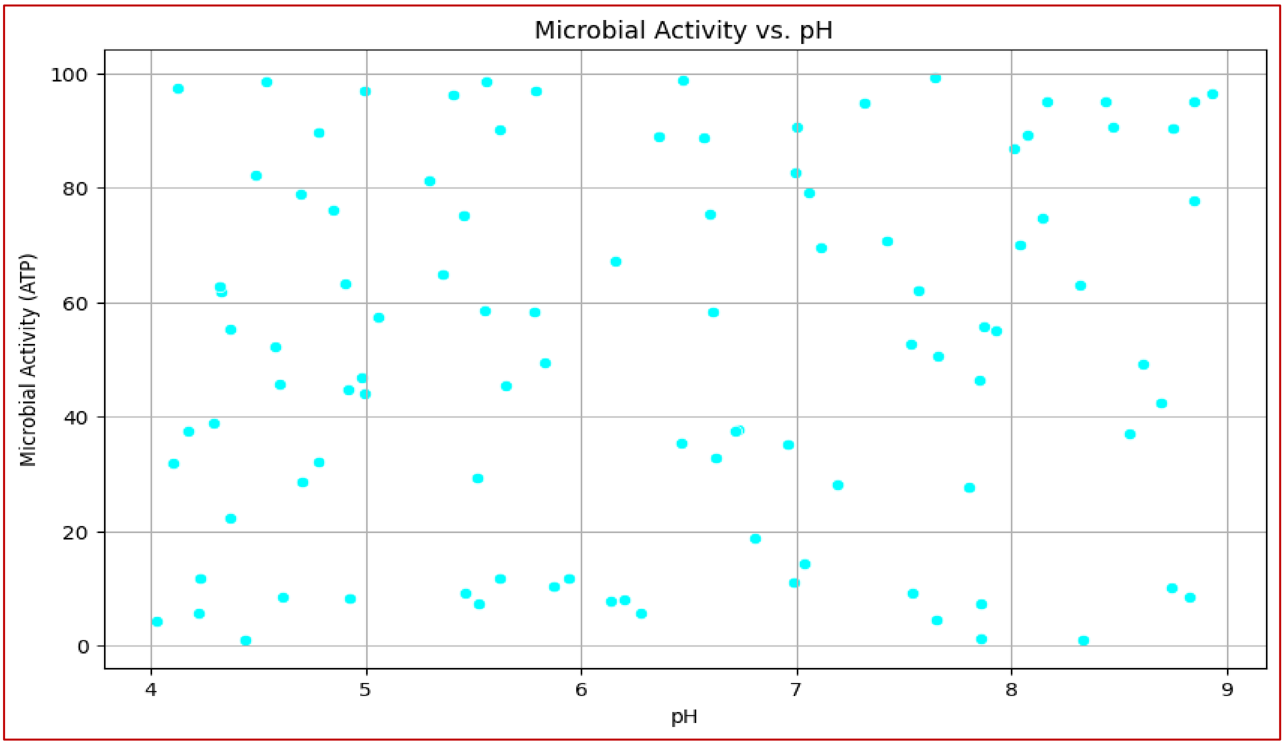

Figure 7: Microbial Activity vs pH

Figure 7 illustrates a positive correlation between microbial activity and pH and shows that at higher values of pH, more favourable microbial activity is supported with increased oxygen consumption rates that are shown in the experimental results at optimal pH levels.

