Artificial Neural Network Model For Optimization Of Palm Kernel Oil Yield Extraction Machine

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***Abstract*— In this study, Artificial Neural Network (ANN) model for optimization of palm kernel oil yield extraction machine is presented. The ANNs model was employed in the optimization of the oil extracted from palm kernel using the dataset of a 10-ton palm kernel oil (PKO) extracting machine located in Akwa Ibom State as the case study. The input parameters in the case study dataset include the moisture content of the palm kernel, the shaft speed of the machine and the cone gap of the machine while the optimized PKO produced is the model output. The 5000 records case study dataset was split into 75 % for model training and 25 % for the model validation. The feature importance result showed that the moisture content with average impact of 0.16 was the most important parameter when the ANNS model was used for predicting the PKO output of the extracting machine. Also, the maximum oil yield of 43.4 % was realized with shaft speed of18 rpm, the cone gap of 1.5 mm and the moisture content of 8 %. This means that the operators of the machine should target the identified input parameters setting in order to realize the best oil yield in their plant.**

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Keywords*— *Artificial Neural Network (ANN) Model, Palm Kernel Yield (PKO), Optimization Model, Oil Extraction Machine, Moisture Content

1. Introduction

Nowadays, Artificial Intelligence (AI) has gained wide spread applications in diverse field (Bianchini, Müller and Pelletier, 2022; Sarker, 2021). AI has become particularly useful in handling data drive solutions, especially those non-linear problems that result in high prediction errors when the conventional multiple nonlinear models are used (Rahmanifard and Gates, 2024; Zhao, 2022).

Remarkably, machine learning models which are artificial intelligence solutions are being increasingly used to tackle such optimization problems that are normally found in the industry (Nagy, Lăzăroiu and Valaskova, 2023; Ahmed, Jeon and Piccialli, 2022; Bécue, Praça and Gama, 2021). Notably, in this work, the focus is on applying the Artificial Neural Network (ANN) model on the case study dataset of a 10-ton palm kernel oil (PKO) extracting machine to optimize the PKO extracted by the machine based on the machine settings and the palm kernel moisture content. In this regard, the ANN model which is one of the earliest intelligent models is employed to read in two machine setting parameters, namely the machine main shaft speed and the cone gap setting and also read in the palm kernel moisture content and then determine the optimal PKO yield (Agu et al., 2023; Said et al., 2018; Adejugbe et al., 2017; Hashim, Tahiruddin and Asis, 2012). The ANN model is trained with adequate data records obtained from the case study PKO extracting machine. The ideas presented in this work are essential for industrial applications regarding data-driven optimization problems.

2. Methodology

In this work Artificial Neural Networks (ANNs) model is employed in the optimization of the oil extracted from palm kernel using a case study 10-ton palm kernel oil (PKO) extracting machine (Iweka et al., 2024, Mohd Najib et al., 2020; Tehlah, Kaewpradit and Mujtaba, 2016). The input parameters include the moisture content of the palm kernel, the shaft speed of the machine and the cone gap of the machine while the optimized PKO produced is the model output.

2.1 The Artificial Neural Networks (ANNs) Model Training and Evaluation

The Artificial Neural Networks (ANNs) is trained and used for optimizing the oil yield of the palm kernel oil extraction machine. The ANNs model architecture is presented in Figure 1.

