



Artificial Intelligence-Based Prediction of Biomass Higher Heating Value Using Proximate Analysis

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ABSTRACT

The higher heating value (HHV) is a critical factor to assess when analysing and selecting biomass substrates for combustion and power generation. Traditionally, the determination of HHV is conducted in a laboratory setting utilising an adiabatic oxygen bomb calorimeter. In the meantime, this method requires significant effort and financial resources. Therefore, it is crucial to investigate alternative possibilities. This study utilised two distinct techniques based on artificial intelligence: a support vector machine (SVM) and an artificial neural network (ANN) to develop models for predicting biomass HHV based on proximate analysis. The input variables, which include ash, volatile matter, and fixed carbon, were combined to develop four distinct inputs for the prediction models. The comprehensive results indicated that both the ANN and SVM methodologies can ensure precise predictions across all input combinations. The best prediction performances were noted when fixed carbon and volatile matter were combined as the input variables. The results indicated that the ANN surpassed the SVM, achieving the lowest root mean squared error of 0.0008 and the highest correlation coefficient of 0.9274. This study concluded that the ANN is favoured over SVM for predicting biomass HHV based on the proximate analysis.

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INTRODUCTION

Increased demand for energy, the dwindling fossil fuel reserves, and the urgent need for environmentally sustainable energy sources have driven worldwide attention towards renewable energy. Renewable energy sources like wind, solar, hydro, and biomass are clean and abundant, offering promising potential to replace fossil fuels for thermal energy and electricity generation (Bello & Dodo, 2025). Biomass is recognised as one of the most abundantly available renewable energy sources, following wind and solar. It includes a variety of materials such as sewage sludge, energy grasses, algae, wood, food wastes, bagasse, straw, forest wastes, agro residues, and more (Dodo et al., 2021). To achieve the best design and functionality of biomass-fuelled energy systems, it is essential to thoroughly examine and analyse specific

characteristics of the feedstock. The primary consideration is the calorific value, also referred to as the heating value, as it indicates the energy content of the biomass substrate (Agha et al., 2025; Ezzahra Yatim et al., 2022). The heating value is classified as either a higher heating value (HHV) or a lower heating value (LHV). The HHV includes the condensation enthalpy of water when a unit weight or volume of fuel is combusted to release thermal energy, whereas the LHV is determined without considering the condensation enthalpy of water.

The heating value is traditionally assessed in a laboratory setting utilising an oxygen bomb calorimeter under standard conditions. In the meantime, the energy audience is adopting methods that depend on proximate or ultimate analyses for predictions, as the experimental procedures are expensive, labour-

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intensive, and necessitate skilled personnel for sample preparation to prevent inaccurate results (Dodo et al., 2022; García Nieto et al., 2022). The comprehensive analysis details the contents of nitrogen, hydrogen, carbon, sulphur, and oxygen, whereas the preliminary analysis outlines the ash, fixed carbon, volatile matter, and moisture content of the biomass fuel. In a similar vein, the expense associated with an elemental analyser, along with the necessary expertise for its operation and the specific sample preparation protocols that must be adhered to, poses significant challenges to depending on ultimate analysis for predicting heating value. Consequently, the pursuit of an alternative method that can deliver optimal outcomes while minimising stress and cost has emerged as a crucial endeavour, and the proximate analysis aligns with these criteria (Ezzahra Yatim et al., 2022).

Moreover, the utilisation of artificial intelligence (AI) to address intricate challenges across diverse domains has garnered significant attention in recent times. Consequently, techniques like artificial neural networks, adaptive neuro-fuzzy inference systems, and Gaussian process regression can provide strong alternatives to traditional laboratory investigations of biomass heating value. For example, (Ezzahra Yatim et al., 2022) developed ANN algorithms to estimate the HHV of biomass. The optimal model exhibited a root mean square error of 1.17527 and a correlation coefficient of 0.75377. (Qian et al., 2018) utilised 49 lines of proximate analysis data to forecast the HHV of poultry waste. The accuracy of the best-fit regression model was superior when evaluated against the error metrics.

