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Impact of ultrasound-assisted process on enzymatic extraction of polyphenols from purple rice bran in Vietnam: Experimental kinetics and innovative artificial approach

Impacto del proceso asistido por la ultrasonido en la extracción enzimática de polifenoles de la caña de arroz púrpura en Vietnam: Cinética experimental y enfoque artificial innovador

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Abstract

Ultrasound waves is one of the emerging innovative techniques, that widely applied to assist the extraction process. Besides, enzymatic extraction process also considered as green technology. In addition, in Asian countries, especially in Vietnam, the rice bran is abundant, which contained many health benefits compounds. This study is aimed to investigate the effect of power of ultrasound (20-100%) on the kinetic of recovery yield (RY, %) and total polyphenol content (TPC, mgGAE/g) in the extract. The statistical and artificial analysis were applied to study the behavior of extraction process. Among 5 statistical models, the first-order model showed the best prediction the extraction characteristics of ultrasound-assisted enzymatic extraction process under different levels of sonication waves (R^2 > 99%). Artificial statistical analysis with 2 inputs (sonication power and extraction time) and two outputs (RY and TPC), also reflected more quick and powerful for prediction with the large and complex dataset with the structure of 2-5-2. The fitting between actual and predicted data set of statistical and artificial model presented that the artificial remained more advantage for describing the extraction process than the first-order model. Further studies could consider this approach for using in other extraction process in other kinds of materials.
Keywords: rice bran, modelling, artifical neural network, polyphenols, innovation.

Resumen

Las ondas de ultrasonido son una de las técnicas innovadoras emergentes, que se aplican ampliamente para ayudar al proceso de extracción. Además, el proceso de extracción enzimática también se considera como tecnología verde. Además, en el país asiático, especialmente en Vietnam, el trigo de arroz es abundante, que contenía muchos compuestos beneficiosos para la salud. Este estudio tiene como objetivo investigar el efecto del poder de ultrasonido (20-100%) sobre la cinética del rendimiento de recuperación (RY, %) y el contenido total de polifenoles (TPC, mgGAE/g) en el extracto. Se aplicó el análisis estadístico y artificial para estudiar el comportamiento del proceso de extracción. Entre los 5 modelos estadísticos, el modelo de primer orden mostró la mejor predicción de las características de extracción del proceso de extración enzimática asistida por ultrasonido bajo diferentes niveles de ondas de sonicación (R^2 > 99%). El análisis estadístico artificial con 2 entradas (fuerza de sonicación y tiempo de extracción) y dos salidas (RY y TPC), también reflejó más rápido y potente para la predicción con el conjunto de datos grande y complejo (2-5-2). La combinación entre los conjuntos de datos actuales y predecibles de los modelos estadísticos y artificiales presentó que el artificial seguía siendo más ventajoso para describir el proceso de extracción que el modelo de primer orden. Más estudios podrían considerar este enfoque para el uso en otros procesos de extracción en otros tipos de materiales.
Palabras clave: molde de arroz, modelado, red neural artificial, polifenoles, innovación.