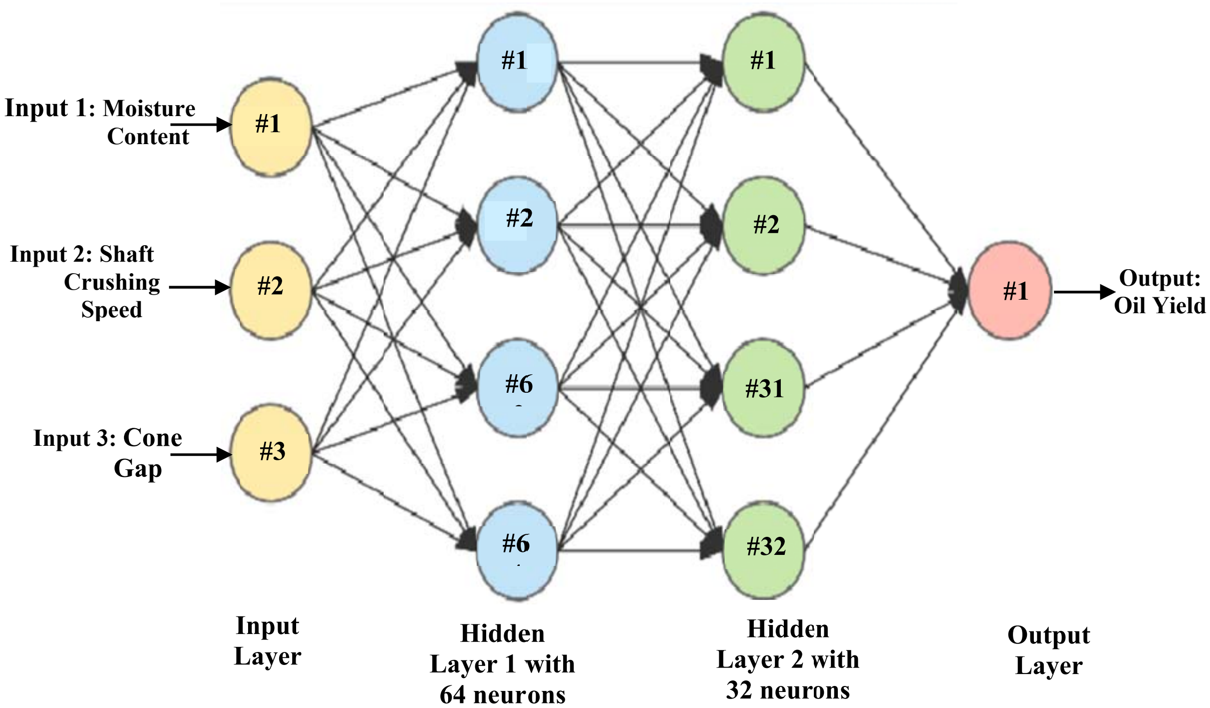


Figure 1 The Anns Model Architecture

The ANN maps the machine pattern or behavior which is the oil yield (represented as y) based on three input parameters combination, where the input parameters are x_1 used for representing the shaft speed, x_2 used for representing the cone gap, and x_3 used for representing the palm kernel moisture content.

$$f(x_1, x_2, x_3) \approx y \qquad (1)$$

According to the architecture in Figure 1, the ANN model has multiple layers of neurons, which it uses to transform each of the input by using a weighted sum in conjunction with activation function. Basically, the ANN consist of the following three layers;

i. Input layer: This is the layer the receive the features (x_1, x_2, x_3) used for the determination of the output y
ii. Hidden layers: processes the input data combinations through the weighted sums along with the activation functions
iii. Output layer: This is the that produced the output which is the oil yield, $\hat{y}$

An ANN with one-layer feedforward architecture is defined as follows :

$$h_j = \sigma\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right) \qquad (2)$$

$$\hat{y} = \sum_{j=1}^{m} v_j h_j + c \qquad (3)$$

Where, h_j represents he activation output function for the hidden neuron j, w_{ij} represents the weights that links between the input i and the hidden neuron j, v_j represents the weight that between link the hidden neuron j and the output neuron, b_j, c represents the bias terms, and $\sigma(\cdot)$ represents the activation function.

This structure captures nonlinear dependencies between oil yield and input parameters. The hidden layers also has the ReLU (Rectified Linear Unit) activation defined as:

$$\sigma(x) = \max(0, x) \qquad (4)$$

The linear activation function is employed in the regression task at the output layer:

$$f(x) = x \qquad (5)$$

For, ANN applies forward propagation in each layer to predict the oil yield:

$$H = \sigma\left(W^{(1)} X + b^{(1)}\right) \qquad (5)$$

$$\hat{y} = W^{(2)} H + b^{(2)} \qquad (6)$$

Where, $b^{(2)}$ represents the bias vectors, $W^{(1)}$ and $W^{(2)}$ represents weight matrices, X represents the input vector $[x_1, x_2, x_3]$, $b^{(1)}$, while H represents the hidden layer output. This is the process which the ANN model use to transform the given set of inputs into predicted set of outputs or output as the case may be.

The ANN model works by minimizing the Mean Squared Error (MSE) loss as follows:

$$L = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (7)$$

The gradient descent is used by the ANN model during training via backpropagation to update its parameters values as follows:

$$\frac{\partial L}{\partial W} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial W} \quad (8)$$

$$W^{(t+1)} = W^{(t)} - \eta \frac{\partial L}{\partial W} \quad (9)$$

Where, η represents the rate of learning. In order to improve the learning rate, the ANN model employs the Adam optimizer, which works by combining the momentum (moving average of gradients) and the adaptive learning rate adjustment with the update equations expressed as follows;

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (10)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (11)$$

$$\widehat{m}_t = \frac{m_t}{1-\beta_1^t}, \hat{v}_t = \frac{v_t}{1-\beta_2^t} \quad (12)$$

$$W_t = W_{t-1} - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} \widehat{m}_t \quad (13)$$

At the end of the model training the ANN model then gives the predicted oil yield, $\hat{y}$ using the equation:

$$\hat{y} = W^{(2)} \cdot \sigma\left(W^{(1)} X + b^{(1)}\right) + b^{(2)} \quad (14)$$

