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Application of artificial neural networks and multiple linear regression for predicting asymptotic gas production of agricultural by-products

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Abstract This research explored the correlation between the chemical composition and asymptotic *in vitro* gas production (AGP) of diverse agricultural by-products, intending to develop predictive models for AGP using advanced computational methods. The research employed two complementary analytical approaches: artificial neural networks (ANN) and multiple linear regression (MLR), to assess their efficacy in forecasting AGP based on compositional parameters. Two datasets were utilized: a training dataset compiled from previously published literature and a testing dataset comprising experimentally derived chemical profiles and AGP measurements of selected by-products. Following the determination of chemical constituents (e.g., neutral detergent fiber [NDF], acid detergent fiber [ADF], organic matter [OM], and crude protein [CP]) and AGP values, the datasets were merged and subjected to multivariate cluster analysis. This analysis revealed two statistically distinct clusters (A and B), with intra-group similarity thresholds exceeding 80% for Cluster A and 90% for Cluster B. The study focused on Cluster A, which encompassed the selected by-products, for subsequent Pearson correlation and predictive modeling. Key findings included significant inverse relationships between AGP and fiber components (NDF: $r=-0.65$; ADF: $r=-0.72$), whereas positive correlations emerged with OM ($r=0.58$) and CP ($r=0.49$). Comparative model performance demonstrated ANN's superiority ($r^2=0.78$, RMSE=5.39) over MLR ($r^2=0.24$, RMSE=18.36), highlighting its potential for accurate AGP prediction in agricultural by-products.

Keywords: agricultural by-products, gas production, neural networks, cluster analysis, multilinear regression, prediction

Introduction

Over the past decades, the researcher has increasingly turned its attention to gas production (GP) techniques as a promising alternative to conventional *in situ* and *in vitro* methods for assessing the nutritional quality of feedstuffs. This innovative approach offers several distinct benefits compared to traditional methodologies (Getachew et al., 1998). Moreover, GP data can be leveraged to derive estimates for critical parameters, including dry matter (DM) intake, metabolizable energy, organic matter (OM) digestibility (Menke and Steingass, 1988) and short-chain fatty acid production (Getachew et al., 1998).

A substantial body of research has established strong associations between total gas production and key metrics such as feed intake (Hetta et al., 2007), digestible DM, and animal growth (Blummel and Ørskov, 2003). Furthermore, significant relationships have been identified between GP kinetics (parameters b and k) and feed intake or DM digestibility (Rodrigues et al., 2002; Kamalak et al., 2005).

Investigations have also revealed notable correlations between GP kinetics and chemical fractions in specific feed types, including oats and pasture grasses (Kafilzadeh and Heidary 2013; Kulivand and Kafilzadeh, 2015; Marcos et al., 2019). Efforts have been directed toward developing GP prediction equations using forage chemical fractions (Marcos et al., 2019), where linear models were constructed to estimate GP rate and fermented OM based on these fractions.

Artificial neural networks (ANNs) are sophisticated computational frameworks designed to emulate the functionality of biological neural systems. Unlike traditional regression methods, ANNs are highly effective in processing both linear and nonlinear data (Haykin, 1998).

In recent years, the application of ANNs in ruminant research has gained significant interest, particularly in cases where the relationships between input and output variables are complex or not well-defined (Ganesan, 2014; Adebayo et al., 2020). For example, ANNs have been successfully utilized to predict the molar fraction of rumen volatile fatty acids (VFA) using milk fatty acid profiles (Craninx et al., 2008) and rumen passage rates (Moyo et al., 2017). Notably, ANNs have demonstrated greater precision than multiple linear regression in predicting VFA production during GP tests, using carbohydrate fractions as independent variables (Dong and Zhao, 2013). Despite these advancements, research on ANN modeling of feed GP remains limited. Therefore, this study seeks to explore the potential of ANN and MLR in predicting GP kinetics based on the chemical composition of agricultural by-products.