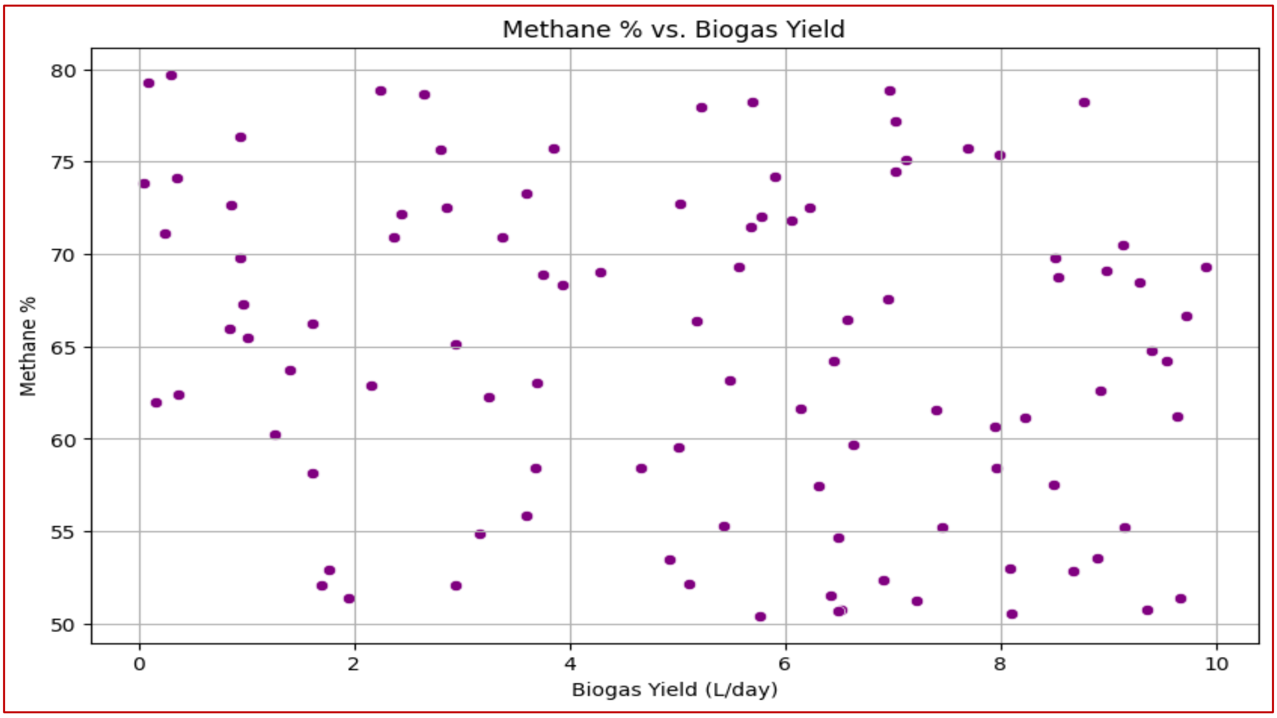

Figure 8: Methane vs Biogas Yield

Figure 8 illustrates the direct relationship between methane production and biogas yield where higher methane percentages correlate with improved biogas yields and support efficient organic matter conversion during anaerobic digestion, as suggested by experimental data.