Rostami and Baghban (2018) developed machine learning prediction models utilising 100 data points from ultimate analysis variables. Güleç et al. (2022) developed ANN models that were trained by integrating ultimate-proximate analysis variables to estimate the HHV of biomass. The sigmoidal transfer functions yielded better prediction outcomes than the linear activation function. The model established by Dai et al. (2021) demonstrated the potential advantages of extreme machine learning in forecasting biomass HHV. García Nieto et al.

(2022) utilised an experimental dataset to develop models for predicting HHV, employing SVM with the grid search (GS) optimiser, along with a multilayer perceptron neural network. The SVM-GS model demonstrated a higher level of accuracy.

Utilising a limited number of experimental data sets or employing heating value predictive models based solely on a single biomass substrate is a prevalent approach. In the meantime, the prediction models utilised for this investigation do not ensure precise prediction performances, particularly when it comes to forecasting the heating values of various biomass materials. Moreover, the review of relevant studies indicates that the trend in applying AI to predict biomass heating values is primarily led by an ANN technique. Therefore, it is essential to investigate an alternative AI method to determine if it can yield more accurate prediction outcomes.

The current investigation sought to develop and evaluate the precision of two AI-driven models (support vector machine and artificial neural network) for predicting the higher heating value (HHV) of biomass. This was achieved by utilising an extensive collection of experimental datasets that encompass a diverse array of feedstock in relation to the proximate analysis. The variables for moisture-free proximate analysis, including ash, fixed carbon (FC), and volatile matter (VM) expressed in wt.%, were chosen to develop four distinct inputs for the models. The dataset was adjusted to allocate 75% for training purposes and the remaining 25% for testing, reflecting the principle that increased training data enhances the performance of prediction models (Msheliza & Dodo, 2025). The accuracy of the implemented models was evaluated through the use of statistical metrics. The outcomes of this study are expected to provide a framework for the energy community in exploring effective, rapid, and cost-efficient methods for assessing the HHV of various biomass materials.

MATERIALS AND METHODS

Data Pre-processing

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This study applied two AI-based techniques, specifically SVM and an ANN, to predict the HHV of biomass using moisture-free proximate analysis parameters, including FC, ash, and VM. The experimental datasets, which include 474 instances from the works of Estiati et al. (2016), Gunamantha (2016), Nhuchhen & Salam (2012), Phichai et al. (2013), Qian et al. (2018), and Uzun et al. (2017), were employed for model implementation. The dataset includes a diverse array of biomass feedstock, comprising grasses (57 samples), seed hulls (34 samples), sewage sludge (41 samples), sawdust (28 samples), animal manure (71 samples), agro wastes (111 samples), wood wastes (40 samples), and solid wastes (92 samples). The equation was utilised to normalise the dataset to a standard scale ranging from 0 to 1, enhancing the integrity of the data and ensuring that variations in the signals of various variables exert uniform effects on the characteristics of the networks, irrespective of their magnitudes.

$$x_n = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

In this context, the normalised and unnormalised variables are denoted by x_n and x_i , while the maximum and minimum values of the dataset are represented by x_{\max} and x_{\min} , respectively.

In the process of developing predictive models, certain independent variables exert considerable influence on the target variable, whereas others demonstrate minimal or negligible effects. It is essential to determine the combination of these independent variables that can yield the highest prediction accuracy. In light of this, the FC, VM, and ash were chosen for sensitivity analysis as outlined in Table 1 for subsequent application in the ANN and SVM tools.

Table 1: Input selection

Model input	Variable combination
C1	VM, ash
C2	FC, ash
C3	FC, VM, ash
C4	FC, VM

Typically, the ANN frameworks and their equivalents in MATLAB utilise a data division of 20%, 20%, and 60% for validation, testing, and training, respectively. This can be adjusted to align with the more common testing-training divisions of 40% and 60%. In numerous studies, data is typically divided into proportions such as 30% for testing and 70% for training, or 25% for testing and 75% for training. This approach aligns with the understanding that prediction models perform better when they are trained on a larger dataset (Dodo et al., 2022). This study implemented a dataset division for testing and training at a ratio of 25% and 75%, respectively. The effectiveness of the developed models in making predictions was assessed through the use of statistical indices. Figure 1 illustrates the chart representing the study methodology.

