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APPLICATION OF ARTIFICIAL NEURAL NETWORKS AND STATISTICAL METHODS IN COCONUT OIL PROCESSING

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ABSTRACT

The efficient and economical utilization of feed stocks is highly essential in oil producing industries. The identification of optimal pretreatment conditions of coconut nut kernel is of high importance to maximize the yield of oil produced from coconut kernels at low cost. Data analysis has become a fundamental task in food industries due to the great quantity of analytical information provided by modern analytical instruments. These requirements can be achieved by incorporating reliable and efficient statistical design methodologies such as central composite design (CCD), and ANN.

Experiments were designed according to CCD to study the effects of process variables such as Applied pressure, Pressing time, Roasting temperature, Roasting time and Moisture content. A simple, economical, and highly efficient model was developed to predict the yield of oil from coconut kernels in a hydraulic press. Experiments showed that all the above process variables had effect on yield of oil. The responses were analyzed with the help of statistical methods such as student's t test, p test, and ANOVA. For comparison, Artificial neural network (ANN) model was developed to predict the yield of oil from coconut kernels. The developed ANN was trained and tested with the experimental data obtained from CCD method. The results were compared with experimental data and it was found that the estimated oil yield from both RSM and ANN models were able to predict the yield accurately. However, the prediction accuracy of the neural network model was significantly improved compared to statistical model, ($R = 0.99$).

Key Words: coconut oil, Hydraulic Press, Mathematical Model, ANN, ANOVA, RSM.

INTRODUCTION:

Coconut palm is the most important perennial source of oil. The cultivation of coconut is spread over the entire coastal belt and also in some interior tracts in India. Coconut has the highest productivity and is less susceptible to abnormal climatic condition as well as consistency in production compared to all other oil seed crops [1]. The coconuts are harvested and crushed to remove the kernels. Some of the kernels are consumed in the raw form, some are in roasted form but a large percentage is used for the production of vegetable oil. The production of coconut oil and its by-products, raw and fried cake, is an important source of income for women in coastal areas of India. The oil is used in the preparation of food and further processed as an ingredient in soap industries [2].

Coconut oil contains a high proportion of glycerides of lower chain fatty acids. The oil is highly stable towards atmospheric oxidation. The oil is characterized by a low iodine value, high saponification value, high saturated fatty acids content and is a liquid at room temperatures of 27°C. As it has a long shelf life and a melting point of 76 °F, it is used in baking industries. Various fractions of coconut oil are used as drugs [1]. Philippines, Indonesia, India, Sri Lanka, Mexico, West Malaysia, and Papua & New Guinea are the 7 countries which produce major quantities of coconut in the world. Coconut is available in two forms viz., wet and dry materials commonly known as wet coconut and dry coconut or copra. The oil can be extracted from both these raw materials. However, in India and Srilanka, it is a general practice to use only copra for oil extraction and the oil is used for food and cosmetic purposes. Rotaries and expellers are used for crushing the dry coconuts (known as copra) for recovery of oil. The total production of edible grade coconut oil in the country is about 4.0 lakh tons which is 1.5 lakh tons more compared to that produced in 1980s [3]. In Phillippines, the oil is extracted from wet coconut also and is known as virgin coconut oil. In some countries solvent extraction of the dry coconut followed by refining, bleaching and deodorization is carried out to get the refined bleached and deodorized coconut oil [4, 5, 6].

Coconut oil is removed from its kernel by using mechanical expression in the hydraulic press [7]. This method is widely used because of requirement of low initial and operational costs. Solvent extraction process generally gives impure oil moreover cake cannot be used directly. But hydraulic press produces relatively uncontaminated oil as compared to the solvent extraction process and it allows the use of the cake residue. Many researchers found that oil yield in hydraulic press is dependents primarily on process variables such as moisture content, particle size, heating temperature, heating time, applied pressure and pressing time [7, 8, 9].