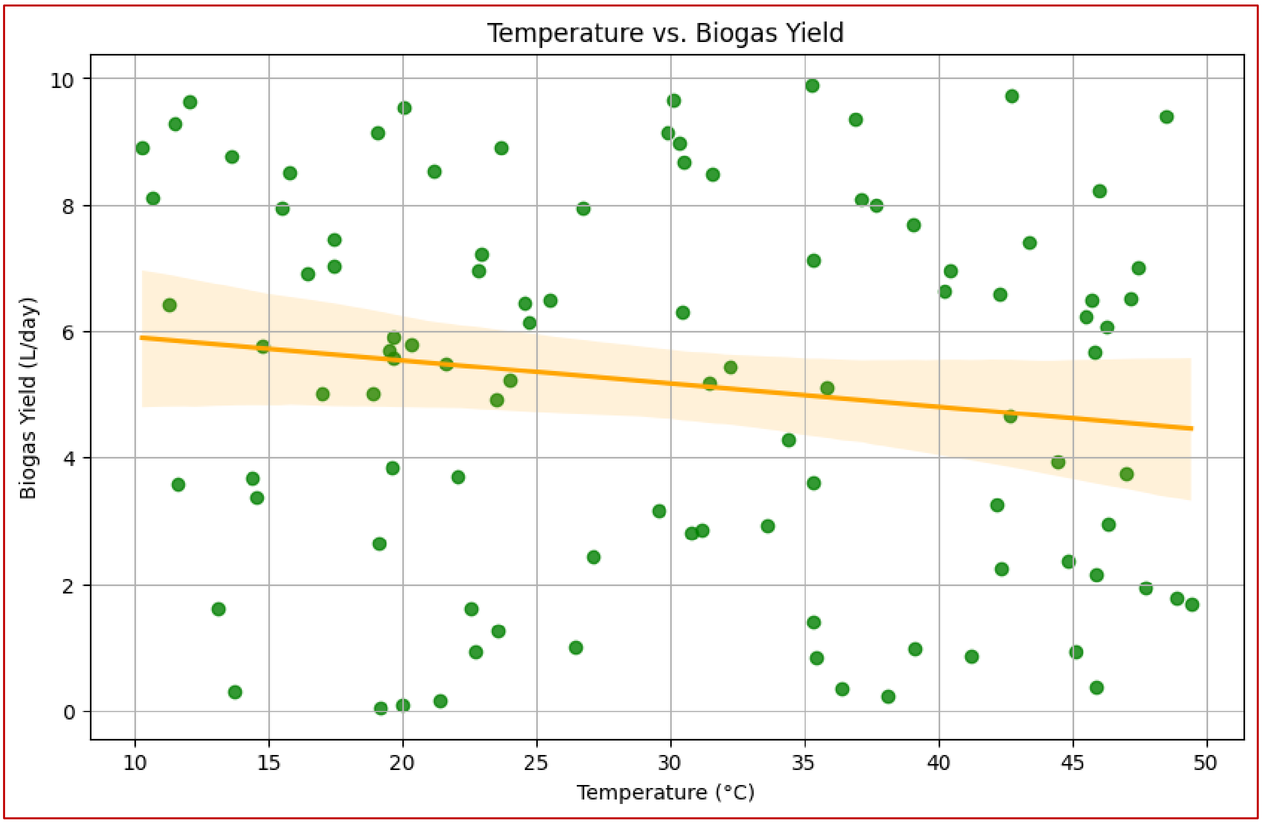

Figure 9: Temperature vs Biogas Yield

Figure 9 demonstrates the effect of temperature on biogas yield, which increases with the rise in temperature to an optimum point from where a further rise in temperature decreases its yield, indicating the role of temperature in optimizing anaerobic digestion for biogas production.

