Optimization of Pumpkin Seeds Extraction via Artificial Neural Network and Response Surface Methodology

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Abstract

Enhancing techniques for obtaining fluted pumpkin seeds oil (PSO), technically known as *Telfairia occidentalis*, was the goal of this study. The main objective was to analyse chemical and physical properties of the extracted oil, expediting the process by using response surface methodology (RSM) and artificial neural networks (ANN). Fluted PS were purchased from a local market, carefully washed, sun-dried, sorted from chaff and crushed. Using a Soxhlet extractor and n-hexane as solvent, PSO was extracted. For optimisation, a three-level, three-factor Box-Behnken design with 17 iterations was used. The sample's weight, solvent volume and extraction time were the main factors taken into account for optimisation. According to the study's findings, RSM optimisation produced a 41.58% (w/w) pumpkin seeds oil yield (PSOY). ANN approach, on the other hand, produced a greater PSOY of 41.66% (w/w), demonstrating its superior capacity to forecast the ideal oil output. Standard industrial procedures were used to determine PSO density, specific gravity, moisture content and acid, saponification, iodine and peroxide values, among other parameters. When ANN and RSM were compared, it was found that the former was more reliable in predicting PSOY, since it had better coeeficients of determination (R^2) and R^2 adj. values (0.9746 and 0.9893) and lower root mean square error values (0.9889 and 0.9965). In conclusion, this study highlights the potential uses of fluted PS across a range of sectors. It emphasises how using statistical analytical approaches can significantly improve production operations.

***Keywords**:* ANN; extraction; percentage PSOY; PS; RSM.

Introduction•

Pumpkin seeds (PS) have gained a lot of attention lately, due to their high nutritional value and possible health advantages. Pumpkins belong to one of the most significant plant genera, *Cucurbitaceae* [1]. *Curcubita maxima*, *Curcubita pepo* and *Curcubita moschata* are the three primary species of pumpkins found around the world [2]. It is believed that it was in Igbo-majority states, south of Nigeria, that Fluted Pumpkin (*Telfairia occindentalis*), its most common variety in the country, first appeared [3]. Packed with antioxidants, vital fatty acids, minerals and bioactive components, pumpkins are prized for their versatility in food and medicine industries. PS are valued nutraceuticals, due to their remarkable flavour, colour and fragrance. According to studies, pumpkin seeds oil (PSO) extracts can help cure leukaemia agents, and have anti-cancer qualities [4, 5]. Recent studies have also emphasised PS' antibacterial, antihypertensive, anti-arthritic, anti-inflammatory and anti-diarrheal qualities. In order to increase the quantity and quality of PS for a variety of applications, efforts are now being made to optimise the extraction of valuable components from them [6, 7]. Using effective extraction techniques is

•The abbreviations list is in page 12.

essential to creating PSO extracts of superior quality. Conventional techniques like solvent extraction and mechanical pressing have been widely employed, although their efficiency, selectivity and yield are frequently questioned. For instance, PSO has been obtained with a 16.446% yield utilising solvent extraction method [3]. In order to obtain PSO, [8] has used the same method, which produced a 19.02% yield. In contrast, Soxhlet technique produced about 52% PSO [1]. Petroleum ether as solvent and Soxhlet process have been used by [9], to extract PSO, achieving a yield higher than 32%.

The focus is still on improving extraction methods to optimise the recovery of bioactive components from PS, even if research in this area is still ongoing. Artificial neural networks (ANN) and response surface methodology (RSM) have emerged as potent optimisation methods in recent years, with applications ranging from extraction procedures to food science. Inspired by the structure and operation of the human brain, ANN are advanced computer models that are able to identify intricate patterns and relationships in input-output data [3, 7]. Researchers have saved time and effort in their investigations by using them to forecast ideal conditions for various extraction methods. RSM, on the other hand, is a statistical technique that looks at the relationships between a number of variables and the intended outcome. The optimisation of process parameters can be accomplished by determining the most effective set of variables to provide the intended result. Higher yields and better-quality extracted components can be obtained by increasing the efficiency of pumpkin seed extraction [3, 10]. This goal can be accomplished by combining RSM for verification and refinement, with ANN for prediction [11].

By combining ANN modelling with RSM, this study seeked to improve the solvent-based extraction of PSO. By combining these two methods, the aim was to forecast ideal extraction circumstances and experimentally verify them. It is anticipated that this enhanced extraction method will increase knowledge of variables affecting quantity and quality of PSO extracts, resulting in their more efficient use in a range of applications.

This study offers important insights into the extraction process, by introducing a systematic technique that may be used in a variety of plant-based extraction procedures. RSM and ANN have the potential to completely transform extraction process optimisation, enhancing efficiency, sustainability, dependability and economic viability.

This study's main goal was to improve PSO extraction techniques, laying the groundwork for future investigation and use in many industries. Compared to conventional methods, the use of ANN and RSM in this work allowed for a more accurate and effective optimisation of the extraction process. While RSM helps with modelling and analysis to identify optimal extraction settings, ANN can learn and adjust to complex data patterns.