Neural network is a new class of information processing techniques. The most basic components of neural networks are modeled after the structure of the human brain; like human information processing systems artificial neural systems or networks acquire, store and utilize knowledge. It has been applied in solving wide varieties of problems. The most common is the use of neural network to forecast what will most likely happen. It has a unique ability to recognize relationship before input and output events. Numerous researches have applied neural networks in the modeling of various systems in which no explicit scientific solutions were available [10, 11, 12, 13, 14, 15, 16].

Many modeling equations have been developed to predict the effect of process parameters on oil yield. The oil yield from sun flower, conorphor nuts, peanut, rice bran and shea nut have been predicted using such empirical equations [17, 18, 19, 20, 21, 22, 23]. However, the prediction power of these models are limited. Hence, in present paper effects of various parameters on coconut yield was studied by using statistical methods and advanced neural network method.

2. MATERIALS AND METHODS: 2.1 Materials

Coconuts collected from coastal area were broken into pieces and dried in sunlight for three weeks. Coconut kernels were separated from the shell and they were de-husked and cut into small sizes (i.e 1cm x1cm) with the help of a knife. These samples were subjected to hydraulic press under different conditions as mentioned in experimental procedure.

2.2 Experimental Procedure

The effect of various process parameters such as Applied pressure (x_1), Pressing time (x_2), Roasting time (x_3), Roasting temperature (x_4) and Moisture content (x_5) on coconut oil yield (y) was studied by using half fraction factorial Central Composite Design (CCD). A CCD with 32 experiments was used for the optimization of process parameters for removal of coconut oil from its kernels. All independent variables were coded to five levels as X_i according to equation-1.

$$X_i = \frac{(X_i - X_{oi})}{\Delta X_i}, \quad i = 1,2,3,\ldots\ldots k \text{ ------------ (1)}$$

Where X_i is independent variable, x_i is the real value of an independent variable, x_{oi} is the real value of the independent variable at the centre point, and Δx_i is the step change. A polynomial (Equation-2) was developed to estimate the behavior of the coconut oil yield.

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k-1} \sum_{i=2}^{k} \beta_{ij} X_i X_j + \sum_{i=1}^{k} \beta_{ii} X_i^2 \text{ ----------------------(2)}$$

Where Y is the response, β_0 was the intercept term, β_i were linear effects, β_{ij} were the squared effects and β_{ij} were the interacting effects.

3. RESULTS AND DISCUSSION

The statistical analysis of the experimental results shows that percentage of coconut oil yield was a function of Applied pressure, Pressing time, Roasting time, Roasting temperature and Moisture content. The design matrix used with the observed responses obtained was shown in table -1. Responses shown in table-1 were the average values of three replicates for all the experimental runs. The main effects of all parameters on percentage oil yield were determined and shown in figure -1. Analysis of Variance gives the information about quadratic and interaction effects along with the normal linearised effects of the parameters. Model was developed from ANOVA to represent the effect of above parameters on percentage of oil yield and was shown in equation-3.

$$Y_1 = -13.0727 + 0.8768 X_1 - 3.2951 X_2 + 0.233 X_3 + 0.2519 X_4 + 0.5966 X_5 - 0.0206 X_1^2 - 0.0983 X_2^2 - 0.0009 X_3^2 - 0.0009 X_4^2 - 0.0294 X_5^2 + 0.0029 X_1X_2 - 0.0016 X_1X_3 + 0.0013 X_1X_4 - 0.0074 X_1X_5 - 0.0011 X_2X_3 - 0.0181 X_2X_4 + 0.0005 X_2X_5 + 0.0006 X_3X_4 - 0.008 X_3X_5 + 0.0012 X_4X_5 \text{ ------------ (3)}$$

Experimental data along with the predicted results obtained from the above model were shown in table-1. The proposed model was evaluated by regression coefficients, standard error, t-values, p-values and correlation coefficient (R). The model indicates that the applied pressure, pressing time and roasting temperature had a strong effect; linear and quadratic terms had more influence in comparison to the interaction terms. From the table-2 it is clear that all parameters effects were significant at 95% confidence levels. Here, the value of correlation coefficient (R= 0.999), R^2 (0.987) indicates a high agreement between the experimental and predicted values and its significance. The model adequacy was tested by using ANOVA (Table-3). Lower P values for regression model equation imply that the second-order polynomial model fitted to the experimental results well.