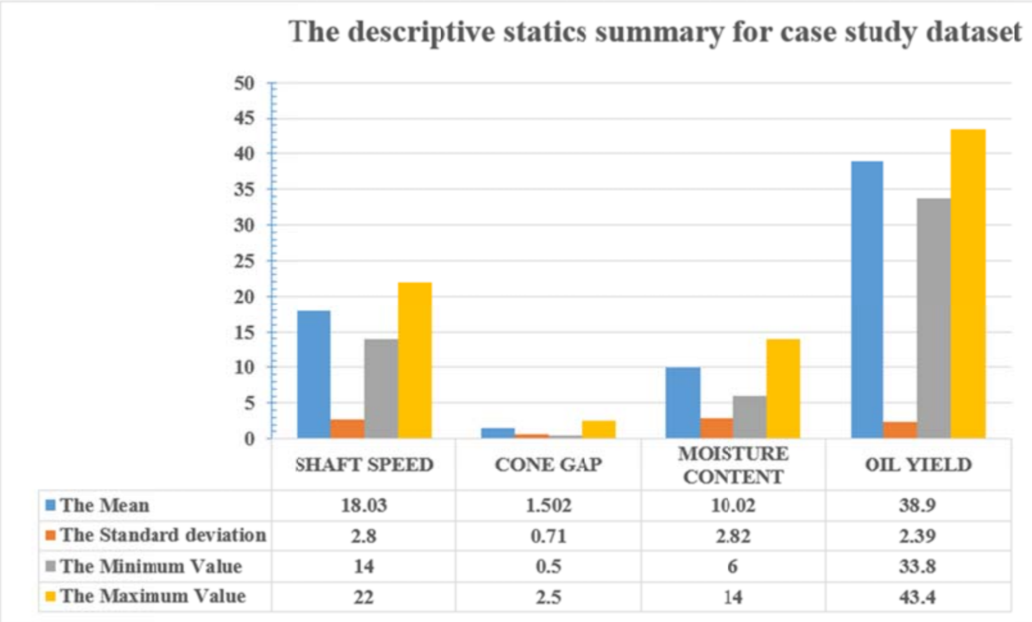
The ANN model's hyperparameters used in this work along with their values are summarized in Table 1.

Table 1 The ANN model's hyperparameters used in this work along with their values

Hyperparameter	Value	Explanation
Number of hidden layers	2	Two fully connected hidden layers
Number of neurons per layer	64, 32	64 neurons in the first hidden layer, 32 neurons in the second
Activation Function (Hidden Layers)	ReLU	Rectified Linear Unit (ReLU) for introducing non-linearity
Activation Function (Output Layer)	Linear	Used for regression output
Loss Function	MSE	Measures the difference between actual and predicted values
Optimizer	Adam	Adaptive moment estimation for efficient learning
Learning rate	0.001	Controls the step size during weight updates
Batch size	32	Number of samples per training batch
Epochs	100	Number of times the model sees the entire dataset
Dropout rate	0.2	Prevents overfitting by randomly deactivating neurons
Regularization	L2 (0.001)	Helps prevent overfitting by adding a penalty to large weights