Combining ANN and RSM to optimise PSO extraction is a novel strategy that capitalises on each technique's advantages. This approach provides insightful information on the extraction process that may be difficult to obtain from traditional experimental techniques. The ultimate goal of this research was to develop PSO extraction methods, setting the stage for further investigation and useful applications in chemical, food and pharmaceutical sectors.

Materials and methods

Materials

PS used in this study were purchased at Udua Ukam market, in the Nigerian state of Akwa Ibom's Mkpat Enin LG. Throughout the experiment, a variety of lab apparatuses were used, including beakers, flasks, measuring cylinders, separating funnels, density bottles, burettes, muslin cloth with filter paper, Soxhlet extractors (500 mL and 5 L), water baths, digital weighing balances, incubator shakers, refractometers, ovens and UV-Digital Libra S21 spectrophotometers. These instruments were essential to ensure accurate analysis and reliable study outcomes.

Experimental procedures for PSO extraction

The production of PS powder involved a multi-step, meticulous procedure. Firstly, PS were cleansed from any contaminants, and then left to dry in the sun, for five days. To guarantee purity, they were then separated from chaffs, using a process called winnowing. Pure PS were then processed in a milling machine to a powder. A flowchart provided a visual representation of this procedure (Fig. 1). The outcome was a premium PSO powder that was ready for further extraction.

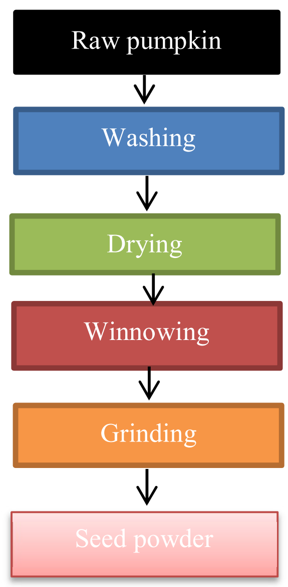


Figure 1: Flowchart for the preparation of PS powder.

PSO extraction procedures

A 500 mL Soxhlet apparatus and n-hexane solvent were employed to extract oil from PS powder. There was a set amount of PS powder added to the apparatus. A round-bottomed flask with a condenser and a predetermined amount of n-hexane attached was used for this experiment. The extractor was also connected to this flask. To get the setup to 70 °C, a water bath was utilised.

Following extraction, any remaining liquid oil was heated to the same temperature in a heating mantle, in order to recover it. The amount of oil that was removed was determined by gravimetric analysis. PSOY was determined by comparing the weight of the extracted oil with that of PS powder sample, using Eq. 1. After that, extracted PSO was stored for further analysis.

$$\%\ \text{PSOY (w/w)} = \frac{\text{weight of extracted oil (g)}}{\text{weight of powder sample (g)}} \qquad (1)$$

Physicochemical characterization of extracted PSO

Its refractive index, moisture content (MC), relative density, viscosity, percentage of free fatty acids, acid, saponification and peroxide values, specific gravity (SG), mean molecular mass, higher heating value and pH were among physicochemical characteristics assessed using Analysis Association of Analytical Chemists methods. Furthermore, Wij's method was used to calculate iodine value [12].

Determination of oil quality

A set of criteria was employed to assess the quality of extracted PSO, including acid, saponification, peroxide and iodine values, refractive index, viscosity, Totox number and p-anisidine [12].

Moisture content (MC)

A 5 g oil sample was meticulously weighed and placed into a moisture dish, with a tight-fitting, slip-over lid that measured 5 cm in diameter and 2 cm in depth. This was put inside a vacuum oven that was set to function at a temperature higher than the boiling point of water (125 °C), with a working pressure of 95 mm Hg, at 30 min intervals. The dried sample's weight was recorded each time the oven reached a constant weight, and no more than 0.05% was lost. Eq. 2 was used to determine MC percentage.

$$\%MC = \frac{W_1 - W_2}{W_2} \tag{2}$$

where W_1 is SW and W_2 is dried SW.

Value of *pH*

The pH value of the PSO sample was determined using a meter that had been calibrated with the buffer solution. The electrode was placed in the sample to accurately measure pH.

Specific gravity (SG)

The density of the PSO sample was determined by utilizing a SG bottle.

Cetane number

Cetane number was computed using the equation below.

$$\text{Cetane No} = 46.3 + \left[\frac{5458}{Saponification\ value}\right] - (0.225 \times Iodine\ value) \tag{3}$$

Aniline point

This was determined by the equation cited by [13].

$$\text{Aniline point} = \frac{\text{Diesel index x 100}}{\text{API}} \tag{4}$$

PSO extraction experimental design

In order to maximise PSO extraction, this study focused on RSM technique, specifically employing ANN and Box-Behnken design (BBD) [11]. Three-level-three-factors design was used in BBD, producing 17 experimental runs. This allowed for the evaluation of the curvature effect, by providing information on the interior of the experimental region, through the use of six factorial points, six axial points and five central points. Based on early research, the following parameters were chosen for PSO extraction. Sample weight (SW [g]) was X1, extraction time (ET [min]) was X2 and solvent volume (SV [mL]) was X3, based on preliminary studies. Three independent variable combinations are depicted in Table 1, and the matrix produced by BBD is shown in Table 2. 17 experimental runs were produced for ANN design, considering the same chosen factor used in previous BBD [11].