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1 Introduction

Cereal by-products are appreciated for their high content of bioactive compounds such as polyphenols and dietary fiber. Ferulic and sinapic acids, categorized as phenolic compounds, are typically found in cereals and grain by-products, but are absent in fruits and vegetables. To achieve maximum health benefits, it is advisable to follow a well-rounded diet that incorporates fruits and vegetables high in polyphenols, along with grains (Wang *et al*., 2014). Rice (*Oryza sativa* L.) is a staple meal in many locations worldwide, especially in Asian countries where it is of great agricultural significance. Rice's health advantages are linked to three groups of antioxidant molecules present in it as know as γ-oryzanol, tocopherols, and phenolic compounds (Ngo *et al*., 2023). Rice bran is a byproduct of the rice milling process, which including several beneficial elements, although it is susceptible to oxidative and hydrolytic spoilage. Rice bran is frequently refined to extract fat and produce rice bran oil, a nutrient-dense product. Defatted rice bran remnants are sold as inexpensive animal feed. Research showed that defatted rice bran contains high levels of nutrients, such as 15% protein, 13% fiber, and abundant antioxidants (Chaisuwan & Supawong, 2022). Especially, purple rice bran that is pigmented has a significant amount of nutrients and a large quantity of bioactive phytochemicals, including phenolic compounds, phytosterols, tocopherol, proanthocyanin, and anthocyanin. These components have a higher level of antioxidant activity compared to bran from rice that is not pigmented (Avinash & Sharma, 2023; Leonarski *et al*., 2024b). Biologically active compounds, such as phenolic compounds, have been linked to several health advantages, including a reduced risk of chronic diseases (Vivarelli *et al*., 2023). Anthocyanin and proanthocyanidin are the primary pigments that can withstand oxidative stress generated by various substances, hence safeguarding cells from harm (Li & Ahammed, 2023). However, approximately 74% of the phenolics in rice are insoluble, as reported by Das *et al*. (2017). Phenolic compounds, secondary metabolites present in plants, have a part in activities like combating free radicals and exhibiting antibacterial properties. It displays various physiological properties including anti-inflammatory, antioxidant, antibacterial, anticancer, and antidiabetic actions (Ji *et al*., 2020). The extraction of phenolic compounds from plant tissues is mainly affected by the tissue composition, requiring the creation of specialized extraction methods and procedures (Franco-Vásquez *et al*., 2023). Hydrolytic enzymes can improve the extraction of both bound and free polyphenols.

Diverse conventional and unconventional methods can be employed to extract polyphenols (Franco-Vásquez *et al*., 2023). Traditional methods such as refluxing, Soxhlet extraction, and boiling are inefficient due to hydrolysis and oxidation (Das *et al*., 2017). To tackle these issues, researchers have investigated advanced techniques as ultrasound-assisted extraction (UAE), microwave-assisted extraction (MAE), and super-critical fluid extraction (Das *et al*., 2017; Sánchez-Mesa *et al*., 2020). Novel extraction technologies can successfully extract phytochemicals in an environmentally friendly way, with shorter extraction periods, lower energy costs, better compound yields, and enhanced extract quality. Multiple studies have shown that the extraction process has a considerable effect on extraction yields (Bitwell *et al*., 2023; Shen *et al*., 2023). We used ultrasound-assisted extraction (UAE) to extract total polyphenols (TPC) from rice bran (Bunmusik *et al*., 2023; Leonarski *et al*., 2024a), however the extraction yield was limited and time-consuming. Therefore, it is essential to research a more efficient method to increase the TPC extraction yield from rice bran. Ultrasound-assisted enzymatic extraction (UAEE) is an innovative extraction technique employed in the pharmaceutical and food industries. The process has advantages such as high efficiency, little energy and solvent consumption, ecologically friendly properties, and simple operation. UAEE has been used to extract polyphenols from different plant sources in recent research. Plant cell walls and cell membranes inhibit the release of intracellular chemicals. Polysaccharides in the cell wall can impede the extraction of TPC by interacting with polyphenols through hydrophobic interactions and hydrogen bonding (Mapholi & Goosen, 2023; Yun *et al*., 2023). Breaking down these cell structures is essential to improve the retention of polyphenols. Pectinase, cellulase, and tannase are commonly employed as the principal enzymes for degrading cell wall components (Xu *et al*., 2023).

Scholars have proposed different mechanism models for extraction in varied operational and environmental situations (Zhong *et al*., 2023). In addition, various mathematical modeling techniques are utilized to optimize, simulate, plan, and control operations in order to improve the efficient utilization of energy, time, and solvent (Agu *et al*., 2021; Katsimichas *et al*., 2023; Sridhar *et al*., 2021). The efficacy of hybrid modeling primarily stems from the synergy across multiple models. Hybrid modeling as ANN (artificial neural network) has attracted considerable attention in biology, chemistry, and other fields (Figueroa-Garcia et al., 2021; Lara-Cerecedo *et al*., 2023). The approach utilizes data-driven modeling to redirect attention from proposing a feasible mechanism to obtaining high-quality data and establishing kinetic parameters. The data-driven model is utilized to extract complex relationships that the mechanism model cannot capture. The mechanism model forms the basis of the hybrid model by reducing the impact of irrelevant or duplicated information in the sample on the data-driven model (Yousef *et al*., 2023). It can prevent the established hybrid model from conflicting with the mechanism and common sense. This study aims to compare the statistical and artificial models on capacity of prediction of extraction process and develop a dynamic hybrid model for extraction polyphenols from rice bran for further development.