In achieving the set goal of the study, an artificial neural Network (ANN) was trained and validated. A total of 96 data sets obtained from the experimental work was used in this study. About

60 sets of these data sets we assigned the training set while the remaining 36 sets were used as the validation sets. There are five input variables, which are: applied pressure, pressing time, moisture content, heating temperature and heating time. The desired output is the oil yield from the coconut kernel. The ANN was trained using standard back propagation architecture with BFGS training algorithm and this architecture used was comprised of two layers. Fig-2 shows the architecture of the network used. The tansigmod function was used as the transfer function in the hidden layer due to its suitable application for the data set of this kind. The output layer was made up of pure lineartransfer function. The optimal hidden layer was determined by varying the total number of neurons from 1 to 20. The results of ANN during training and testing were given in table-4. The stop criteria were based on mean square error (MSE) on the validation set for model generalization. The optimum hidden layer comprised of 5 neurons. Incremental training style is used where the weights and biases of the network are updated each time an input is presented to the network.

4. CONCLUSION

Effect of various parameters on coconut oil yield in hydraulic press could be predicted well by both response surface method and ANN. Prediction ability of both the methods were very high (>99%) however, ANN gave more accurate results. Back propagation neural network model was designed, trained and validated for the prediction of oil yield from groundnut kernels. The network had five input variables. The network performed well during validation. The accuracy of prediction was significantly improved compared to statistical model. The neural network model developed could better predict the properties than the previously regression model. The network model had R = 0.999 which showed that the neural network model was capable of learning the relationships among the input and output variables for given data set.

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Tables and Figures:

Run Order	X_1	X_2	X_3	X_4	X_5	% Yield Observed	% Yield Predicted
1	17.5	1	45	80	10	24.672	17.5
2	17.5	7	45	80	10	31.472	17.5
3	17.5	7	45	80	10	31.472	17.5
4	25	4	60	60	15	26.496	25
5	25	10	30	100	5	30.197	25
6	17.5	7	45	80	10	31.472	17.5
7	10	10	60	60	15	27.481	10
8	2.5	7	45	80	10	22.26	2.5
9	10	4	60	60	5	25.841	10
10	17.5	7	75	80	10	33.212	17.5
11	17.5	7	45	40	10	27.287	17.5
12	25	4	60	100	5	32.611	25
13	25	10	30	60	15	31.564	25
14	32.5	7	45	80	10	30.518	32.5
15	17.5	13	45	80	10	30.3	17.5
16	25	10	60	60	5	33.763	25
17	10	4	60	100	15	26.26	10
18	25	4	30	60	5	25.954	25
19	25	4	30	100	15	29.9505	25
20	17.5	7	45	80	10	31.472	17.5
21	17.5	7	45	80	10	31.472	17.5
22	10	10	60	100	5	29.579	10
23	10	4	30	60	15	21.5987	10
24	17.5	7	45	80	0	29.454	17.5
25	25	10	60	100	15	31.744	25
26	10	10	30	60	5	27.489	10
27	17.5	7	45	80	20	26.712	17.5
28	10	10	30	100	15	25.3154	10
29	17.5	7	45	120	10	31.867	17.5
30	10	4	30	100	5	24.945	10
31	17.5	7	15	80	10	27.157	17.5
32	17.5	7	45	80	10	31.453	17.5