Table 1: Variable factors considered for PSO extraction.

Variable	Symbol	Coded factor levels		
		-1	0	+1
SW (g)	X_1	50	60	70
ET (min)	X_2	50	55	60
SV	X_3	200	220	240

Table 2: BBD matrix for three independent factors.

Std run	X_1	X_2	X_3
1	-1	-1	0
2	1	-1	0
3	-1	1	0
4	1	1	0
5	-1	0	-1
6	1	0	-1
7	-1	0	1
8	1	0	1
9	0	-1	-1
10	0	1	-1
11	0	-1	1
12	0	1	1
13	0	0	0
14	0	0	0
15	0	0	0
16	0	0	0
17	0	0	0

Results and discussion

Optimization of PSO extraction

The results of PSO extraction process were analysed using Design Expert software version 11.1.0.1. The optimisation of the extracted oil was conducted using a three-level, three-factor RSM and ANN approach, categorised as Randomised [12]. The experimental design implemented was BBD, comprising 17 runs, utilising a Quadratic design model with three factors: SW, ET and SV. This study presents coded experimental parameters in Table 3, which includes projected values, residual values obtained through RSM and pumpkin seed oil yield (PSOY).

Table 3: Experimental data for PSOY, showing predicted and residue values of RSM and ANN.

Std run	X_1	X_2	X_3	PSOY% (W/W)	Predicted		Residual	
					RSM	ANN	RSM	ANN
1	-1	-1	0	41.70	41.58	41.666	0.1238	0.034034
2	-1	-1	0	35.28	35.41	35.256	-0.1263	0.024384
3	-1	1	0	25.72	25.59	25.762	.01262	0.042146
4	1	1	0	35.1	35.22	35.097	-0.1238	0.0028669
5	-1	0	-1	27.91	28.10	27.818	-01938	0.092433
6	-1	0	-1	27.54	27.48	27.557	0.0562	0.0166
7	-1	0	1	25.26	25.32	25.343	-0.0563	0.083009
8	1	0	1	29.59	29.40	29.576	0.1937	0.013656
9	0	-1	-1	35.13	35.06	35.14	0.0700	0.010279
10	0	1	-1	29.59	29.52	29.608	0.0675	0.017626
11	0	-1	1	37.1	37.17	37.107	-0.0675	0.006646
12	0	1	1	26.47	26.54	26.379	-0.0700	0.091388
13	0	0	0	30	29.32	29.334	0.6800	0.66582
14	0	0	0	30	29.32	29.334	0.6800	0.66582
15	0	0	0	28.3	29.32	29.334	-1.02	1.0341
16	0	0	0	30	29.32	29.334	0.6800	0.66592
17	0	0	0	28.3	29.32	29.334	-1.02	1.0341

Design Expert 11.1.0.1 and Neural Power 21356 software were employed to assess the numerical significance of coefficients and independent variables within a comprehensive quadratic model equation. Predictive capability of the regression model was evaluated using analysis of variance (ANOVA), with results detailed in Table 4. The model exhibited an F-value of 69.35 and a p-value of 0.0001, at 95% confidence level, indicating statistical significance ($p < 0.05$) [14-16]. The model terms X_1, X_2, X_1X_2, X_1X_3, X_2, X_3, X_2^2 and X_3^2 demonstrated statistical significance. The model's inadequate fit, evidenced by low F-values and elevated p-values, implies that it did not significantly deviate from pure error, which is advantageous for model fitting. Table 5 presents results of significance tests for the model. The model's accuracy and precision were validated using R^2 and $Radj^2$ values. An R^2 value of 0.9889 signifies that 98.89% of data corresponded to predicted data and its variability. A adj R^2 value of 0.9746 indicates an acceptable model fit [17]. A signal-to-noise (S/N) ratio exceeding 4 is considered advantageous. S/N ratio of 130.65 confirms the model's adaptability within the design space, and reinforces its statistical significance [18] (Table 5).

Table 4: Test of significance of regression coefficient.

Source	Sum of squares	Df	Mean square	F-value	p-value	
Model	323.73	9	35.97	69.35	<0.0001	Significant
X_1	5.99	1	5.99	11.54	0.0115	
X_2	130.65	1	130.65	251.89	<0.0001	
X_3	0.3828	1	0.3828	0.7380	0.4187	
X_1X_2	62.41	1	62.41	120.32	<0.0001	
X_1X_3	5.52	1	5.52	10.65	0.0138	
X_2X_3	6.48	1	6.48	12.49	0.0095	
X_1^2	0.4211	1	0.4211	0.8119	0.3975	
X_2^2	97.57	1	97.57	188.10	<0.0001	
X_3^2	17.89	1	17.89	34.49	0.0006	
Residual	3.63	7	0.5187			
lack of fit	0.1628	3	0.0543	0.0626	0.9769	not significant
pure error	3.47	4	0.8670			
correction	327.36	16				

Table 5: Model significant test.