Material and methods

Datasets

Two datasets were utilized in the study. In the context of the first dataset (comprising literature-derived data from previous studies), a systematic literature search was conducted to identify relevant publications on the application of artificial neural networks and regression models for predicting *in vitro* gas production and digestibility parameters in ruminant nutrition. The search was performed in three major databases: Scopus, Web of Science, and PubMed, using the following key search terms and Boolean operators: (“gas production” OR “*in vitro* gas” OR “rumen fermentation” OR “feed digestibility” OR “asymptotic gas production”) AND (“ruminant*” OR “cattle” OR “sheep” OR “goat” OR “by-product*”). No date restrictions were applied, and only peer-reviewed articles published in English were included. The initial search yielded approximately 150 records. After removing duplicates and screening titles and abstracts for relevance (i.e., (including organic matter: OM, crude protein: CP, neutral detergent fiber: NDF, acid detergent fiber: ADF, and hemicellulose: HemCel) and asymptotic gas production (b) of the feedstuffs/by-products), 64 papers were selected for detailed review and inclusion in the first dataset. Subsequently, experiments that conducted gas production tests using bovine rumen fluid instead of sheep rumen fluid were excluded from the database, as were those that did not utilize the Menk and Steingass (1988) method for gas production testing. This rigorous selection process ensured consistency and comparability of the data used for model development. After excluding 48 of the 64 papers, a baseline dataset was constructed, comprising 16 articles with 42 observations (Table 1). The dataset utilized the mean values reported in the original studies for chemical composition and gas production. All chemical composition parameters were converted to percentages and expressed on a dry matter (DM) basis (% of DM). Similarly, asymptotic gas production was measured and reported in mL/200 mg dry matter to ensure consistency and harmonization of the data across the literature-derived and experimental datasets.

The second dataset (dataset 2) consisted of original *in vitro* gas production data generated in the laboratory using the Menke and Steingass (1988) method with sheep rumen fluid. This dataset comprised 34 distinct batches representing five main types of agricultural by-products, such as by-products included soybean hulls (SBH), soybean mill run (SBMR), cottonseed hulls (CSH), sunflower hulls (SFH), and sugar beet pulp (SBP), with multiple batches per type to account for natural variation in chemical composition and fermentation characteristics. The chemical composition parameters determined for each batch was analyzed in duplicate for CP, OM, and ether extract (EE) following the AOAC guidelines (AOAC, 1990). The determination of NDF and ADF was conducted in accordance with the methodology outlined by Van Soest et al. (1991). Hemicellulose content was calculated by subtracting ADF from NDF.

Rumen fluid was obtained from three cannulated sheep and filtered through four layers of cheesecloth. Gas production (GP) was measured at intervals of 2, 4, 6, 8, 12, 24, 48, 72, and 96 hours. A series of blank samples were included to ensure accuracy, and the gas produced from each treatment was calculated by subtracting the gas output of the control blank from the gas produced in each treatment (Menke and Steingass, 1988).

Statistical analysis and models

The volume of gas production (GP, mL/200 mg DM) was fitted to the model using the NLIN procedure of SAS (2011): $G=b\times(1-e^{-kt})$, where G, b, and k represent the volume of GP at time t, the asymptotic GP (mL per 200 mg DM), and the rate of GP (h^{-1}) from the slowly fermentable feed fraction b, respectively.

Multivariate hierarchical cluster analysis was performed on the pooled datasets (datasets 1 and 2) using the Ward's method with SAS statistical software

(García-Rodríguez et al., 2019) to group the feedstuff based on chemical composition and asymptotic GP (b). The resulting graph illustrates the distances between clusters.

The PROC CORR statement in SAS (2011) was used to display Pearson linear correlation coefficients between the variables examined in the pooled dataset. The PROC REG statement in SAS (2011) was used to predict the asymptotic GP (b). Stepwise multiple regression was conducted by including the most significant datasets in the model, with the significance level set at P≤0.01.