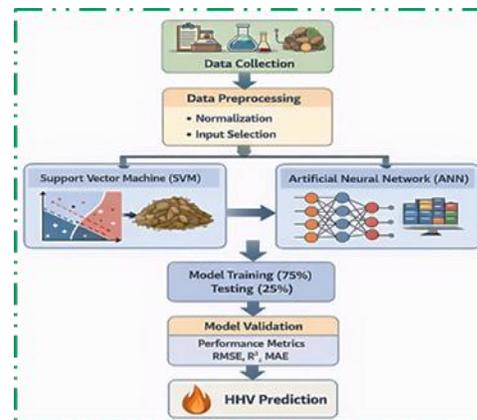


Fig. 1: Study methodology

Support vector machine

Support vector machine (SVM) is a frequently analysed machine learning algorithm known for its minimal tuning requirements to attain high performance levels. Initially developed in 1995 by Vladimir Vapnik, the SVM is a supervised machine learning model that is mainly employed to address issues related to regression and classification, specifically support vector classification and support vector regression (Dodo et al., 2022). The principles underlying SVM involve minimising structural risk and drawing from statistical learning theory, focusing on the transformation of initial training data samples into

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a higher-dimensional feature space through the use of non-linear kernel functions. This method enables the conversion of issues from non-linear to linear, allowing for an optimal solution to be achieved. The regression function of the SVM is articulated in equation (2) (Msheliza & Dodo, 2025).

$$f(x) = b + w\phi(x) \quad (2)$$

Here, b and w stand for the bias and weight vectors, respectively, while the non-linear function for mapping the initial input vectors into a higher-dimensional feature space is represented by $\phi(x)$

The Lagrange multipliers and optimality constraints expressed in eq. (3), are used to determine the regression function of Eq. (2) (Msheliza & Dodo, 2025).

$$f(x) = \sum_{k=1}^n (\beta_k - \beta_k^*) Q(x, x_k) + b \quad (3)$$

Where $Q(x, x_k)$ represents the kernel function and the term $\beta_k - \beta_k^*$ represents the Lagrange multipliers.

Choosing the ideal kernel function for modelling the HHV of biomass from the proximate analysis involved a trial-and-error technique. This approach utilised root mean square error as the performance evaluation index, given the absence of established criteria for kernel selection in existing literature. This method provided greater validation for the linear kernel function. Additionally, a widely used method for evaluating the performance of an SVM model is cross-validation. The 10 k-fold cross-validation method, widely recognised in scholarly works for its effectiveness in assessing the generalisation and accuracy of prediction models, was employed to validate the dataset (Elmaz et al., 2019; Msheliza & Dodo, 2025).

Artificial neural network

The advancement of artificial neural networks (ANN) is grounded in the investigation of

the human brain and nervous system. Specifically, ANN models emulate the electrical activity of the nervous and brain systems. Components that handle information, typically referred to as neurons, are linked together via weighted connections (Msheliza & Dodo, 2025). Layers or vectors are typically organised in a stacked configuration, with the output from one layer acting as the input for the subsequent layer, and possibly for further layers too.

Feed-forward back-propagation network (FFBN), recurrent neural network, radial basis function neural network, Kohonen self-organising neural network, convolutional neural network, and modular neural network exemplify a range of various ANN architectures suited for different problems (Bello & Dodo, 2025). FFBN was chosen for this study because of its established effectiveness in tackling challenges related to pattern prediction and pattern matching. In a feedforward neural network, each neuron within a layer is connected in a unidirectional manner, combining the weighted sum of its inputs with a bias and utilising an activation or transfer function to produce an output that does not return to the input neurons. The generalized expression for FFBN is represented in eq. (4) (Bello & Dodo, 2025).

$$y = k \{ B_2 + h [B_1 + f(x) W_1] W_2 \} \quad (4)$$

The input and output vectors were represented by y and k , respectively. f , h , and k are the transfer functions while B_i and W_i are the weight and bias vectors (Bello & Dodo, 2025).

$$\phi(x) = \frac{2}{e^{-2x} + 1} \quad (5)$$

The training function utilised in this study is the Levenberg-Marquardt (trainlm). As the most efficient FFBN formalism available, trainlm is often suggested as the go-to supervised learning algorithm, even though it demands more memory than alternative algorithms (Bello & Dodo, 2025).