2 Materials and methods

2.1 Rice bran preparation

"Câm" rice was purchased at local farm in Tien Giang province (Vietnam), which further de-husked by local machine. The purple rice bran was collected during polishing process and then removed the fat by solvent method (Loan *et al*., 2023a). The observed rice bran would mill, sieve to pass 100 mesh, and store in the dark bag at -18^{o}C for further experiment.

2.2 Ultrasound-assisted enzymatic extraction of polyphenol from purple rice bran

In this study, enzyme cellulase from *Aspergillus niger* (22178) were purchased from Sigma-Aldrich. Enzymatic processing conditions of rice bran were optimized based on preliminary trials in the lab. Following the research of 1% of cellulase enzyme was the highest conditions to recovery the antioxidant from rice bran. Therefore, the process of enzymatic extraction antioxidants from purple rice bran also followed the procedure of this study. Briefly, 1 g of defatted rice bran was mixed with 10 ml of acetate buffer (pH = 3.0) containing cellulase (1%) and then treated with assistance of different levels of ultrasonic wave power (Loan & Vinh, 2024). The ultrasound bath (M2800H-J, 110 W, Japan) was used for operating the extraction process at constant temperature of 40^{o}C as the optimzed temperature for remaining activity of enzyme (Sethi *et al*., 2013). The mixture after ultrasonic treatment was continute incubated and took the sample at different time points also was centrifuged to collect the rice bran extract for analyzing the recovery yield and total polyphenol content. Three replications were conducted for each treatment.

2.3 Yield recovery calculation and determination of total phenolic content

To determine the percent recovery, bubbling of the sample solution was done by using vacuum evaporation method (Loan *et al*., 2023b). Then the weight of extract was measured. Finally, the extraction yield (Y) was calculated. Percent extraction of antioxidants was calculated from the following equation:

$$Y\% = 100 \times \left(\frac{W_1}{W_2}\right) \tag{1}$$

where W_1 is weight of extract after evaporating and W_2 is weight of dry rice bran.

The dried extract was redissolved in methanol to 1 mL volume for further investigation of total phenolic content. The total phenolic content of the extracts was examined using the Folin–Ciocalteu method described by Loan *et al*. (2023b). The results were expressed as milligrams of gallic acid equivalents per gram of rice bran powder (mg GAE/g rice bran).

2.4 Data analysis and model fitting

The obtained data of recovery yield and total polyphenol content (C_t) at different time point (t) was fitted with five models presenting in Table 1. The R-square (R^2) and Mean square error (MSE) were the model criteria for selecting the best fitness model.

The artificial neural network (ANN) was also utilized for data analysis. The ANN model utilized two input and output factors, sometimes referred to as variables and responses, in order to determine the appropriate size of the neural network. The quantity of concealed neurons in an artificial neural network (ANN) model is essential in influencing its capacity to generalize and achieve high performance. Overfitting can occur when there is an excessive number of neurons in the hidden layer of a network. This leads to the model becoming overly specialized in fitting the training data, resulting in poor performance when applied to new data (Basheer & Hajmeer, 2000). In order to determine the optimal network design, the number of hidden neurons was systematically varied during the experiment, spanning from 2 to 10. The accuracy of estimated results, the effectiveness of the model, and the deviation of experimental data from predictions were evaluated using several metrics, such as the coefficient of determination (R-square) and mean square error (MSE) (Ahmad & Singh, 2024). Based on the preliminary test and recent stuidies (Çakmak & Yıldız, 2011; Islam *et al*., 2003; Yang et al., 2023), the performance and functional configuration of the Artificial Neural Network (ANN) model were summarized in Table 2.