Table 1. Summary of the training datasets

Feedstuffs/by-products	ID	OM	CP	NDF	ADF	HemCel	AGP	References
Linseed straw	OB1	74.05	3.61	84.58	71.14	13.44	14.98	Sallam et al., 2007
Date stone	OB2	88.23	7.27	61.35	44.21	17.14	46.69	Sallam et al., 2007
Sugarcane bagasse	OB3	97.9	1.29	77.00	47.60	29.40	39.46	Sallam et al., 2007
Dussa	OB4	93.61	2.17	68.59	46.92	21.67	41.33	Sallam et al., 2007
Cowpea pod	OB5	92.36	12.25	71.44	52.35	19.09	34.33	Akinfemi et al., 2012
Maize offal	OB6	92.47	2.54	69.68	51.74	17.94	37.00	Akinfemi et al., 2012
Vigna sinensis hay	OB7	88.2	14.40	60.80	45.10	15.70	42.10	Aderao et al., 2018
Acacia nilotica (leaves)	OB8	87.6	14.50	69.50	46.80	22.70	40.90	Aderao et al., 2018
Ziziphus nummularia (leaves)	OB9	87.4	14.00	65.70	47.30	18.40	37.90	Aderao et al., 2018
Wheat straw	OB10	87.56	5.07	73.48	45.93	27.55	41.30	He et al., 2015
Juniperus communis	OB11	94.33	5.62	56.98	34.22	22.76	51.92	Kamalak et al., 2004
Dillenia spp.	OB12	90.14	9.59	53.33	41.70	11.63	42.03	Giridhar, 2018
Corn straw	OB13	92.97	4.59	79.26	46.54	32.72	45.16	He et al., 2015
Pomegranate seed	OB14	88.80	11.20	64.00	46.00	18.00	48.59	Delavar et al., 2014
Corn cob	OB15	87.70	3.00	66.50	48.80	17.70	64.60	Chanthakhoun and Wanapat, 2013
Fresh pangola	OB16	89.30	8.14	62.60	36.00	26.60	54.00	Tikam et al., 2015
Pangola hay	OB17	91.50	8.05	63.50	36.90	26.60	50.80	Tikam et al., 2015
Pangola silage	OB18	86.70	8.24	61.30	34.60	26.70	57.30	Tikam et al., 2015
Saccharum officinarum (leaves)	OB19	94.80	2.30	69.80	48.20	21.60	27.80	Elghandour et al., 2013
Andropogon gayanus (leaves)	OB20	88.10	4.40	57.90	41.00	16.90	46.60	Elghandour et al., 2013
Napier grass	OB21	89.60	7.60	59.60	33.10	26.50	47.30	Tikam et al., 2015
Sorghum straw	OB22	93.00	4.30	61.40	38.60	22.80	49.00	Elghandour et al., 2013
Gundelia tournefortii	OB23	68.30	5.24	62.54	48.07	14.47	51.57	Kulivand and Kafilzadeh, 2008
Finger millet straw	OB24	92.68	3.04	65.05	38.54	26.51	53.06	Kiran and Krishnamoorthy, 2007
Barley straw	OB25	92.56	4.22	72.73	53.23	19.50	43.79	Rodrigues et al., 2002
Rice straw	OB26	87.34	4.56	71.45	44.65	26.80	46.74	He et al., 2015
Berseem hay	OB27	88.80	15.32	54.90	38.31	16.59	50.92	Sallam et al., 2007
Descurania Sophia	OB28	81.80	11.95	49.52	39.06	10.46	44.58	Kulivand and Kafilzadeh, 2008
Chick pea	OB29	91.6	11.70	52.00	34.80	17.20	60.90	Karabulut et al., 2007
Tifton hay	OB30	93.34	4.81	77.79	41.76	36.03	45.10	Baffa et al., 2003
Pineapple silage	OB31	93.74	8.90	59.51	38.10	21.41	24.59	Baffa et al., 2003
Lemon pulp	OB32	94.54	9.54	16.69	15.13	1.56	43.60	Lashkari and Taghizadeh, 2015
Grapefruit pulp	OB33	94.13	9.14	16.66	13.09	3.57	44.39	Lashkari and Taghizadeh, 2015
Lime pulp	OB34	91.88	8.16	17.49	14.53	2.96	44.04	Lashkari and Taghizadeh, 2015
Orange pulp	OB35	94.49	8.5	14.74	11.95	2.79	40.96	Lashkari and Taghizadeh, 2015
Taraxacum officinale	OB36	92.71	24.64	40.84	26.17	14.67	28.20	Kiran and Krishnamoorthy, 2007
Cottonseed meal	OB37	93.11	43.15	27.34	16.20	11.14	48.20	Kiran and Krishnamoorthy, 2007
Groundnut meal	OB38	94.10	39.09	29.87	10.92	18.95	51.20	Kiran and Krishnamoorthy, 2007
Rapeseed meal	OB39	91.80	37.72	27.46	15.05	12.41	48.20	Kiran and Krishnamoorthy, 2007
Sesame cake	OB40	87.96	29.55	32.61	17.84	14.77	45.60	Kiran and Krishnamoorthy, 2007
Soybean meal	OB41	92.42	47.52	22.67	11.05	11.62	59.20	Kiran and Krishnamoorthy, 2007
Sunflower meal	OB42	94.77	27.93	48.91	29.78	19.13	35.90	Kiran and Krishnamoorthy, 2007