	R^2	R^2 (pred.)	R^2 (adj)	RSM
RSM	98.89	97.55	97.46	3.47
ANN	99.65	99.46	98.93	0.47

ANOVA for response surface quadratic model for intercept

The results presented in Table 6 indicate that ANOVA was performed for the intercept of the response surface quadratic model. Standard error values for intercepts, independent variable factors, interactions and quadratic terms were all found to be low. This indicates that the regression model effectively fitted the data, resulting in precise predictions.

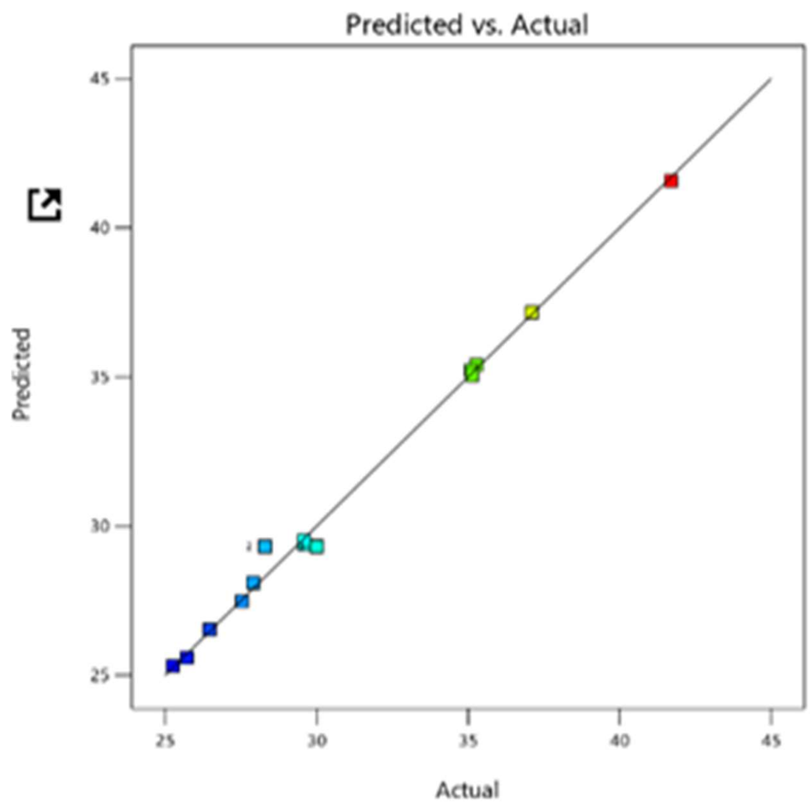
Table 6: ANOVA for response surface quadratic model for intercept.

Factor	Coefficient estimate	Df	Standard error	95% CI low	95% CI high	VIF
Intercept	29.32	1	0.3221	28.56	30.08	
X_1-SW(g),	0.8650	1	0.2546	0.2629	1.47	1.0000
X_2-ET(min)	-4.04	1	0.2546	-4.64	-3.44	1.0000
X_3 SV(ml)	-0.2188	1	0.2546	-0.8209	0.3834	1.0000
X_1X_2	3.95	1	0.3601	3.10	4.80	1.0000
X_1X_3	1.18	1	0.3601	0.3235	2.03	1.0000
X_2X_3,	-1.27	1	0.3601	-2.12	-0.4210	1.0000
$X^1{}_2$	0.3162	1	0.3510	-0.5137	1.15	1.01
X_2^2	4.81	1	0.3510	3.98	5.64	1.01
X_3^2	-2.06	1	0.3510	-2.89	-1.23	1.01

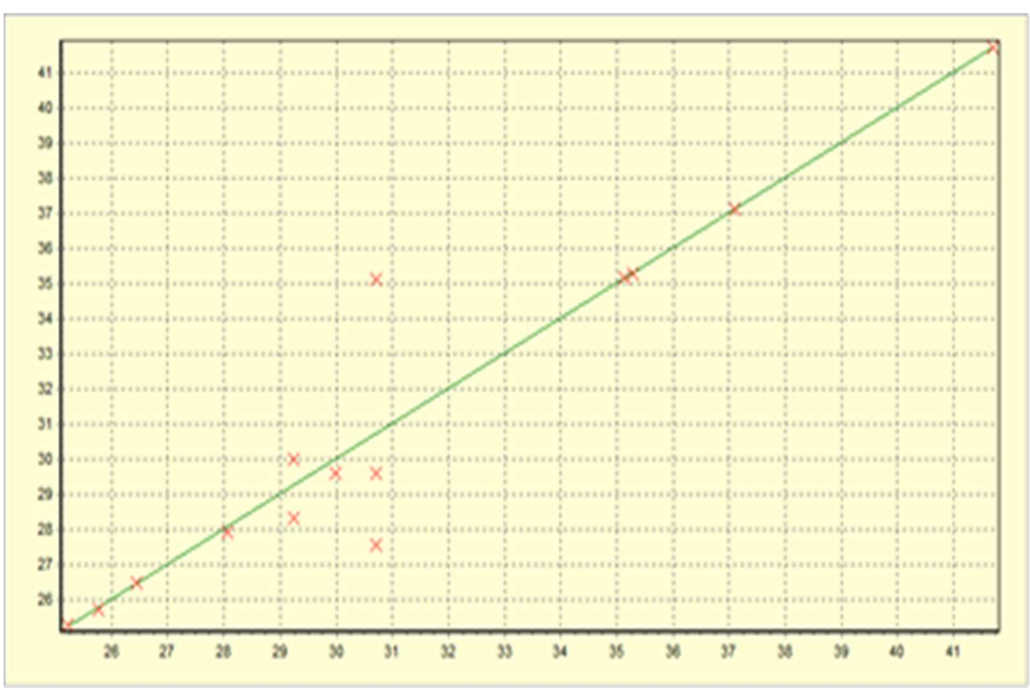
The estimated coefficient, where all other variables were held constant, shows anticipated change in reaction to a one-unit change in factor value in a perpendicular configuration. In the design, average response is represented by the intercept. Coefficients show departures from this average response, and they were ascribed to the chosen factors. VIF are a measure of multicollinearity. Higher VIF values indicate stronger correlations between factors. When factors are perpendicular, VIF are equal to 1. In general terms, VIF under 10 are deemed acceptable.