Table 1. Selection model for this study.

Model name	Model equation	Reference
First-order model	$C_t = C_{eq}(1 - e^{-kt})$	(Yedhu Krishnan & Rajan, 2016)
Second-order model	$C_t = \frac{C_{eq}t}{k+t}$	(Harouna-Oumarou *et al.*, 2007)
Elovich's model	$C_t = E\ln(t) + a$	(Dong *et al.*, 2014)
Power-law model	$C_t = Bt^n$	(Dong et al., 2014)
Peleg's model	$C_t = \frac{t}{(k_1+k_2t)}$	(Kayahan & Saloglu, 2020)

Table 2. Setting ANN structure for data analysis.

Parameters	Characteristics
Input	Ultrasound power (20, 40, 60, 80, 100%) Extraction time (5, 10, 15, 20, 25, 30, 45, 60, 75, 90 min)
Output	Yield recovery (%) Total phenolic content (mgGAE/g)
Data	70% of experimental data selected at random for training 15% of experimental data chosen at random for testing 15% of experimental data selected at random for validation
Training function	Levenberg–Marquardt back propagation
Adaption learning function	LEARNGDM
Transfer Function	LOGSIG
Performance function	MSE

3 Results and discussion

3.1 *Impact of sonication power on extraction yield by fitting with different statistical models*

The impact of ultrasonic power on the kinetics of rice bran extraction was assessed by measuring the recovery yield. Various power levels, ranging from 20% to 100% of the total, were evaluated using an ultrasonic bath. The extraction kinetics at various time intervals are depicted in Figure 1 for the different experimental conditions. It is evident that increasing the power supply results in a larger quantity recovery of the extract. The acoustic energy delivered into the medium is directly proportional to the extent of the ultrasonic effects. Therefore, increasing the ultrasonic power applied will result in a higher intensity of cavitation. Cavitation enhances the solvent's ability to enter the matrix and facilitates the transport at the interface, hence improving the extraction efficiency of antioxidant chemicals in the sample. The cavitation force of ultrasounds can successively accelerate the heat and mass transfer rate, disrupt plants cell walls and facilitate the release of extractable compounds (Khadhraoui *et al.*, 2021). Ultrasounds can also facilitate swelling and hydration and cause an enlargement in the pores of the cell walls. Therefore, the diffusion process is improved, and the mass transfer is enhanced (Li *et al.*, 2024; Singla & Sit, 2021). It also could be seen that at the beginning stage, the recovery yield greatly influenced by sonication power. However, at later stage (after 60 min), the yield reached the equilibrium point and almost remain unchanged. Therefore, the importance effects of sonication process on extraction yield are the extraction time and ultrasound amplitude of machince.

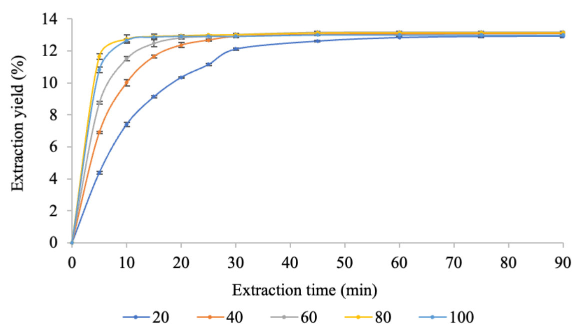

Figure 1. Influence of sonication power on yield of extract from rice bran by ultrasound-assisted enzymatic extraction.

The experimental values were modelled and fitted in the four statistical kinetic models. Table 3 shows effect of different levels of sonication on the kinetic parameters, rate constant and equilibrium concentration as well as other constant.

From Table 3, the R-square (R^2) of first-order model, second-order model, Elovich's model, Power-law model, Peleg's model when fitting the actual values into regression equations were range from 99.93 to 99.99%, from 84.80 to 97.35%, from 53.96 to 91.27%, from 52.21 to 83.75%, from 98.89 to 99.59%, respectively. First-order model presented the highest R^2 in all of treatment as well as the lowest MSE also found in this model when analizing the datasets.