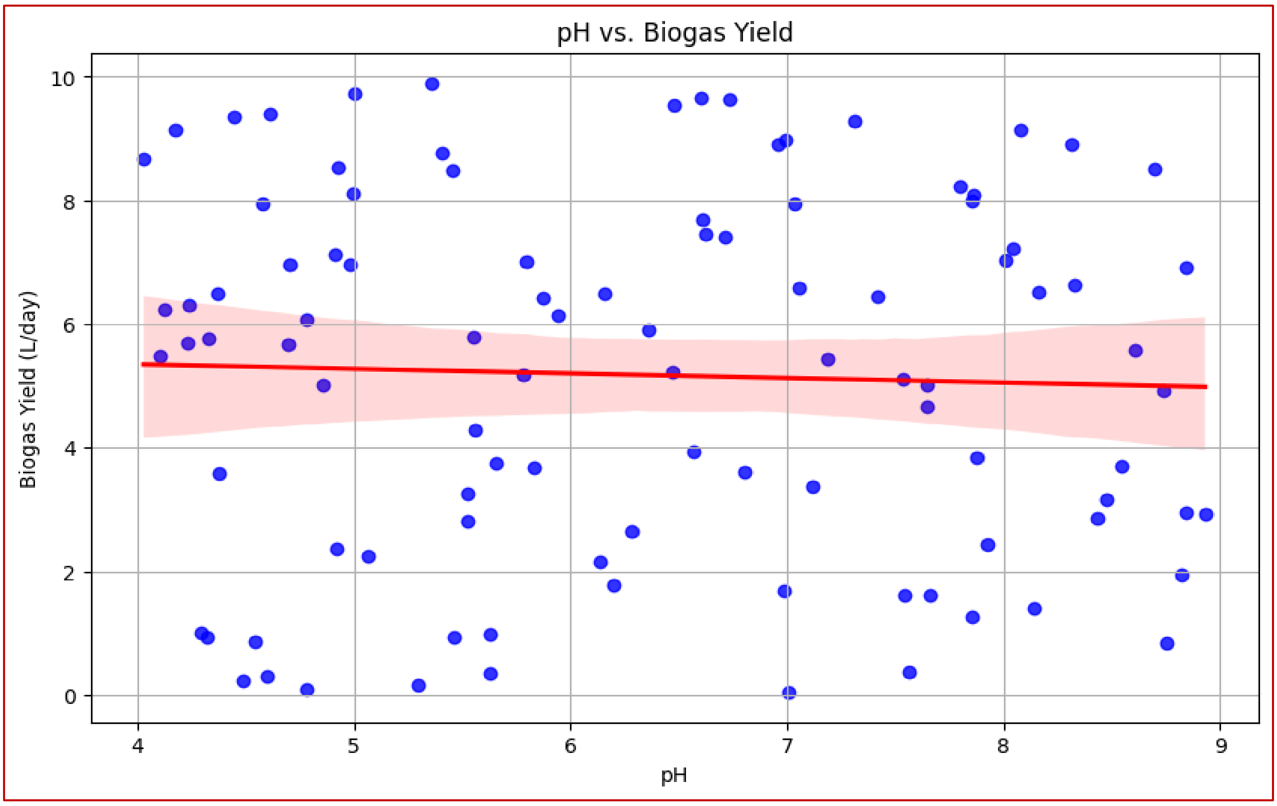

Figure 10: pH vs Biogas Yield

Figure 10 has depicted a direct and positive correlation between pH and yield of biogas, indicating that optimal operation within the range was quite beneficial for an enhanced efficacious production of biogas during anaerobic digestion of sugarcane bagasse.