Model representation of the impacts of variable factors on PSOY

Plots of expected yield against actual yield produced using RSM and ANN software are shown in Figs. 2a and 2b. These charts clearly show the ways in which different factors affect PSOY. Data points are clearly in tight alignment with one another when comparing experimental findings with expected values, suggesting that projected values from RSM and ANN and actual results fit each other well.



(a)



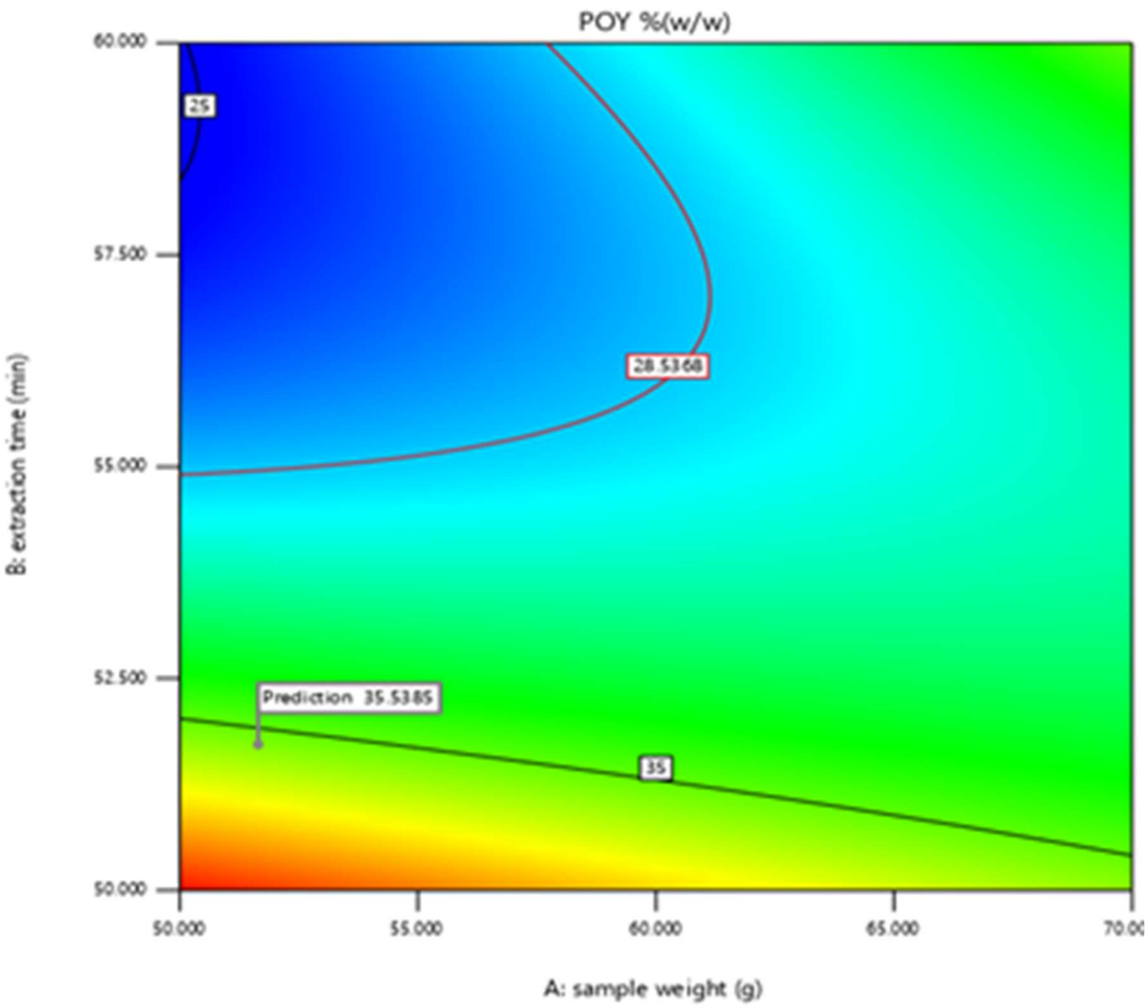
(b)

Figure 2: Graphs of predicted PSOY against actual PSOY- **(a)** RSM; **(b)-** ANN.