Table 3. Statistical model constants - Influence of sonication power on yield of rice bran extract by ultrasound-assisted enzymatic extraction.

Model	Power level (W)	Model constant		R^2	MSE
$C_t = C_{eq}(1- e^{-kt})$	20	C_{eq} = 12.935	k = 4.9600	99.93	0.0001
	40	C_{eq} = 13.050	k = 8.8754	99.99	<0.0001
	60	C_{eq} = 13.098	k = 12.9192	99.96	0.0001
	80	C_{eq} = 13.004	k = 26.8777	99.95	0.0001
	100	C_{eq} = 12.942	k = 21.7409	99.98	<0.0001
$C_t = \frac{C_{eq}t}{k+t}$	20	k = 9.6168	C_{eq} = 14.954	97.35	0.2431
	40	k = 4.2162	C_{eq} = 14.2573	93.74	0.2806
	60	k = 2.4230	C_{eq} = 13.9314	92.89	0.1555
	80	k = 0.6479	C_{eq} = 13.3290	94.97	0.0117
	100	k = 0.9414	C_{eq} = 13.3414	84.80	0.0778
$C_t = E \ln(t) + a$	20	E = 2.9536	a = 0.8454	91.27	0.8004
	40	E = 1.8892	a = 5.6465	76.32	1.0623
	60	E = 1.2617	a = 8.2659	68.88	0.6584
	80	E = 0.4159	a = 11.5115	71.07	0.0675
	100	E = 0.5362	a = 10.9414	53.96	0.2364
$C_t = Bt^n$	20	B = 4.3102	n = 0.2653	83.75	0.2653
	40	B = 7.1830	n = 0.1501	70.44	1.3262
	60	B = 8.9868	n = 0.0972	65.93	0.7446
	80	B = 11.5914	n = 0.0319	69.92	0.0702
	100	B = 11.0893	n = 0.0412	52.21	0.2447
$Ct = \frac{t}{(k_1+k_2t)}$	20	k_1 = 0.6430	k_2 = 0.0669	98.89	0.2160
	40	k_1 = 0.2957	k_2 = 0.0701	98.63	0.2494
	60	k_1 = 0.1739	k_2 = 0.0718	99.21	0.1382
	80	k_1 = 0.0486	k_2 = 0.0750	99.94	0.0104
	100	k_1 = 0.0705	k_2 = 0.0750	99.59	0.0692

The increasing of extraction rate of constant (k value) was found when the rasing the power of ultrasound treatment. The equibrilium yield of extraction was reached the value of apporoximately of 13%, which is higher than previous results in the study by Loan *et al*. (2023a) when using microwave assisted extraction method after 15 min extraction. The experimental values are plotted with the error of lower than 5% which shows good agreement between experimental and predicted values. As maximum equibrilium extraction yield was obtained in treatment of 60% sonication amplitute and follows by 40% and 80% sonicated-power.

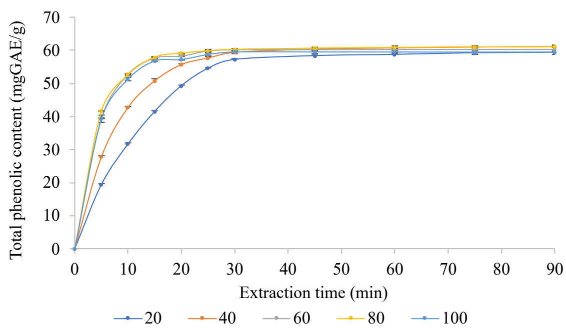

Figure 2. Influence of sonication power on yield of polyphenols from rice bran by ultrasound-assisted enzymatic extraction.