OM: organic matter, CP: crude protein, EE: ether extract, NDF: neutral detergent fiber, ADF: acid detergent fiber, HemCell: Hemi-cellulose. AGP: Asymptotic gas production.

All chemical composition data are presented as percentages of dry matter (% DM). AGP values are expressed as mL/200 mg DM.

The artificial neural network (ANN) modeling process was executed using RapidMiner software (version 9.3.001) with the Deep Learning operator. Deep learning was based on a multi-layer feed-forward ANN trained with stochastic gradient descent using back-propagation. The deep network used in the current study consisted of three layers of nodes: the input layer (with nodes corresponding to the selected chemical composition parameters), a single hidden layer containing 13 neurons, and an output layer with one node representing the predicted asymptotic gas production (b, mL/200 mg DM). The Maxout activation function was applied to each neuron within the hidden layer. Training parameters included a maximum of 600 epochs, with adaptive learning rate enabled and a rho value of 0.99. Early stopping was activated to prevent overfitting (training halted if no improvement was observed in validation performance over consecutive epochs). The dataset was divided into 75% for training and 25% for testing/validation. The Performance operator was used to statistically evaluate the model's performance, providing RMSE and R^2 values.

Results and discussions

Chemical composition of agricultural by-products

The chemical composition of selected feedstuffs is presented in Table 2. The crude protein (CP) content varied among the by-products, with soybean mill run (SBMR) exhibiting the highest values (20.49% of DM), likely due to its relatively high proportion of seed kernel. The chemical composition of soybean hulls (SH) and SBMR was within the range reported by Ipharraguerre and Clark (2003). Higher levels of neutral detergent fiber (NDF) were noted for ground peanut hulls (GPH), sunflower hulls (SFH), and cottonseed hulls (CSH), while lower levels were recorded for SBMR and sugar beet pulp (SBP). A similar pattern was observed for acid detergent fiber (ADF).