Performance evaluation

The metrics employed to evaluate the predictive capabilities of the models encompassed

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the mean square error (MSE), root mean square error (RMSE), coefficient of determination (R^2), and correlation coefficient (R), as detailed in Eqs. (6)-(9). The selection of these evaluation criteria is based on their successful application in numerous studies of a comparable nature, effectively demonstrating the accuracy of prediction models (Bello & Dodo, 2025). A prediction model tends to demonstrate improved performance and accuracy when the MSE and RMSE values are lower. The values of R and R^2 range from 0 to 1. They indicate how closely a model aligns with the data. A higher R^2 and R value indicate that the model implemented demonstrates a significant level of accuracy.

$$MSE = \frac{1}{n} \sum_{i=1}^n (HHV_{e(i)} - HHV_{p(i)})^2 \quad (6)$$

$$R^2 = 1 - \frac{(HHV_{e(i)} - HHV_{p(i)})^2}{(HHV_{e(i)} - \overline{HHV_{e(i)}})^2} \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (HHV_{e(i)} - HHV_{p(i)})^2} \quad (8)$$

$$R = \sqrt{1 - \frac{(HHV_{e(i)} - HHV_{p(i)})^2}{(HHV_{e(i)} - \overline{HHV_{e(i)}})^2}} \quad (9)$$

RESULTS AND DISCUSSION

Prediction performances of the standalone models

The use of quantitative and visual representations of the results played a vital role in assessing the impacts of different input combinations and the accuracy of the predictive models in computational analysis. Therefore, as illustrated in Table 2, every input combination (C1-C4) utilised in both the ANN and SVM methodologies ensures accurate predictions, supported by their elevated coefficients of correlation and determination during both the training and testing phases. The closer these metrics approach unity, the more effective the prediction models become. The combination of ash and VM (i.e., C1) in both the ANN and SVM models exhibited the least effective prediction capability, with C2 and C3 following closely behind. In the meantime, remarkable performances were observed when the VM and FC were utilised as input combinations for the prediction models. Fig. 2 presents boxplots that visually summarise the predicted and experimental HHV data across both training and testing phases. The distribution of data and the whiskers for C4 utilising ANN and SVM showed a correlation with their corresponding experimental HHV during both training and testing phases, followed by C3, C2, and C1 in a descending order of prediction performance.

Table 2: Prediction models' performance evaluation results

	Training Phase				Testing Phase				
		R^2	R	MSE	RMSE	R^2	R	MSE	RMSE
SVM	C1	0.7851	0.8861	0.0022	0.0471	0.8429	0.9181	0.001	0.0323
	C2	0.8018	0.8954	0.002	0.0453	0.8488	0.9213	0.001	0.0317
	C3	0.8034	0.8963	0.002	0.0451	0.8508	0.9224	0.001	0.0315
	C4	0.7973	0.8929	0.0021	0.0458	0.8527	0.9234	0.001	0.0313
ANN	C1	0.8029	0.896	0.002	0.0453	0.8689	0.9322	0.0009	0.0295
	C2	0.8095	0.8997	0.002	0.0445	0.8699	0.9327	0.0009	0.0294
	C3	0.8025	0.8958	0.0021	0.0453	0.8257	0.9087	0.0012	0.034
	C4	0.8154	0.903	0.0019	0.0438	0.8786	0.9374	0.0008	0.0284