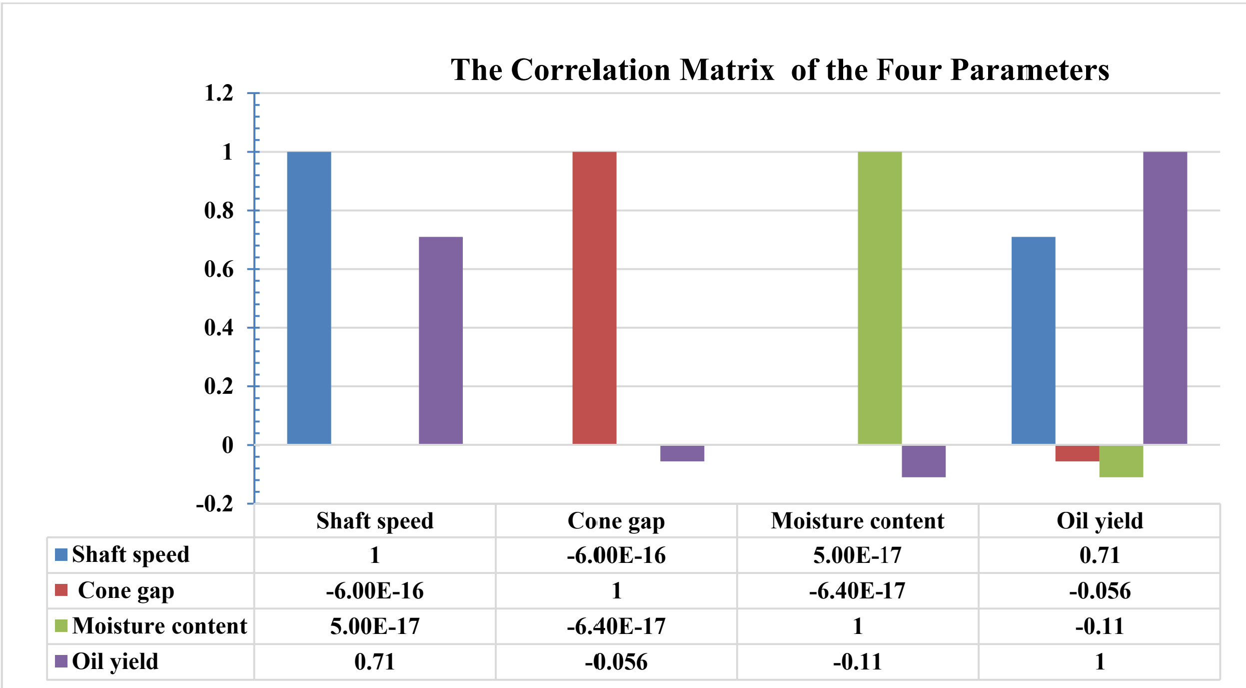
2.2 The case study dataset

The case study dataset was acquired from a 10-ton PKO extracting machine in Akwa Ibom State. The dataset has four parameters, namely, the moisture content of the palm kernel, the shaft speed of the machine, the cone gap of the machine and the PKO produced. The dataset was preprocessed which included the descriptive statistical analysis, outlier determination and the data normalization which employed the MinMax approach. There are 5000 data records in the dataset and there is no outlier and no missing data. The descriptive statics summary for the four parameters in the case study dataset is presented in Figure 2 while the summary of the correlation matrix for the four parameters in the case study dataset is presented in Figure 3. Eventually the 5000 data records was split into 3750 data records (which is 75 % of the case study dataset) for the model training and the remaining 1250 data records (which is 25 % of the case study dataset) for the validation of the model. The model training and validation were conducted using Python programming tools and libraries.



	SHAFT SPEED	CONE GAP	MOISTURE CONTENT	OIL YIELD
The Mean	18.03	1.502	10.02	38.9
The Standard deviation	2.8	0.71	2.82	2.39
The Minimum Value	14	0.5	6	33.8
The Maximum Value	22	2.5	14	43.4

Figure 2: The descriptive statics summary for the four parameters in the case study dataset



	Shaft speed	Cone gap	Moisture content	Oil yield
Shaft speed	1	-6.00E-16	5.00E-17	0.71
Cone gap	-6.00E-16	1	-6.40E-17	-0.056
Moisture content	5.00E-17	-6.40E-17	1	-0.11
Oil yield	0.71	-0.056	-0.11	1

Figure 3: The summary of the correlation matrix for the four parameters in the case study dataset

3. Results and discussion

3.1 The Results of the impact of the inputs and the predicted oil yields for the ANNS

The results show the impact of the inputs on the prediction performance of the **ANNS** model is presented in Figure 4. According to Figure 4, the moisture content with average impact of about 0.16 is the most important parameter when the ANNS model is used for predicting the PKO output of the extracting machine.

Again, the error metrics results over epochs presented in Figure 5 whos that the ANN model has mean absolute error (MAE) of 0.016519 and means square error (MSE) of 0.000443. The ANN model plot of the actual versus the predicted oil yield is presented in Figure 6.