Table 2. Chemical composition (mean±SD, % of DM) of the agricultural by-product batches used in the second dataset

	OM	CP	NDF	ADF	HemCel
SBH	99.50±0.05	9.36±0.10	69.45±0.35	51.35±0.35	18.30±0.00
SBMR	93.80±0.20	20.49±0.54	49.65±0.15	39.05±0.25	10.06±0.40
CSH	79.05±1.75	5.50±0.53	84.10±0.50	69.02±0.50	11.90±0.00
SFH	79.95±5.75	3.51±0.01	88.15±0.05	68.50±0.90	19.65±0.85
SBP	98.50±0.20	9.96±0.08	48.65±0.05	25.95±0.75	22.70±0.99
GPH	95.90±0.28	4.79±0.08	89.15±0.50	76.75±0.50	12.40±0.99

SD: standard deviation, OM: organic matter, CP: crude protein, EE: ether extract, NDF: neutral detergent fiber, ADF: acid detergent fiber, HemCell: hemi-cellulose. SBH: soybean hull, SBMR: soybean mill run, CSH: cottonseed hull, SFH: sunflower hull, SBP: sugar beet pulp, GPH: ground peanut hull.

Gas production assay

The gas production (GP) trend of the agricultural by-products (dataset 2) is illustrated in Figure 1. The agricultural by-products exhibited different behaviors regarding the rate at which they produced gas. Table 3 presents the total gas produced by the incubation of selected agricultural by-products at various time points and the corresponding GP kinetics (b and k). In the present study, selected agricultural by-products demonstrated a wide range of gas production, from 26.10 to 107.29 mL after incubation for 96 hours. Soybean hulls and SBMR recorded the highest values of gas production at 96 hours, while GPH, SFH, and CSH showed lower gas production. Similar trends were observed for incubation at 24 and 72 hours.

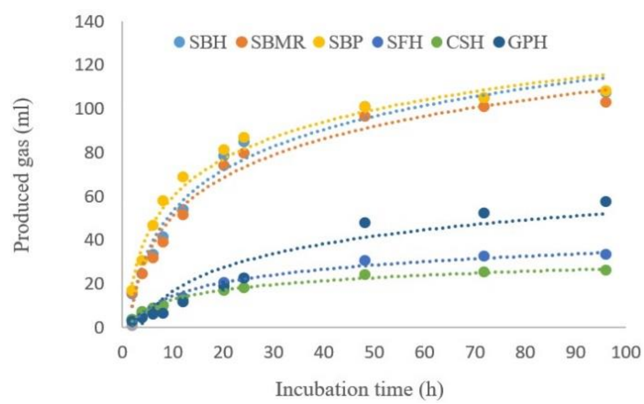


Figure 1. Evolution of gas production from several agricultural by-products
SBH: soybean hulls, SBMR: soybean meal residue, CSH: cottonseed hulls, SFH: sunflower hulls, SBP: sugar beet pulp, GPH: ground peanut hulls

Table 3. Gas volume and gas production kinetics (mean±SD) for selected agricultural by-products

	Agricultural by-products					
	SBH	SBMR	CSH	SFH	SBP	GPH
Gas volume (mL/200 mg DM)						
24 h	85.21±12.63	79.75±7.86	22.50±2.65	22.06±2.16	86.93±10.27	17.75±5.74
72 h	105.29±15.45	100.85±6.06	52.10±3.63	32.50±3.78	105.63±11.03	24.58±6.86
96 h	107.29±15.42	102.90±5.66	57.5±6.15	33.6±3.59	108.25±11.00	26.1±6.89
Gas production kinetics (96 h)						
AGP *(mL)*	107.01±18.80	102.38±5.85	76.30±15.20	33.40±4.41	104.41±11.22	25.01±6.07
k (% h^{-1})	0.069±0.020	0.063±0.010	0.017±0.005	0.047±0.005	0.092±0.010	0.060±0.020

SBH: soybean hull, SBMR: soybean mill run, CSH: cottonseed hull, SFH: sunflower hull, BP: pistachio by-product, SBP: sugar beet pulp, GPH: ground peanut hull.