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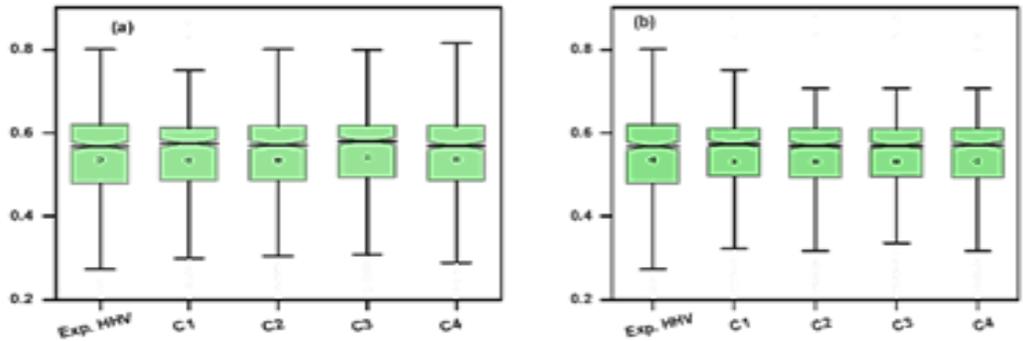
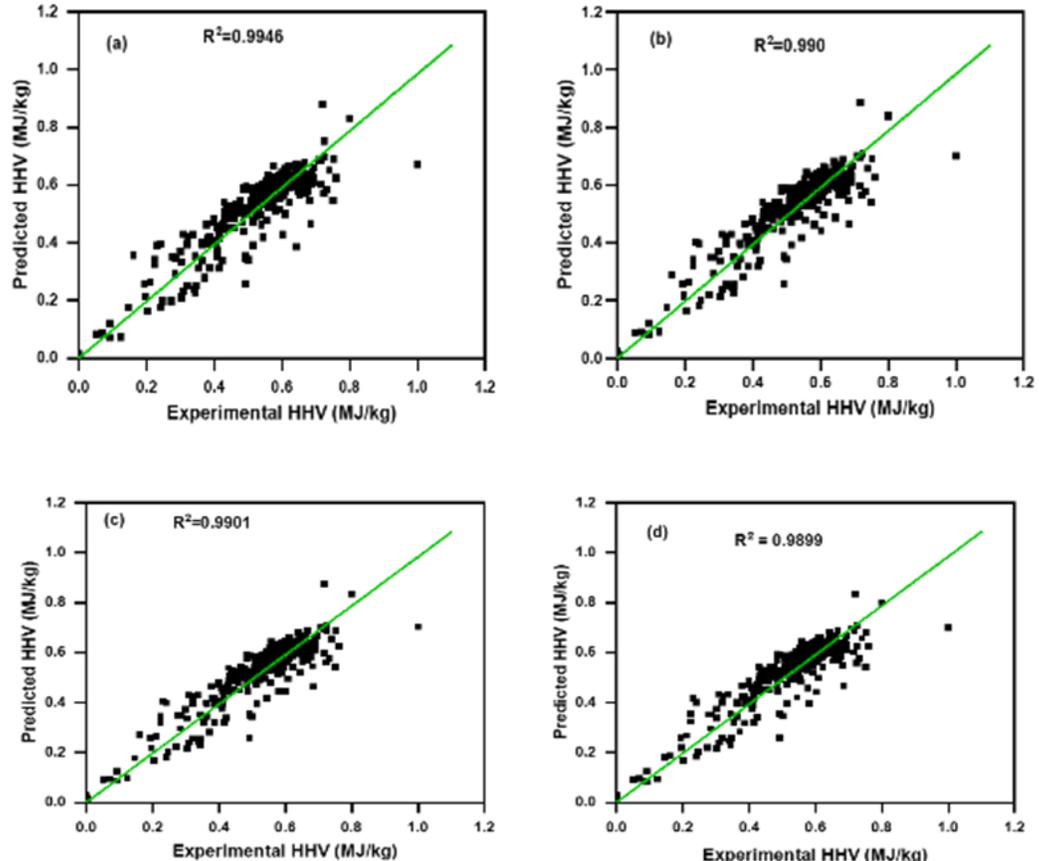


Fig. 2: Box plots: (a) ANN (b) SVM

Moreover, the time series plots in Fig. 3 illustrate that the predicted HHV pattern aligns closely with the experimental HHV, as observed in the testing dataset. These findings suggest robust

correlations between the experimental HHV and the predictions made using ANN and SVM models. The models that have been implemented demonstrate consistency and accuracy in their predictive capabilities.