Table-1: CCD plan matrix in coded values and Responses

Term	Constant	SE	t	P
b0	-13.0727	4.48338	-2.916	0.014
b1	0.8768	0.14026	6.251	0
b2	3.2951	0.35066	9.397	0
b3	0.233	0.0732	3.183	0.009
b4	0.2519	0.05917	4.257	0.001
b5	0.5966	0.20654	2.888	0.015
b1 * b1	-0.0206	0.00201	-10.224	0
b2 * b2	-0.0983	0.01259	-7.804	0
b3 * b3	-0.0009	0.0005	-1.852	0.091
b4 * b4	-0.0009	0.00028	-3.192	0.009
b5* b5	-0.0294	0.00453	-6.487	0
b1* b2	0.0029	0.00682	0.422	0.681
b1* b3	-0.0016	0.00136	-1.167	0.268
b1* b4	0.0013	0.00102	1.236	0.242
b1* b5	0.0074	0.00409	1.804	0.099
b2* b3	-0.0011	0.00341	-0.309	0.763
b2* b4	-0.0181	0.00256	-7.061	0
b2* b5	0.0005	0.01023	0.05	0.961
b3* b4	0.0006	0.00051	1.145	0.277
b3* b5	-0.008	0.00205	-3.933	0.002
b4* b5	0.0012	0.00153	0.751	0.468

Table- 2: Response Surface Regression of percentage of oil yield

Source	DF	Seq SS	Adj MS	F	P
Regression	20	312.468	15.6234	41.46	0
Linear	5	216.275	8.8078	23.37	0
Square	5	68.451	13.6903	36.33	0
Interaction	10	27.742	2.7742	7.36	0.001
Residual Error	11	4.145	0.3768		
Lack-of-Fit	6	4.145	0.6908	11480.92	0
Pure Error	5	0	0.0001		
Total	31	316.613			
S = 0.6138 R-Sq = 98.7% R-Sq(adj) = 96.3%					

Table-3: Analysis of Variance for % Yield using CCD

Network Name	MLP 5-5-1
Training Performance	0.999871
Test performance	0.995029
Training Error	0.000812
test error	0.004660
Training Algorithm	BFGS 45
Error function	SOS
Hidden activation	Tanh
Output activation	Identity

Table-4: ANN results

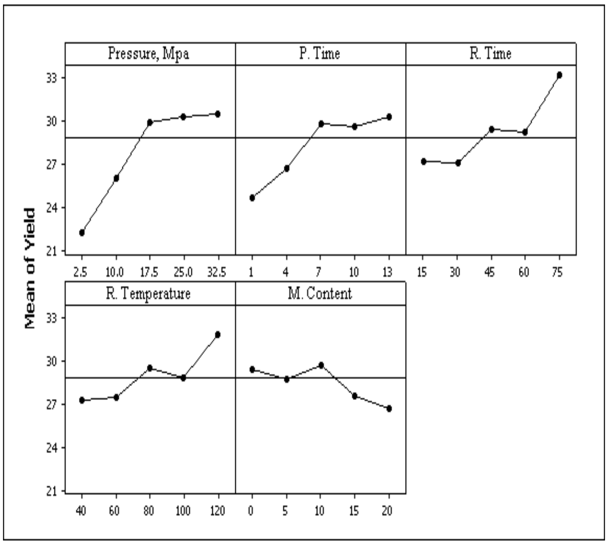

Fig-1: Main Effects plots of % coconut oil yield

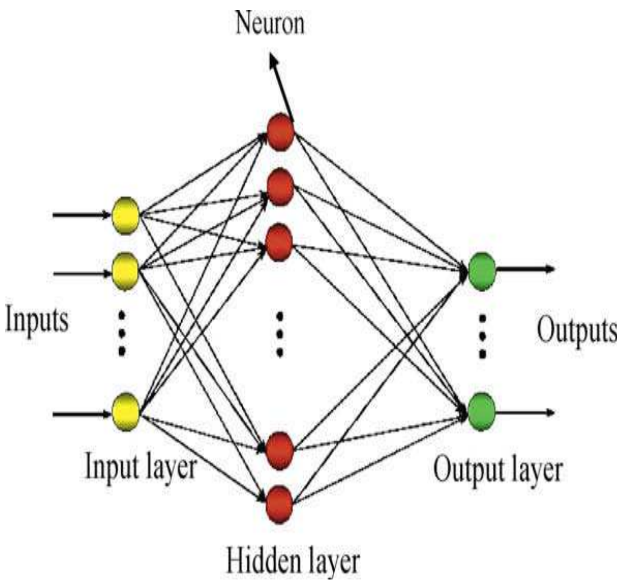

Fig-2. Multilayer Perceptron Neural Network