Cluster analysis

The results of the cluster analysis on the pooled datasets (1 & 2) are presented in Figure 2. The samples were grouped into two clusters (A & B); the degree of similarity among the by-products within each group being greater than 80% and 90% for clusters A and B, respectively. Group A included samples OB1-31; and SBH, SBMR, CSH, SFH, SBP, and GPH (dataset 2). Cluster B grouped samples OB32-44. Cluster A was distinguished from Group B with a similarity of 55%. Group B included lemon pulp, grapefruit pulp, lime pulp, orange pulp, dandelion (*Taraxacum officinale*), cottonseed meal, peanut meal, rapeseed meal, sesame cake, soybean meal, sunflower meal, and chickpea.

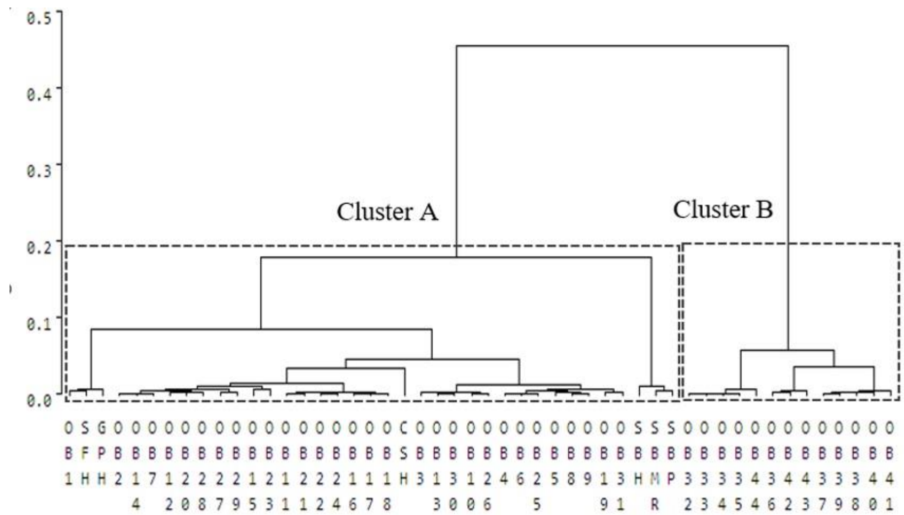


Figure 2. Plot of multivariate cluster analysis demonstrating groupings of various feedstuffs and by-Products according to similarities in their chemical composition and asymptotic gas production (b)

In this study, cluster analysis was employed to group similar agricultural by-products into distinct clusters. It has been demonstrated that cluster analysis can effectively classify agricultural by-products based on their chemical composition and fermentation characteristics (Haddi et al., 2003). Cluster B consisted of feeds with low cell wall content or, in the case of meals, high protein content. Group A included dataset 2 and the remaining by-products from dataset 1. Bizzuti et al. (2023) classified agricultural by-products into a clear cluster with three distinct groups based on chemical composition, *in vitro* gas production, organic matter degradability, and ruminal fermentation kinetics.

Table 4 presents the correlation coefficients between chemical composition and produced gas potential (b) in cluster A. Negative correlations (P<0.01) were observed between asymptotic gas production (b) and NDF and ADF. The negative correlation between AGP and cell wall components (NDF and ADF; -0.47 and -0.41, respectively) in this study is consistent with previous research (Blummel and Ørskov, 1993; Haddi et al., 2003). Kafilzadeh and Heidary (2013) examined 18 different oat cultivars and found a significant negative correlation between NDF (r=0.48) and ADF (r=0.83) with AGP or gas production rate. Although lignin was not examined in this study, much of the adverse effect of cell wall components on gas production may be attributed to the presence of lignin in NDF and ADF. Lignin forms a physical barrier that reduces the access of rumen microbes to fermentable cell wall components. Studies have shown a strong and negative correlation between GP kinetics and ADL content of agricultural co-products (Chen et al., 2008, Moyo et al., 2017).