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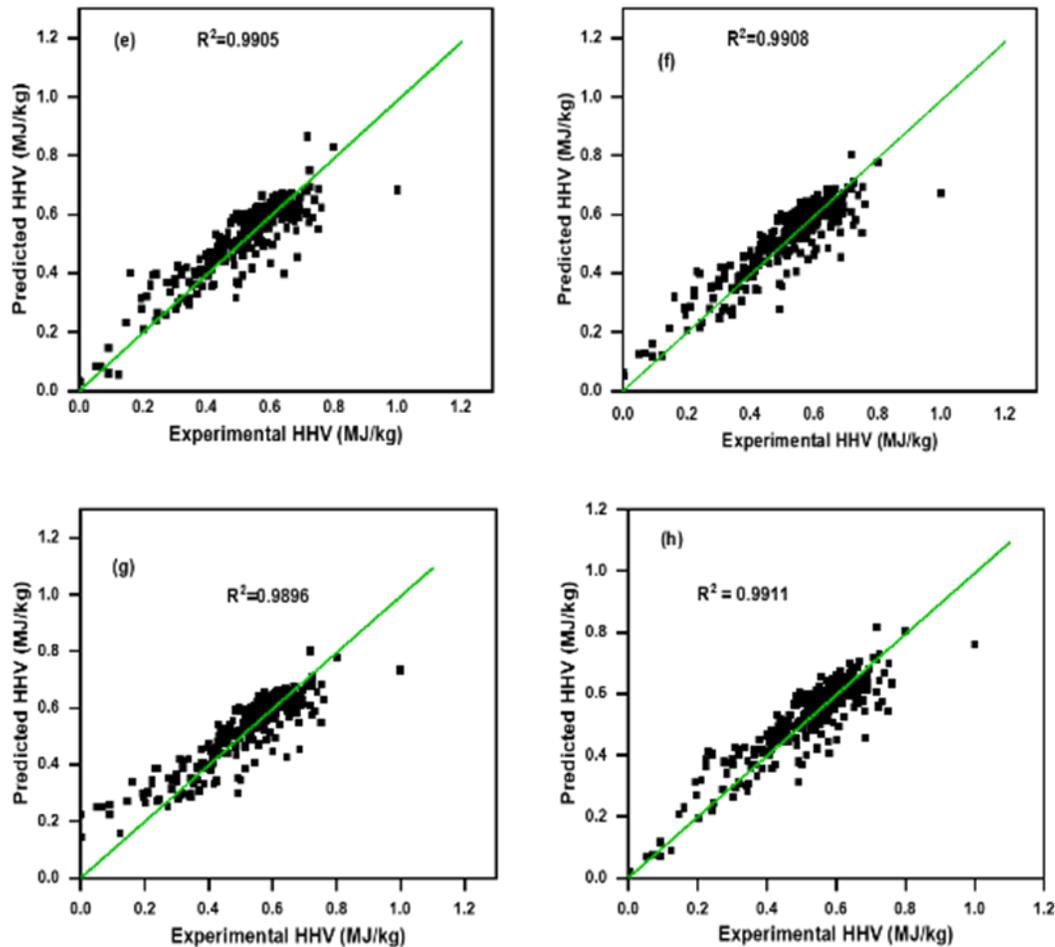


Fig. 3: Correlation plots of the input combinations: (a) SVM-C1, (b) SVM-C2, (c) SVM-C3, (d) SVM-C4, (e) ANN-C1, (f) ANN-C2, (g) ANN-C3, (h) ANN-C4