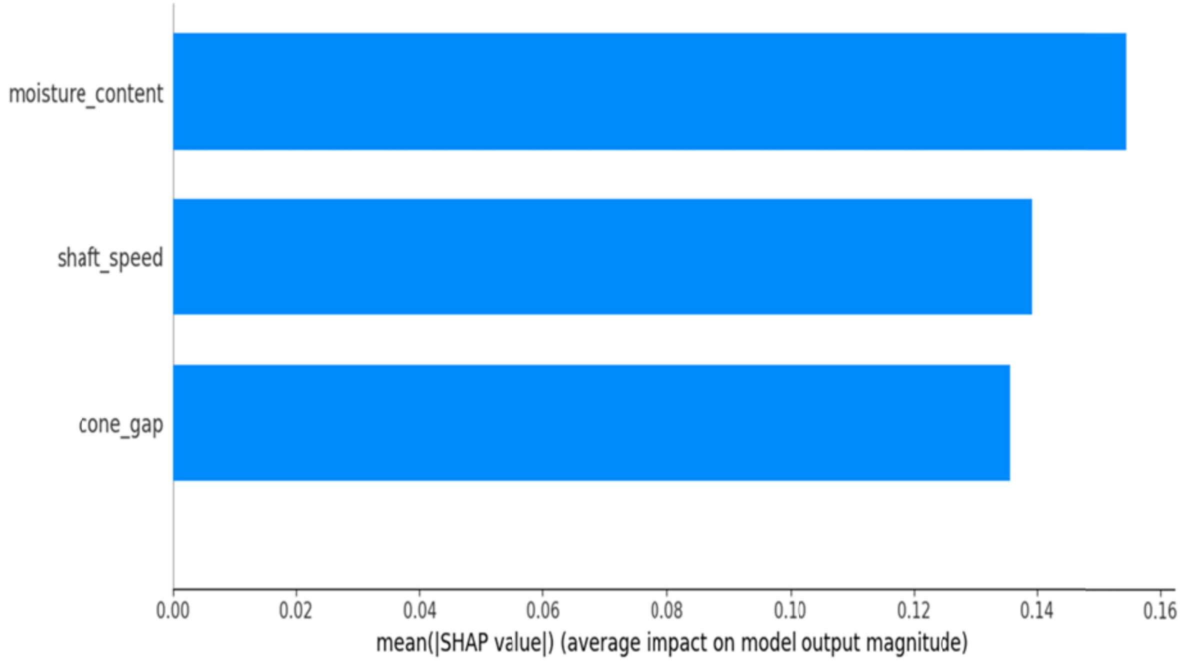


Figure 4: Average impact of the inputs on the ANNS model output

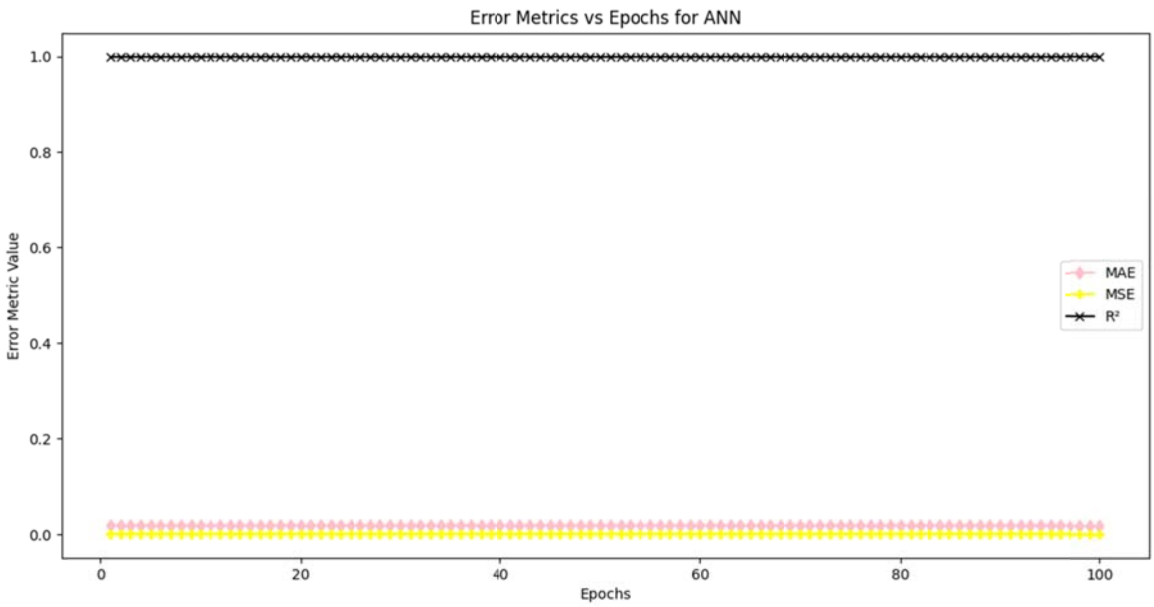


Figure 5 The ANN Model Error Metrics Over Epochs Plot

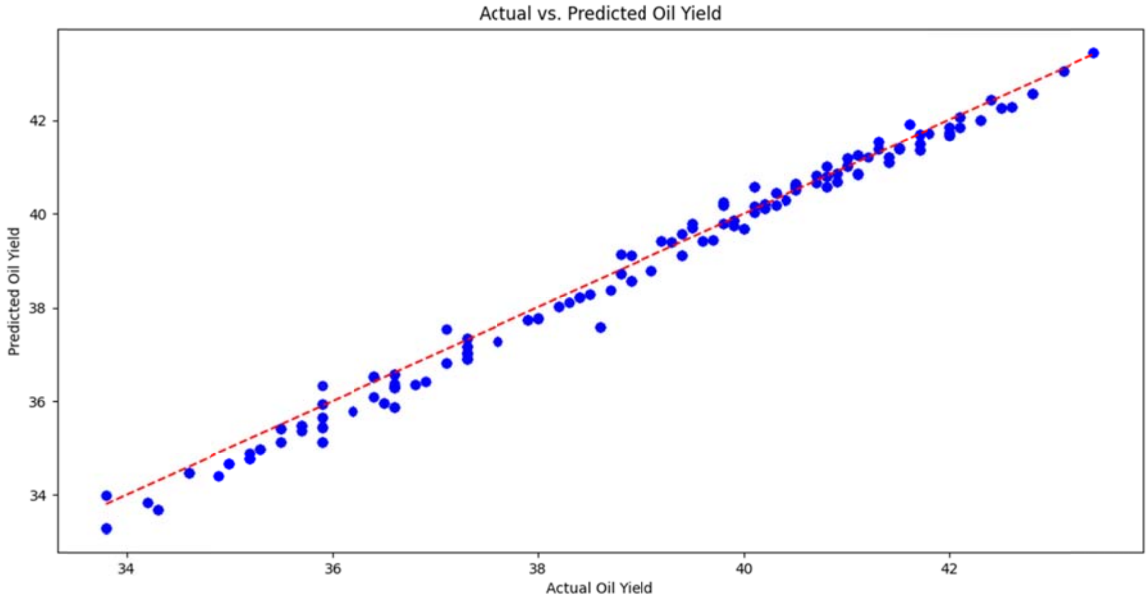


Figure 6: The ANN Model plot of the Actual Versus the Predicted Oil Yield

The oil yield versus cone gap line chart for constant shaft speed and