Table 4. Correlation of chemical composition with *AGP*

	AGP
Organic matter	0.32*
Crude protein	0.37*
Neutral detergent fiber	-0.47**
Acid detergent fiber	-0.41**
Hemicellulose	-0.04

* P<0.05, **P<0.01

It has been reported that cumulative *in vitro* gas production after 12-48 hours of fall-oat diets was negatively correlated with NDF, hemicellulose, lignin, and ash (Nherera et al., 1999). These findings are further supported by the data from the present study, which indicated that by-products with the highest levels of cell wall content exhibited the lowest gas production (see Tables 2 and 3).

There were positive correlations (P<0.05) between organic matter (OM) and crude protein (CP) of agricultural by-products and asymptotic gas production (b). Similarly, the results of Kulivand and Kafilzadeh (2015) reported a positive correlation between the CP content of pasture grasses with asymptotic GP and the rate of GP after 96 hours of incubation. Additionally, Nherera et al. (1999) observed a positive and significant correlation between the nitrogen content of some diets and GP kinetics (b and k) after 96 hours of incubation. It has been reported that the minimum CP concentration to support microbial activity is 7% of DM (Hariadi and Santoso, 2010). Interestingly, in the present study, co-products with CP content below this level (i.e., CSH, SFH, and GPH) had the lowest cumulative GP.

Model development

The multiple linear regression (MLR) and artificial neural network (ANN) models utilized data from Cluster A only, with four input variables-OM, CP, NDF, and ADF-selected based on their significant correlations with asymptotic gas production. This ensured that the models focused on the most influential chemical components.

The multiple linear regression (MLR) model for asymptotic gas production (AGP) and the statistical parameters for the ANN and MLR models are summarized in Table 5. Asymptotic gas production (AGP) was explained by multiple regression equations using organic matter (OM), crude protein (CP), and neutral detergent fiber (NDF) as independent variables (r^2=0.24). The r^2 and root mean square error (RMSE) for predicting b, using ANN, were 0.78 and 5.39, respectively. In comparison the results of the ANN with those of the MLR model, the ANN performed better with lower RMSE and higher r^2.

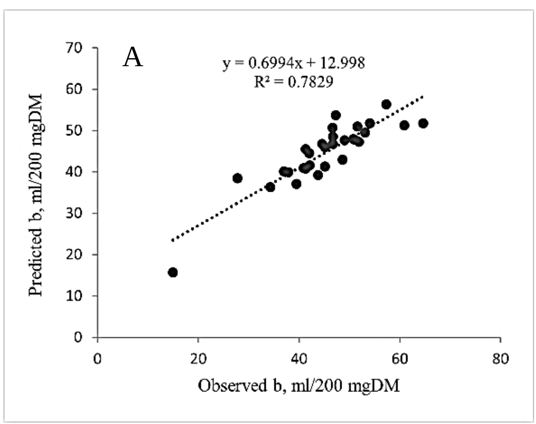
Table 5. Statistical analysis and details of ANN and MLR models for asymptotic gas production

	MLR	ANN
Model	b=26.06+(0.62×OM)+(0.78×CP)–(0.57×NDF)	-
Root mean squared error	18.36	5.39
R^2	0.24	0.78

When the number of nodes in the hidden layer was set to 13 and b was treated as a single output variable in the model, a lower root mean square error (RMSE) and higher r^2 for predicting b were observed.

Dong and Zhao (2013) concluded that the number of neurons in the hidden layer significantly influenced the performance of artificial neural network (ANN) models for predicting ruminal volatile fatty acid (VFA) production. In the current study, the number of neurons was determined through trial and error, and the model with the lowest RMSE and highest r^2 was selected as the optimal model. Fadare and Babayemi (2007) reported a higher R value with a lower standard deviation in neural network models with one hidden layer compared to those with two. In the present study, the number of hidden layers was set to one, as a single hidden layer ANN can approximate any function given a sufficient number of neurons.