Performance comparison of ANN and SVM models

The radar plots in Fig. 4 offer a concise summary of the comparative prediction performance of ANN and SVM, utilising RMSE and R as metrics. In the radar plots, each input combination (C1, C2, C3, and C4) features an axis extending from the centre to parity. The data point closest to the outermost gridline in the model, as indicated by the correlation coefficient (see Fig. 4 (a)), is regarded as demonstrating the most effective predictive performance. The root mean

square error depicted in Fig. 4 (b) indicates that the model demonstrating the highest prediction accuracy is the one whose data point is nearest to the centre. As illustrated in Fig. 4, the ANN exhibited superior ability to predict the HHV of biomass in comparison to the SVM across all input combinations, except C3 (FC, VM, ash), where the SVM outperformed. In C3, the SVM demonstrates a lower RMSE of 0.0315 and a higher R of 0.9224, in contrast to the RMSE of 0.0340 and an R of 0.9087 observed in ANN.

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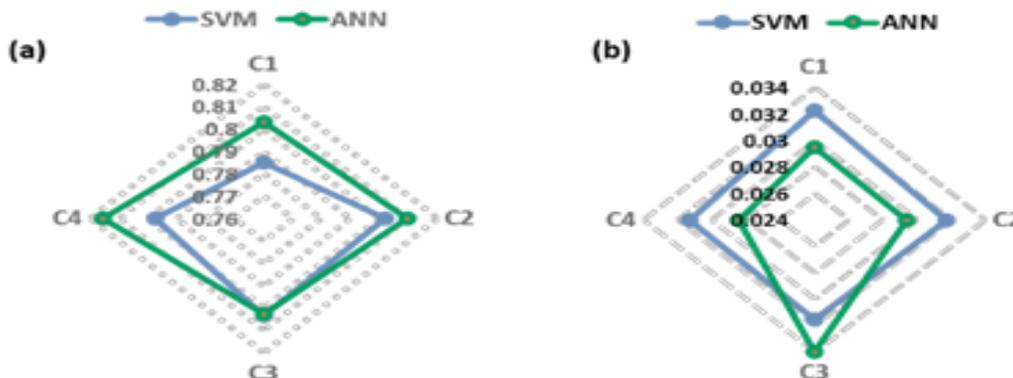


Fig. 4: Radar plots using performance evaluation metrics: (a) R (b) RMSE

Prediction models validation

The computational intelligence models executed by Yaka et al. (2022), encompassing random forest regression, genetic programming, polynomial regression, decision tree regression, multilinear regression, and support vector regression, exhibited mean squared errors reaching as high as 1.7932. Therefore, they are unable to ensure superior performance relative to all the models examined in this study. Additionally, Nhuchhen & Salam (2012) developed 24 empirical models, which exhibited mean squared errors and determination coefficients that varied from 8.72 to 19.28 and 0.0005 to 0.2398, respectively.

The models developed in this study are positioned as more effective alternatives to empirical models for predicting biomass HHV. While the prediction models developed by Uzun et al. (2017) and Akkaya (2016) demonstrate competitive prediction capabilities, they utilise a greater number of input parameters compared to the optimal models C1, C2, and C4 presented in this study. From an economic perspective, a model that incorporates a greater number of input parameters tends to escalate both budgetary and labour demands. This may fail to capture the attention of the energy audience, particularly if a simpler model with fewer input parameters can achieve superior performance.

CONCLUSION

This study involved the application of two heterogeneous AI-based models, specifically SVM and ANN, to develop biomass HHV

prediction models utilising proximate analysis parameters such as ash, VM, and FC. The proximate analysis variables were combined to develop four unique inputs for the models that were implemented. The findings clearly indicate the accuracy of both the ANN and SVM in predicting the biomass HHV. Meanwhile, the ANN demonstrated its superiority in predictive accuracy, achieving the lowest RMSE of 0.0008 and the highest R of 0.9274 when FC and VM were utilised as the input combination. Further studies should be conducted to explore the capabilities of ANN types beyond the feed-forward neural network, as well as other AI techniques like Gaussian process regression and neuro-fuzzy systems, in predicting the HHV of biomass feedstock.

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