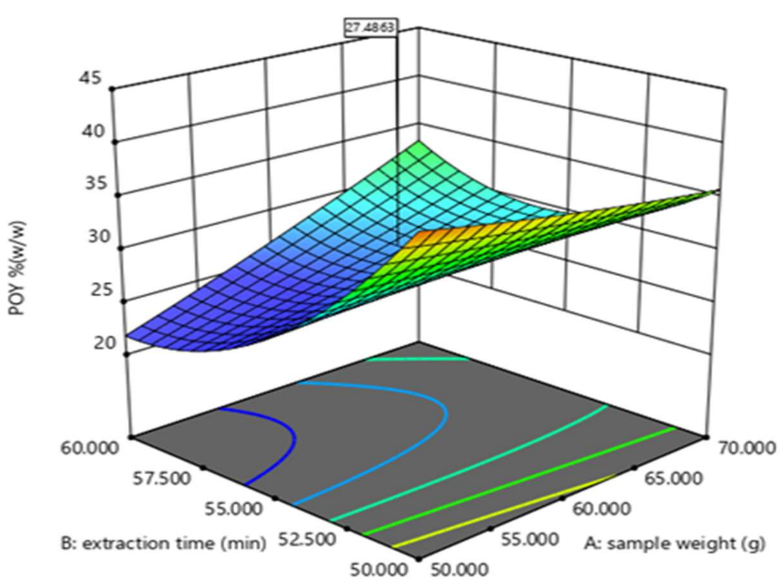
Three dimensional (3D) contour and response surface plot

Using contour and three-dimensional surface plots, regression equation model for maximising PSO extraction is shown in Fig. 3. While Fig. 3b shows 3-D dimensional surface plot for graphically representing regression equation used to maximise PSO extraction efficiency, Fig. 3a shows contour plot. To depict how ET, SW and their interactions affected PSO production, while maintaining constant SV at zero level, Fig. 3a shows response surface map. 3-D dimensional surface map

(Fig. 3b) shows that a larger PSOY resulted from a shorter extraction period. The contour plot depicts the relationship between PSO production, SW and ET. It can be seen that longer ET produced lower PSOY, while shorter one gave the best yields.



(a)



(b)

Figure 3: Effects of ET, SW and their mutual interaction on SPOY, with SV constant at zero level- **(a)** 3D contour plot; **(b)** response surface plot.

Fig. 4 depicts the correlation between SV and ET in PSO extraction. A regression model was developed to ascertain optimal parameters for SV, ET and sample mass. Eq. (5), created with Design Expert software, illustrates the relationship between PSOY and coded values of various variables, along with their interactions.

$$\text{PSOY\%}\ (^{W}/_{W}) = 29.32 + 0.865X_1 - 4.04\,X_2 - 0.2188\,X_3 + 3.95\,X_1X_2 + 1.18\,X_1X_3 - 1.27X\,2\,X_3 + 0.3162\,X_1^2 + 4.81X\,2^2 - 2.06\,X_3^2 \qquad (5)$$

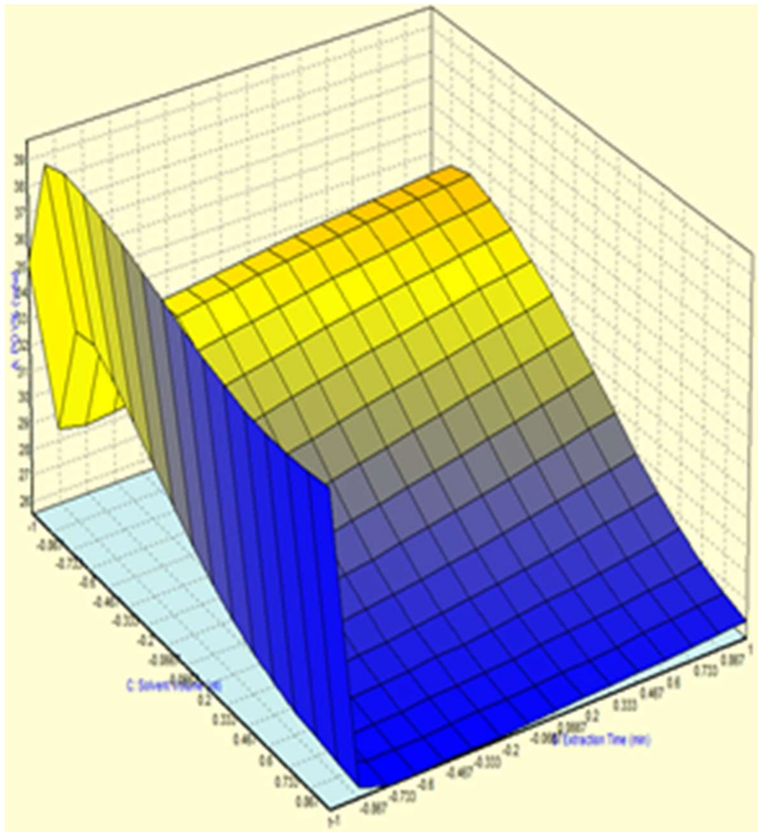


Figure 4: ANN 3D-contour and plot showing the effects of ET and SV on PSOY.