3.2 *Impact of sonication power on yield of polyphenols by fitting with different statistical models*

An increasing pattern of yield of phenolic content in extract was found when the rice bran was operated with ultrasound-asssited enzymatic extraction (Figure 2). At the first 30 min, the recovery yield of total phenolic compounds in extract was increased sharply when the treatment was over 60% of amplitute. After 30 min, the extraction yield was not significantly rise or remain unchange. Applying 5 models for analyzing the obtained dataset, it was observed that the first-oder model has the highest R-square and lowest MSE, which ranged from 99.54-99.99% and approximately 0.001, respectively. Similarly, the rate of extraction constant also increased following the levels of amplitute. The maximum equibrilium concentration of total phenolic compounds was reach at 60.89 mgGAE/g, when the rice bran was extract by 40% power of sonication machine. The ultrasound procedure, characterized by its high shear, mechanical energy, and cavitation, increased the solubility of the substrate, making it more readily available to the enzyme (Yang *et al*., 2024).

Table 4. Statistical model constants - Influence of sonication power on total phenolic content of rice bran extract by ultrasound-assisted enzymatic extraction.

Model	Power level (W)	Model constant		R^2	MSE
$C_t = C_{eq}(1 - e^{-kt})$	20	C_{eq} = 60.17	k = 4.9158	99.54	0.0001
	40	C_{eq} = 60.98	k = 7.2648	99.99	<0.0001
	60	C_{eq} = 60.19	k = 12.6744	99.97	<0.0001
	80	C_{eq} = 60.49	k = 13.3360	99.87	<0.0001
	100	C_{eq} = 59.27	k = 12.1102	99.69	0.0001
$C_t = \frac{C_{eq}t}{k+t}$	20	k = 0.1643	C_{eq} = 69.78	97.47	0.0010
	40	k = 0.0933	C_{eq} = 67.74	98.62	0.0006
	60	k = 0.0410	C_{eq} = 63.99	98.95	0.0004
	80	k = 0.0382	C_{eq} = 64.17	99.41	0.0002
	100	k = 0.0436	C_{eq} = 63.19	99.12	0.0003
$C_t = E\ln(t) + a$	20	E = 0.1399	a = 0.6017	87.05	0.0028
	40	E = 0.1063	a = 0.6231	81.94	0.0024
	60	E = 0.0585	a = 0.6166	67.04	0.0016
	80	E = 0.0564	a = 0.6205	71.90	0.0011
	100	E = 0.0609	a = 0.6077	71.49	0.0014
$C_t = Bt^n$	20	B = 0.5924	n = 0.2672	78.68	0.0046
	40	B = 0.6170	n = 0.1856	75.16	0.0033
	60	B = 0.6141	n = 0.0977	63.00	0.0018
	80	B = 0.6183	n = 0.0939	68.14	0.0014
	100	B = 0.6052	n = 0.1039	67.31	0.0016
$Ct = \frac{t}{(k_1+k_2t)}$	20	k_1 = 0.2355	k_2 = 1.4333	97.47	0.0011
	40	k_1 = 0.1383	k_2 = 1.4752	98.62	0.0006
	60	k_1 = 0.0644	k_2 = 1.5614	98.95	0.0004
	80	k_1 = 0.0598	k_2 = 1.5574	99.41	0.0002
	100	k_1 = 0.0694	k_2 = 1.5815	99.13	0.0003

3.3 ANN fitting model

A conventional feed-forward neural network commonly consists of one or more hidden layers, which enable the network to accurately represent complex and non-linear processes (Bhagya Raj & Dash, 2022). Nevertheless, it is a difficult endeavor to ascertain the optimal number of hidden layers (Abdolrasol *et al*., 2021). Based on the research, it is widely accepted that a single hidden layer is typically enough for accurate prediction and is frequently the favored option for creating practical feed-forward networks (Ali *et al*., 2023). Therefore, this study utilized a neural network consisting of a single hidden layer. It is crucial to highlight that the choice of the number of neurons in hidden layers is of utmost importance as it directly affects the length of training and the neural networks' capacity to generalize. Augmenting the quantity of neurons in the concealed layer can result in the network prioritizing the memorization of certain patterns derived from the training data, rather than extrapolating from them. On the other hand, reducing the number of neurons in the hidden layer can lead to a prolonged training period while the network looks for its optimal representation (Galván & Mooney, 2021). However, there is no universally applicable rule for selecting the number of neurons to include in a hidden layer. Thus, the degree of reliance is determined by the complexity of the system being represented (Kheddar *et al*., 2024). The primary approach used to ascertain the optimal number of neurons in a hidden layer is through iterative experimentation. Therefore, this study utilized the trial and error method to determine the ideal number of neurons in the hidden layer of the network.