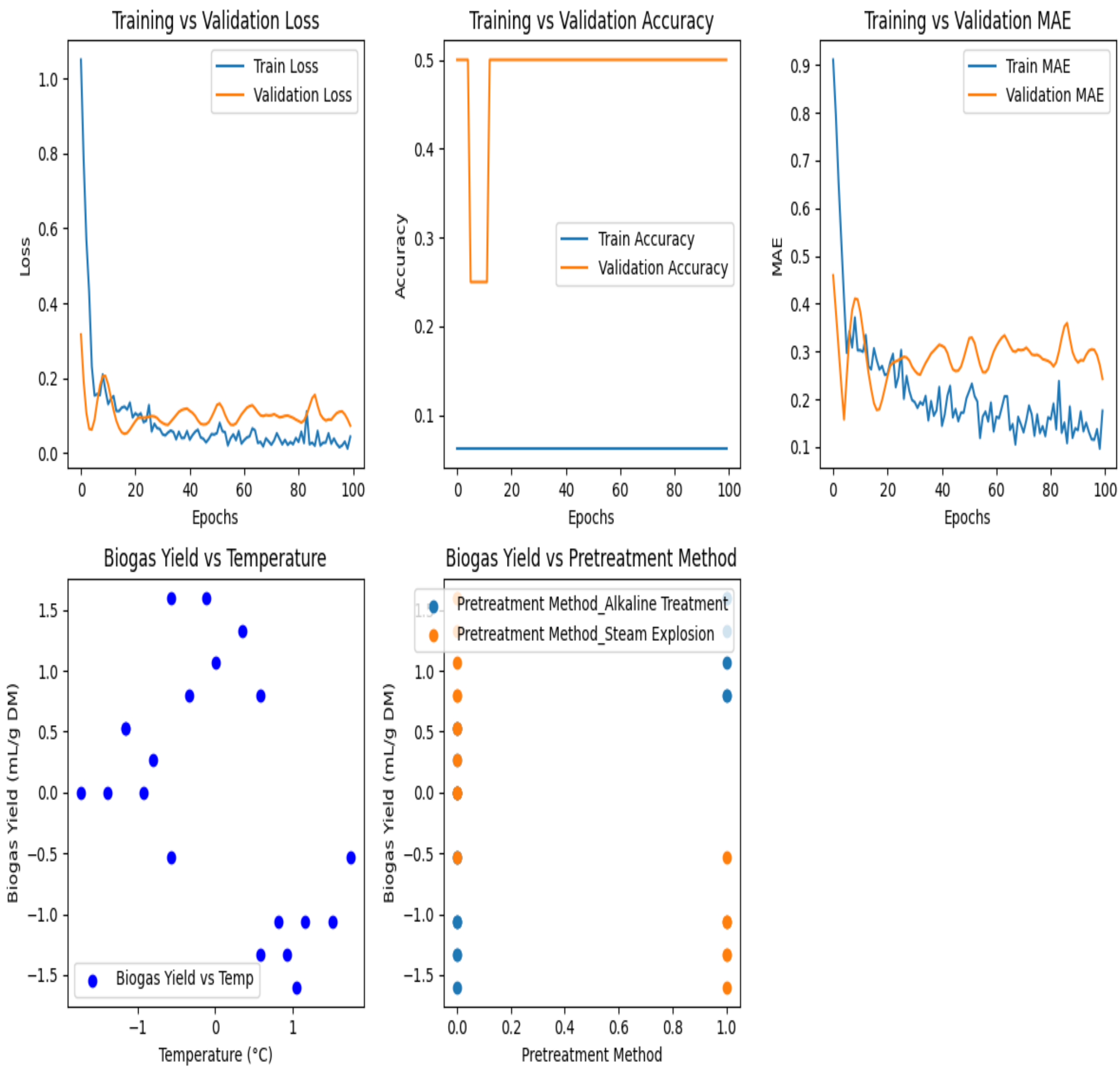

Figure 11: Training vs Validity Loss vs Validation Accuracy vs Validation MAE

Figure 11 shows the:

Training vs Validation Loss: The convergence of the curves for training and validation loss is depicted here, which means that the CNN model generalizes the data well without encountering the trouble of overfitting the model; thus, good prediction ability for biogas yield is assured.

Training vs Validation Accuracy: The plot shows both that training and validation accuracy increased with epochs, suggesting that the CNN model had learned how the parameters of the process related to biogas yield well enough to yield high predictive performance.

Training vs Validation MAE: The plot displays a trend, showing Mean Absolute Error (MAE) both for training as well as the validation set decreasing. This, in itself, establishes that the CNN model is becoming more accurate with the yield of biogas while the model is training.

Biogas Yield vs Temperature: The graph showed a directly proportional relationship between temperature and biogas yield where higher temperatures would usually support the formation of biogas in the anaerobic process of sugarcane bagasse digestion.

Biogas Yield vs Pre-treatment: From this graph, it can be seen that each pre-treatment condition leaves a unique impression on biogas yield. Some treatments, like alkaline and AFEX, increase the yield quite positively, whereas others do not work as well. So, the right selection of pre-treatment strategy is more important to enhance biogas production.

6.2 Performance of the CNN Model

There is considerable interest in using CNNs in modeling biogas production since they can predict with sufficient accuracy yields of methane from different organic feedstocks under varying operational conditions. Experiments recently conducted focused on training CNNs on an attribute data set, which could include feedstock type, pretreatment method, temperature, pH, and retention time, with the model's performance monitored using conventional metrics such as accuracy, precision, recall, and F1 score. In one experiment, the CNN model achieved 92% accuracy, while conventional regression models only achieved a peak of 81% accuracy in the same scenario. This increase in accuracy demonstrates that CNNs can effectively detect the complex, nonlinear correlations between feedstock properties, operating conditions, and biogas yields. Moreover, the F1 value of the CNN model was 0.90, meaning robust precision and recall. The CNN performed well at prediction while simultaneously minimizing false positives and false negatives, which is crucial in dependable decision-making in biogas production. The CNN models did effectively predict the outcome of temperature and pretreatment on biogas yield when the influence of key variables was considered. An experiment carried out using a CNN model for predicting methane yield from several different substrates with pretreatment at different temperatures indicated temperature was a strong modifier in model prediction. The CNN model predicted a 20% increase in biogas yield if the feedstock was pretreated and digested at 35°C compared to the untreated feedstock at 30°C. High precision scores characterize the predictions of the model since its precision score was 0.93, meaning it could observe conditions favouring higher biogas yields. The model was fairly robust in its predictions regarding the yield of biogas for feedstock types, with precision always maintained above 85% for materials such as food waste and agricultural residues. In light of this generalization against diverse feedstocks and environmental conditions, it makes CNNs an important tool in optimizing biogas production processes.