The regression relationship between the observed and predicted outputs is shown in Figure 3. The ANN model exhibited markedly superior performance, with an R^2 of 0.783 compared to 0.235 for the MLR model, as illustrated by the tighter clustering of data points around the line of equality. Similarly, Fadare and Babayemi (2007) used the chemical composition of browse forage as inputs in an ANN trained with the Levenberg-Marquardt algorithm (one hidden layer and eight inputs) to predict *in vitro* gas production (GP) at 24 hours. They reported a high r^2 value between the observed and predicted data.



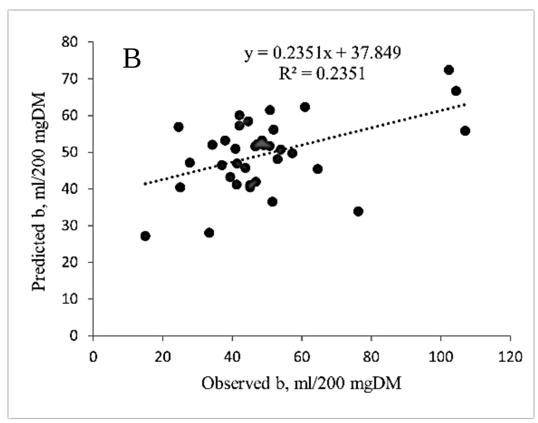


Figure 3. Predicted *vs.* observed asymptotic gas production (AGP) after 96 h for ANN (A) and MLR (B) models

The MLR modeling is a useful tool for identifying the linear relationships between different parameters. Nherera et al. (1999) found a stronger correlation between dietary NDF and nitrogen with *in vitro* AGP at 24 h compared to 96 h. By employing simple and multiple linear equations to predict *in vitro* AGP based on dietary chemical composition, they reported a higher R for predicting gas at 24 h than at 96 h (0.90 and 0.80, respectively). Similarly, Marcos et al. (2019) demonstrated that carbohydrates (sugars and NDF) could be used to predict *in vitro* ruminal GP and OM fermentation of olive cake. The MLR modeling assumes a linear relationship between dependent and independent variables. However, in many cases, the data are complex and not linear (Dongand Zhao, 2013). This is why the ANN models often outperform the MLR models, as observed in this study.

It has been reported that CNCPS carbohydrate fractions can effectively be used as inputs to predict *in vitro* rumen gas production (GP) using MLR, as well as to estimate acetate, propionate, butyrate, and total VFA production through both MLR and ANN approaches (Dongand Zhao, 2013). In this study, the ANN models demonstrated superior performance compared to the

MLR models. The enhanced performance of ANN models over MLR has also been documented in estimating milk production (Sanzogni and Kerr, 2001), goat body weight gain (Chen et al., 2008), and nutrient content of dairy manure (Njubi et al., 2010).

Conclusion

The findings of this study demonstrated that the chemical composition of agricultural by-products can be effectively used to predict the *in vitro* asymptotic gas production (AGP), particularly when employing non-linear modeling approaches. The artificial neural network (ANN) model substantially outperformed the multiple linear regression (MLR) models. The poor performance of the MLR model highlights the complex and predominantly non-linear nature of the relationships between selected chemical components (organic matter, crude protein, neutral detergent fiber, and acid detergent fiber) and asymptotic gas production. In contrast, the ANN's ability to capture these non-linear interactions resulted in significantly more accurate predictions. These results underscore the superiority of deep learning approaches over traditional linear methods for modeling rumen fermentation parameters from agricultural by-products. Further research is warranted to enhance the prediction accuracy, validate the model on a broader range of feedstuffs, and expand the dataset by incorporating the species-specific inoculum sources or developing multi-species models with species as an additional input feature.

Conflict of interest

The author declares no conflicts of interest.

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