There are many learning algorithms described in the literature that can be used to train a network. However, it can be difficult to ascertain the optimal learning method for a specific task. The study utilized the Levenberg–Marquardt back propagation (LM) algorithm to train the Artificial Neural Network (ANN). The Levenberg-Marquardt algorithm is a computational optimization technique that provides an approximation of Newton's approach (Saini & Soni, 2002). This is extremely congruent with the training of the neural network. The strategy employs the second-order derivatives of the mean squared error between the intended output and the actual output to enhance convergence behavior (McLoone et al., 1998). The study's findings indicated that the network consisted of five levels, specifically the input, hidden, and output layers. The hidden layer, with five nodes, was found to produce the most effective outcomes (Table 5).

Table 5. ANN training results at different layer size.

Layer size	Type of dataset	MSE	R-square
	Training	10.0564	0.9905
2	Validation	6.2117	0.9948
	Test	19.0783	0.9853
	Training	1.0236	0.9991
3	Validation	0.6801	0.9994
	Test	1.7704	0.9985
	Training	2.4302	0.9977
4	Validation	37.5984	0.9669
	Test	66.5298	0.9538
	Training	0.3701	0.9997
5	Validation	1.0018	0.9993
	Test	0.1983	0.9998
	Training	8.0655	0.9926
6	Validation	4.2306	0.9974
	Test	12.7795	0.9882
	Training	9.4325	0.9915
7	Validation	2.5207	0.9976
	Test	35.315	0.9691
	Training	0.7553	0.9993
8	Validation	1.9964	0.9985
	Test	5.059	0.9955
	Training	0.5085	0.9995
9	Validation	1.5154	0.9986
	Test	2.1847	0.998
	Training	0.1814	0.9998
10	Validation	5.1965	0.9957
	Test	28.4772	0.9845

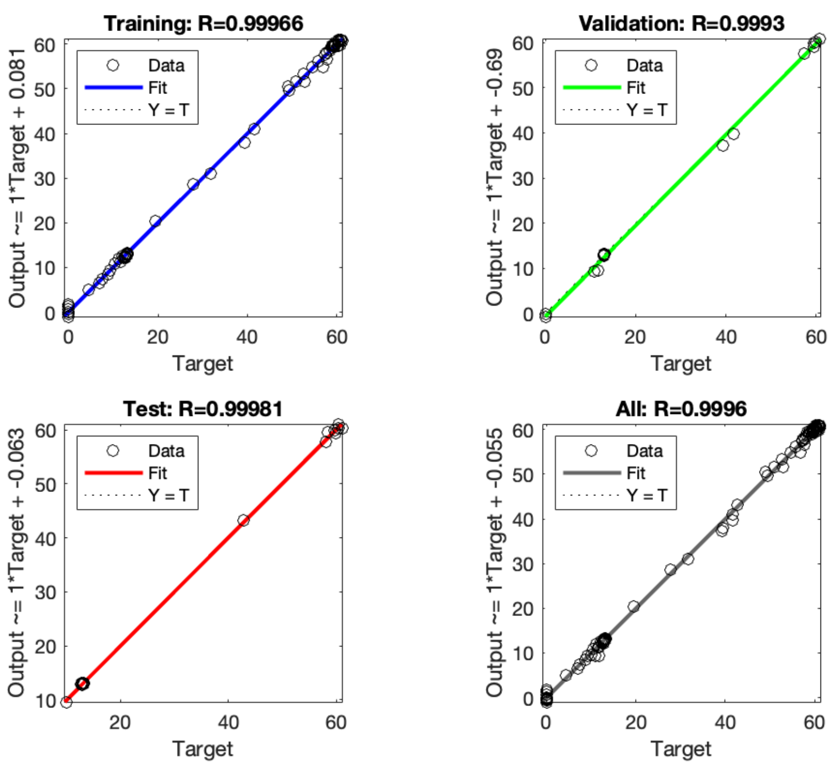

Figure 3. The prediction regression between the actual output and target output by ANN model (5 layers).