with varying moisture content are shown in Figure 7 to Figure 11. According to the results, the maximum oil yield of 43.4 % was realized in Figure 9 where the shaft speed is 18 rpm, the cone gap is 1.5 mm and the moisture content is 8 %.

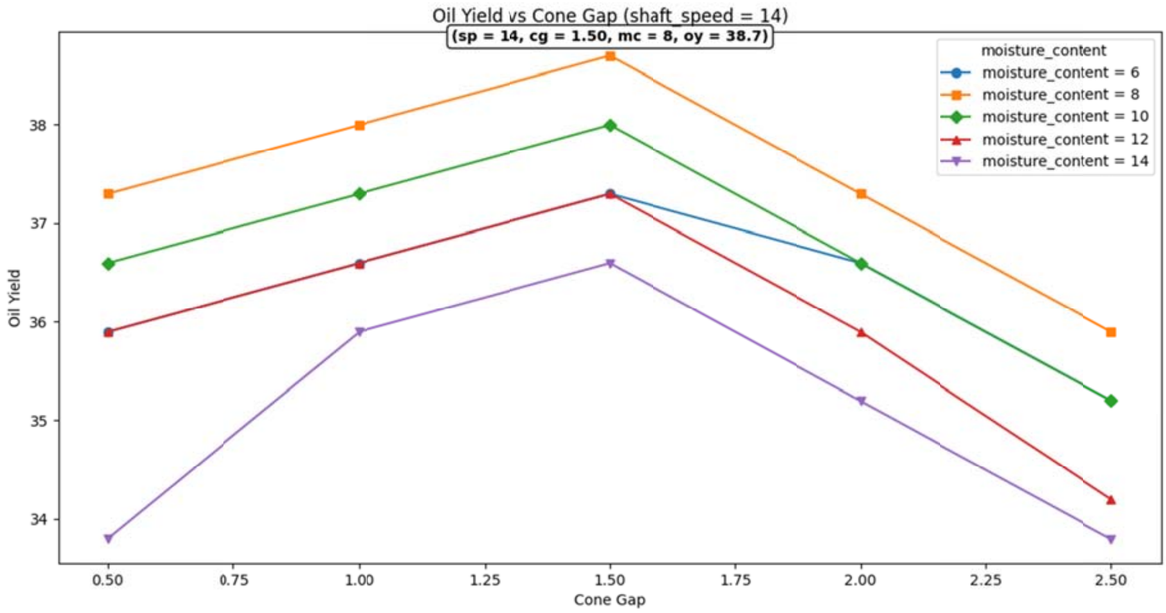


Figure 7: The oil yield versus cone gap line chart for constant shaft speed of 14 rpm with varying moisture content