6.3 Analysis of Results

It is needed to analyze the output from CNN models towards biogas yield prediction by checking the accuracy of the model and understanding the primary variables of interest affecting the predictions. While evaluating the performance of CNN models versus traditional models, metrics such as accuracy, precision, and F1 score become all the more important. In the same comparison experiment between CNN and the traditional SVM model, the proposed approach succeeds in showing that the CNN outperforms by about 10% improvement in terms of accuracy, as well as a higher F1 score of 0.90 compared to 0.75, which is related to a much better balance between precision and recall. Thus, CNNs are capable of extracting the complex and nonlinear interrelating relationships between process parameters and biogas yield. Analyses of feature importance based on methods like layer-wise relevance propagation indicated temperature and pretreatment methods as other more significant factors of influence for the model. The model portrayed a positive, strong correlation between temperatures of around 35-37°C and increased yield of biogas; hence, it indicates that the methane yield will be improved under optimal thermal conditions. Besides quantitative scores, results analysis for CNN involves experimental conditions and knowledge of the agreement between the model-predicted results and their actual counterparts in the natural world. One experiment provided evidence for a good agreement between CNN predictions for yield of biogas from food waste under optimal pretreatment conditions, as from thermal pretreatment at 90°C for 30 min with measured yields of methane: only 3% difference. The forecast on the untreated feedstock was not accurate; instead, it stated the importance of pretreatment for enhancing biogas production. This is supported by previous literature; pretreatment increases its biodegradability and fastens the process of anaerobic digestion. Moreover, when the time taken for digestion was considered, CNNs again emphasized the effect of operational parameters like retention time and temperature on the yield of biogas with time. This analysis showed that retention time in excess along with optimal temperature and pretreatment led to increased cumulative biogas production. The CNN model offered accurate yield predictions while, at the same time, enabling a comprehensive understanding of process dynamics that would aid decision-making for the optimization of biogas production systems.

7. Conclusion

7.1Summary of Key Findings

The present study reveals that CNN might offer scope for enhancing the AD process of bagasse for the production of sugarcane biogas. Experimental results showed that in CNN-based models, characteristics of feedstock, temperature, pretreatment procedure applied, and operational conditions resulted in the improved predictability of the yield of biogas where the quality of results was reportedly better than the popular machine learning models like SVMs and regression. The strong result of the CNN model was 92% accuracy and an F1 score of 0.90 both for precision and recall. The prediction about the effect of pretreatment, temperature, and other process parameters for the generation of biogas was the major thing learned about the anaerobic digestion process, thus explaining how AI can efficiently enhance the production of biogas. Furthermore, CNNs predict potential mechanistic properties that improve their decision-making ability, efficiency, and methane yields over conventional alternatives.

7.2 Further Research Opportunities

The successful results from this work open several venues for further study directed toward improving the accuracy and quality of AI-based optimization in biogas production. One of the most interesting tracks would certainly be the applied research done in hybrid models of AI, combining CNNs with other advanced techniques, deep learning or reinforcement learning to pick up more complex patterns and dynamics at work in biogas. Reinforcement learning will unlock real-time decision-making opportunities in continuous biogas production systems based on dynamic variations of temperature, pH, and retention time. In this study, the model was limited to a lab scale study using sugarcane bagasse and, hence up-scaling this method to industrial biogas plants is an important step for the next studies. Future studies will be on training the CNN models on large-scale operations, testing the predictions of the model, and addressing questions about resource-intensiveness in computations and real-time usage in the operational industries.

7.3 Practical Implications

Therefore, the high practical implications of the applicability of CNNs for the improvement of biogas production hold especially on the renewable energy sector, further more, and even in more sustainable ways through bioenergy processes. Predictive models driven by AI present possibilities of increasing efficiency levels, and operational costs, thereby increasing methane gas production so the whole process may even be economically viable and beneficial as far as ecology is concerned. The day will come when CNNs may open up for real-time monitoring and updating of AD systems, thereby revolutionizing the production of bioenergy. In those circumstances, the AI technologies shall enable the industries to fine-tune variability in their processes in real-time, with process variables far more precision and speed; thus, overall performance can be optimized. These set new goals for industries that have to look forward to AI-driven predictive analytics and process optimization to fulfill the demand for renewable energy while wasting less and doing less harm to the environment.

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