The training set was evaluated and found to have a mean squared error (MSE) of 0.3701 and a coefficient of determination (R^2) of 0.9997. The validation set yielded an MSE of 1.0018 and an R^2 value of 0.9669. Similarly, the testing set produced an MSE of 0.1983 and an R^2 value of 0.9998. The R-squared (R^2) values was calculated for all the datasets, resulting in values of 0.9996 (Figure 3). The results suggest that the model exhibits a significant level of anticipated accuracy. It also could seen that the extraction kinetic was successfully in different kind of study and architecture. For instance, the structure of 3-7-1 was applied for predicting process of extraction essential oil from tarragon using ultrasound pre-treatment (Bahmani *et al.*, 2018). ANN also found the optimal conditions for extraction antioxidants from sweet potato peel with the most appropriate topology for the prediction of 3–9–3 (Kadiri *et al.*, 2019).

The structure with weight and bias was shown in Figure 4. It also shown that it could have the accuracy and done with the complex data and large quantity without the different data analyzing step. Moreover, the goodness of fit between actual and predicted data also found and showed in Figure 5.

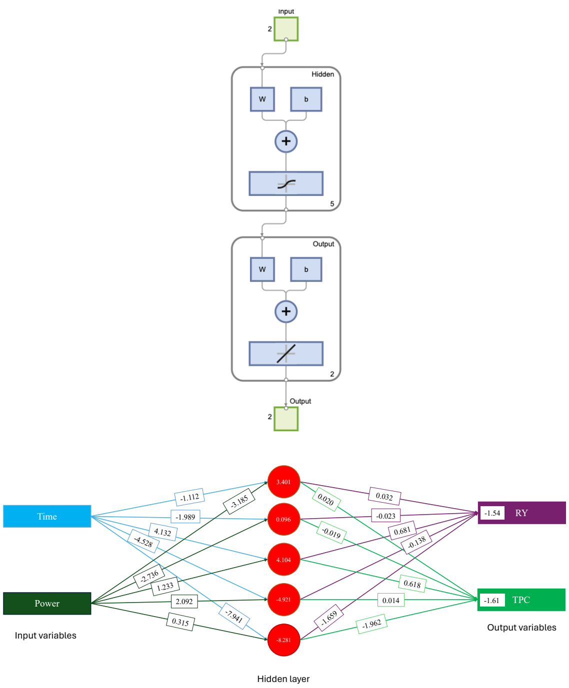

Figure 4. Structure of selected ANN model with weight and bias.

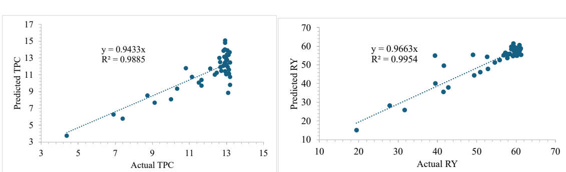

Figure 5. The correlation between the experimental and obtained data from ANN model.

Conclusion

The kinetic of ultrasound-asssited enzymatic extraction of polyphenols from purple rice bran was succesful prediction. It was shown that the high content of polyphenol could observe after 30 min of extraction. Moreover, different models also applied for fitting the experimental datasets. It was found that first-order model gave the best fitness. Comparing with ANN model, the ANN model with structure of 2-5-2 presented the high accuracy of prediction and faster than using single model for each parameter. Further study should concern on optimal extraction process based on the fundametal data of this study, which also could contributed to the sustainable development goals of United Nations.

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