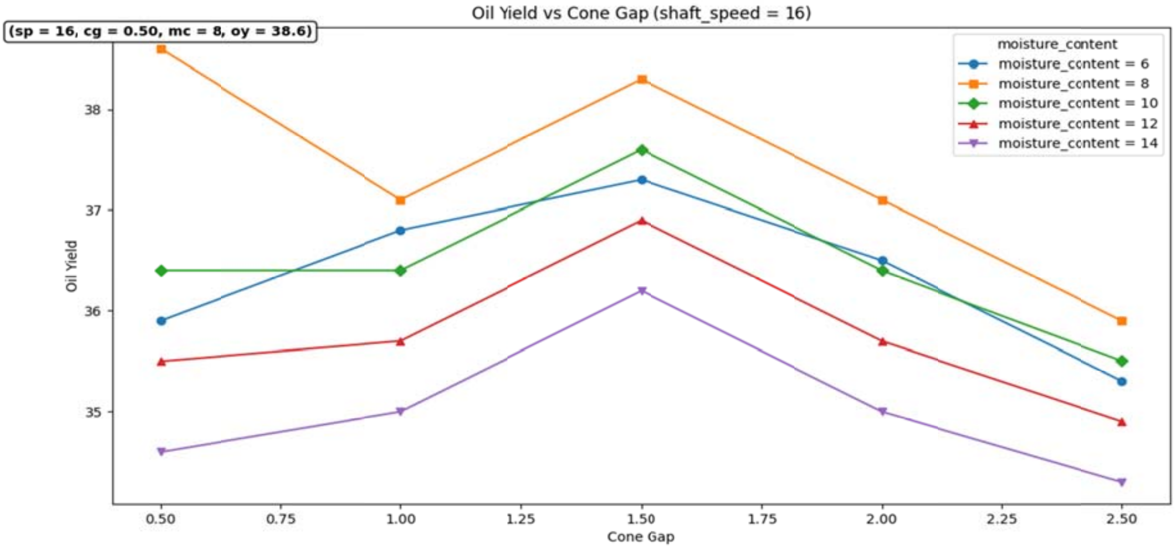


Figure 8: The oil yield versus cone gap line chart for constant shaft speed of 16 rpm with varying moisture content

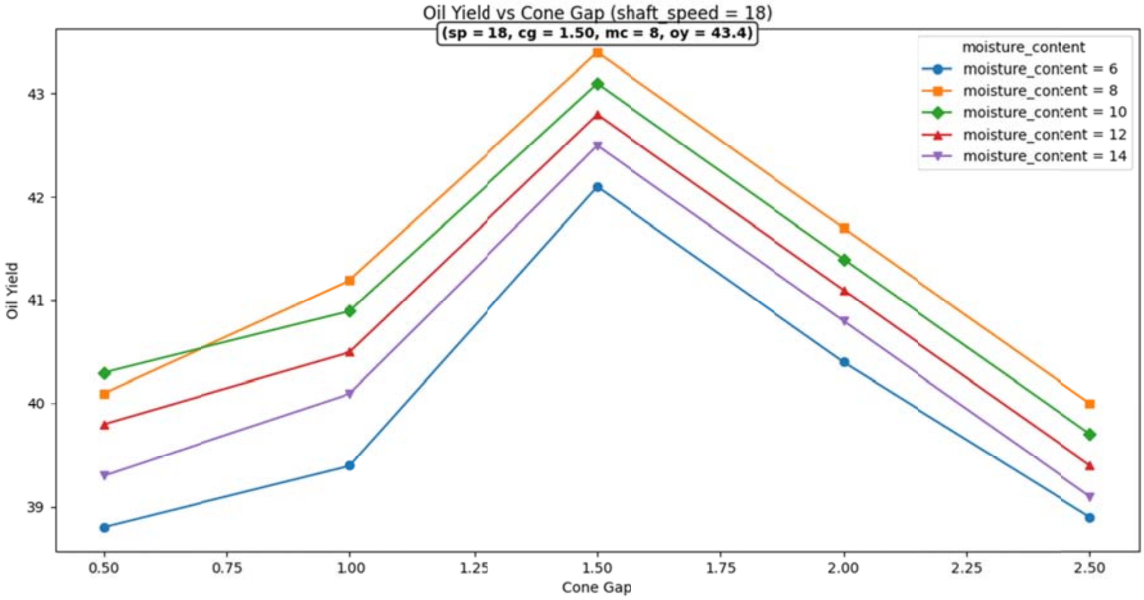


Figure 9: The oil yield versus cone gap line chart for constant shaft speed of 18 rpm with varying moisture content