It has been established that X_1 of 50.00 g, X_2 of 50.00 min and X_3 of 200 mL were optimal parameters for this process. With a 95% prediction interval, anticipated PSO output under these optimal circumstances was Y = 39.6363% (w/w). Three different experiments were conducted using these ideal parameters, and average PSOY of 30.76% (w/w) was obtained, which is within the range anticipated by the model. Through a carefully planned experiment, this study demonstrated the efficacy of RSM in optimising process factors for PSO extraction. Interaction impacts of many variables on PSOY are shown by Genetic Algorithms experimental design, which is illustrated by 3D contours and surface plots (Fig. 4). Fig. 4 illustrates the considerable influence of ET on PSOY, by highlighting the interaction between ET and SV. Additionally, the input and output layers of MFFF Neural Network structure for PSOY prediction are shown in (Fig. 5).

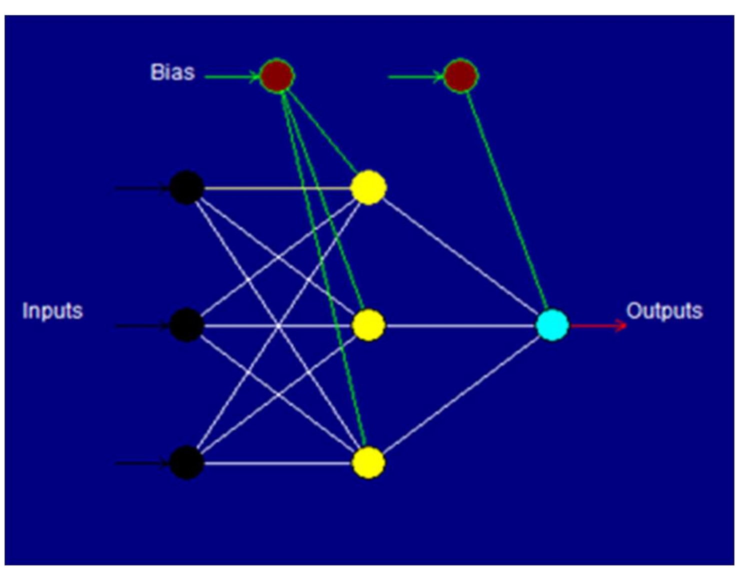


Figure 5: Topology of MFFF neural network for determining PSOY consisting of input and output layer.

In Fig. 6, the significant variable contributions to PSOY by ANN were analyzed. It was found that ET had the highest contribution at 74.96%, followed by SV at

12.60% and SW at 12.43%. The highest PSOY of 41.70% (w/w) was achieved with X1 = -1, X_2 = -1 and X_3 = 0. However, RSM software accurately forecasted statistical results for PSOY of 41.58% (w/w) under the same conditions. These were validated through experimental runs, resulting in an average PSOY of 39.52% (w/w). Similarly, ANN software made a statistical prediction for PSOY of 39.80% (w/w) through experimental runs, with an average content of 39.80% (w/w).

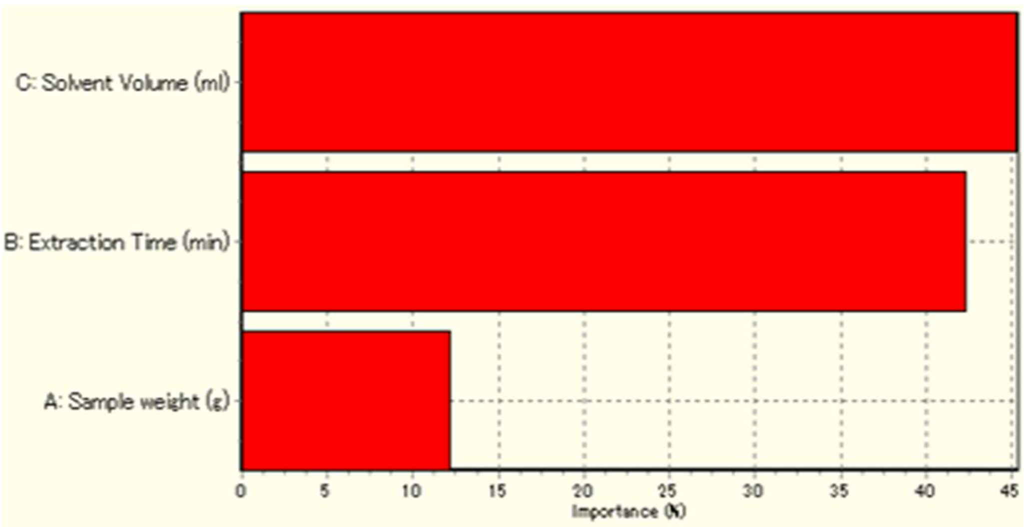


Figure 6: Chart showing the importance of the three variables on PSOY.

Performance test of RSM and ANN models

The results of the study showed that RSM and ANN were both successful in optimising different aspects of PSO extraction. Both ANN and RSM confirmed anticipated PSOY percentage's accuracy. However, in terms of forecasting ideal PSOY percentage, ANN did better than RSM. Several metrics, such as R^2, root mean squared error (RMSE), R^2 adj. and anticipated PSOY were used to evaluate RSM and ANN models [12]. Table 5 provides specifics on the comparison of these factors.