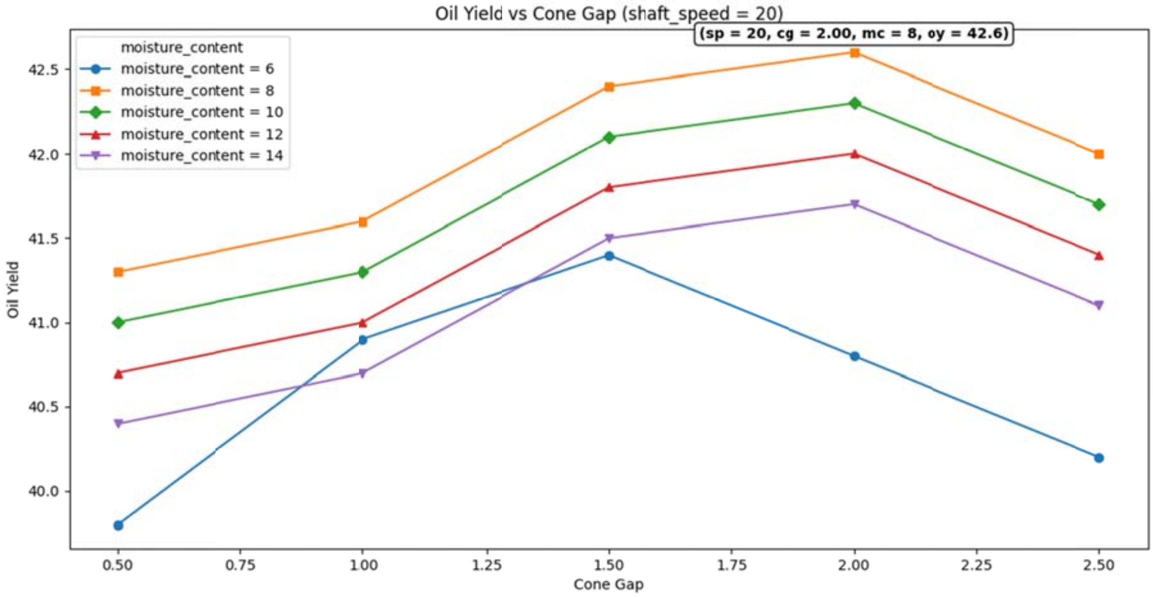


Figure 10: The oil yield versus cone gap line chart for constant shaft speed of 20 rpm with varying moisture content

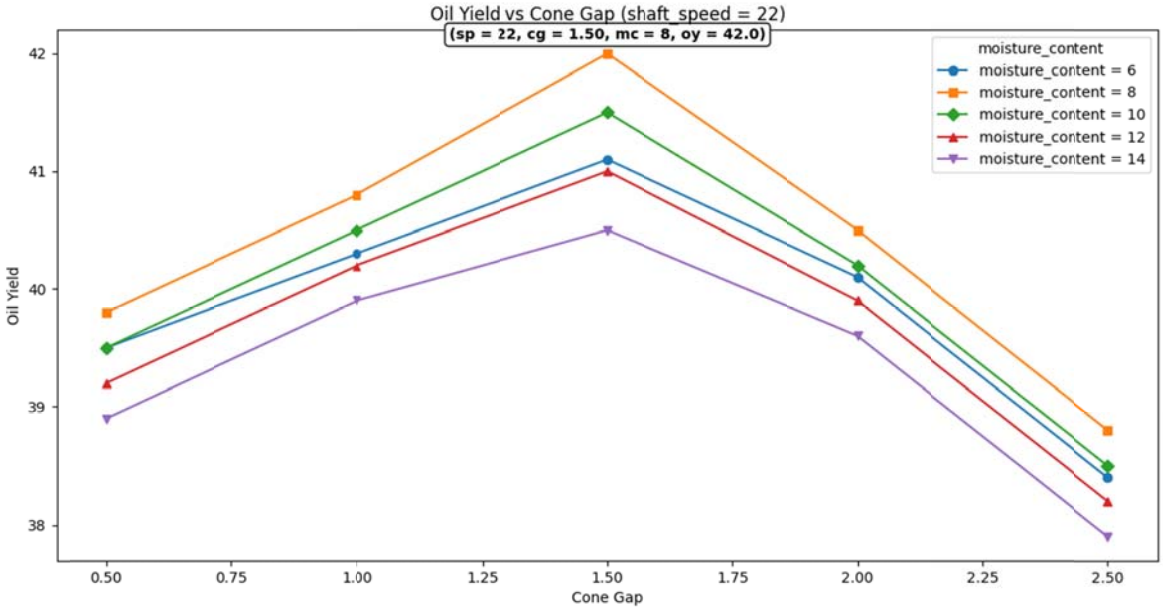


Figure 11: The oil yield versus cone gap line chart for constant shaft speed of 22 rpm with varying moisture content

4. Conclusion

An approach to optimize the palm kernel oil (PKO) extracted using a case study PKO extraction machine is presented. The optimization is carried out using the Artificial Neural Network (ANN) model. The study dataset was obtained from the case study PKO extraction machine. The dataset was preprocessed and then used to train and evaluate the ANN model. The results showed that the moisture content was the most impactful parameter on the oil yield. Also, the highest oil yield occur data specific moisture content, the machine shaft speed and cone gap setting. This means that the operators of the machine should target the identified input parameters setting in order to realize the best oil yield in their plant.

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