ANN had lower RMSE of 0.46752, higher R^2 of 0.9965 and higher R^2 adj. of 0.9893. RSM had RMSE of 3.47, R^2 of 0.9889 and R^2 adj. of 0.9746. Maximum experimental PSOY production was matched by ANN-predicted optimal yield. This demonstrates ANN effectiveness in capturing complexities of PSO extraction procedures. RSM model's comparatively poorer predictive accuracy suggests that it was not very sucessful in capturing nonlinear features of PSO extraction operations [19]. Nonlinearities in the system may be too complex for RSM's second-order quadratic polynomial function [10]. ANN's remarkable predictive accuracy, on the other hand, is due to the fact that it uses transfer functions in both hidden and output layers, which allowed it to capture the dynamics of PSO extraction process in nonlinear terms.

Quality characterization of PSO

Both physical and chemical properties of PSO were evaluated in order to determine its quality. When analysing PSO, physical characteristics like colour, viscosity, density, SG, MC and refractive index were taken into account. In addition, PSO's chemical characteristics—such as acidity, saponification, iodine and peroxide values—should be taken into account when assessing its overall quality [4].

Physical properties of PSO

To assess PSO quality, a thorough examination of its content and composition was conducted through physicochemical analysis. The outcomes of this analysis are detailed in Table 7. PSO displayed a brownish-yellow hue at room temperature, with refractive index of 1.4138, and MC of 1.62%. SG of PSO was determined to be

0.9259. Additionally, PSO viscosity, which indicates its resistance to shear, was measured at 23.7 mPa, at a temperature of 29.4 ℃.

Table 7: Summary of PSO physiochemical properties and other characteristics.

Parameters	PSO
Physical properties	
Density	925.9
Physical state at room temperature	Brownish yellow
MC(%)	0.0162
SG	0.9259
Viscosity (mPa)	23.7
Chemical properties	
Free fatty acid(%)	3.525
Acid value (mg KOH/g oil)	7.05
Saponification value (mg KOH/g oil)	154.976
Iodine value (g I2/ 100g oil)	105.2
Peroxide value (meq O2/kg oil)	52
Higher heating value (Mj/kg)	41.498
Other properties	
Cetane number	57.84
API	21.324
P – anisidene	36.5
Totox number	177

Table 7 displays the findings of an investigation into the chemical characteristics of PSO. The oil's low free fatty acid level (3.525) suggests good quality, since it shows resistance to degradation. PSO's acid value, which was 7.05 mg KOH/g, indicates that the oil has a long shelf life, in addition to being fit for human consumption. A substantial number of ester compounds may be present in the oil, as shown by high saponification value of 154.976 mg KOH/g. Additionally, the oil exhibits a high degree of unsaturation with an iodine value of 105.20 g for I2/100 g PSO. This is further supported by the oil's high unsaturated fatty acid content [2]. Strong resistance to oxidation is shown by low peroxide value, which gauges the amount of hydro peroxides in PSO [9]. For vegetable oils, the measured value of 52 meq Oz/kg for PSO is within an acceptable range. Low peroxide value and High iodine value indicate that PSO can be kept for a long period of time without degrading. All things considered, these findings imply that PSO has advantageous properties for use in cooking and as raw material in several industries.

Conclusions

The main aim of this research was to investigate PSOY and its possible applications in various sectors. The research revealed that maximum PSOY was 41.70% (w/w), under particular extraction conditions. The application of ANN and RSM models for optimisation produced favourable outcomes, with the former demonstrating superior accuracy than that from the latter. Optimised conditions were confirmed through experimental trials, with an average yield of 39.52% (w/w). Physicochemical investigations indicate that PSO may serve as feedstock for industries such as biodiesel production, soap manufacturing and pharmaceutical applications. The study suggests investigating other extraction techniques, including supercritical fluid extraction and aqueous enzymatic extraction, to improve oil yield and quality. This research substantially enhances the domain of extraction operations, by including sophisticated approaches such as ANN and RSM, which provide a more efficient and accurate approach for optimising the process. The application of these modern approaches improves efficiency and accuracy, while decreasing time and expenses related to the extraction process. Moreover, the novel integration of ANN and RSM produces insights that traditional approaches may not provide. This study's novel methodology for enhancing PSO extraction could transform these procedures in multiple sectors.

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Authors' contributions
R. I. David: wrote the original draft; conceptualization; visualization; **O. F. Chidiebere**: reviewed and edited the manuscript; **M. Keke**: reviewed and edited the manuscript. **W. C. Ulakpa**: investigation; data curation; reviewed, edited and visualized the manuscript.

Abbreviations
ANN: artificial neural network
ANOVA: analysis of variance
BBD: Box-Behnken design
ET: extraction time
MC: moisture content
PS: pumpkin seed
PSO: pumpkin seed oil
PSOY: pumpkin seed oil yield
R^2: coefficient of determination
RMSE: root mean square error
RSM: response surface methodology
SG: specific gravity
S/N: signal to noise ratio
SV: solvent volume
SW: sample weight
VIF: Variance Inflation Factors

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