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Support Vector Regression Model For Prediction Of Palm Kernel Oil Extractor Machine Yield

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***Abstract* — Support Vector Regression (SVR) model for prediction of palm kernel oil (PKO) extractor machine yield is presented. The essence of the study is to address the problem of low oil yield and excess wastage of raw material (palm kernel) associated with a case study 10-ton PKO extractor machine settings and the palm kernel moisture content. Accordingly, a dataset consisting of 5000 records of the four parameters; moisture content of the palm kernel, shaft speed, and cone gap settings as the input parameters and the PKO yield as the output parameter. The dataset was used to train and validate the SVR model using a data split of 80% (training set) and 20% (validation set). The results show that the error metrics over 80 epochs remained constant at 0.084175 for the Mean Absolute Error (MAE), 0.007832 for the Mean Square Error (MSE), and 0.992293 for the R-Squared (R^2). The results obtained from SHAP analysis showed that the feature importance value of 0.158 for the moisture content made it the most important feature for the SVR PKO yield prediction. On the other hand, the cone gap had 0.135 feature importance value which made it the least important feature among the three input parameters. Also, the optimal PKO yield of 42.7 % occurred with shaft speed of 20 rpm, cone gap of 1.5 mm and moisture content of 8 %. A closer examination of the optimal configuration using the graphical approach shows that the exact optimal PKO is 43.6 % and it occurred at main shaft speed of 18.4 rpm with cone gap of 1.5 mm. Essential the SVR got the exact cone gap setting but it deviated from the exact optimal PKO yield by 2.06% and from the exact main shaft speed by 2.17%.**

Keywords— Support Vector Regression Model, Palm Kernel Oil Extractor Machine, Optimal Yield, Feature Importance, Regression Problem

1. Introduction

In Nigeria, palm kernel oil (PKO) is one of the most commonly produced and utilized oil at industrial scale [1,2,3]. This is due to the abundance of palm kernel in several parts of Nigeria [4,5]. There is palm oil which is obtained from the palm fruit and then the palm kernel oil which is obtained from the palm kernel [6,7]. This has led to the production of various machines to handle different aspects of the processing of the palm fruit and palm kernel and eventually the machine for the extraction of the PKO from the palm kernel [8.9.10].

In this study the focus is on the palm kernel oil production with emphasis on the application of machine learning model to enhance the machines PKO yield by optimal configuration of the machine's input parameters [11,12,13]. Specifically, the support vector regression (SVR) model is considered in this study for the prediction of the input parameters setting configuration that will always give the highest

PKO from the case study PKO extractor machine [14,15]. Such study is essential to maximize profit and minimize waste and losses. The study rely heavily on the dataset obtained from the case study machine which are employed in the training and evaluation of the SVR model. Also, feature importance analysis is considered to identify the most important input parameters for the optimal PKO yield prediction [16]. The ideas presented in this work is relevant for PKO production and the machine operator and manufacturers.

2. Methodology

Support Vector Regression (SVR) is an extension of Support Vector Machines (SVMs) for regression tasks. Unlike traditional regression models that minimize squared errors, SVR focuses on fitting the best hyperplane within a margin of tolerance (ϵ-tube). In this work, SVR is used to model the relationship between shaft speed, cone gap, moisture content, and oil yield, for a Palm Kernel Oil (PKO) extractor machine, aiming to minimize errors while ensuring robustness against outliers. Given a training set: $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$, where, $x_i \in R^d$ represents the input parameters (shaft speed, cone gap, and moisture content), y_i represents the actual oil yield. SVR constructs a function $f(\mathrm{p}x)$ to approximate the relationship:

$$f(x) = w^T \varphi(x) + b \quad (1)$$

Where, $\varphi(x)$ is the nonlinear mapping to higher dimensional feature space, w and b are model parameters. Instead of minimizing the mean squared error, SVR minimizes a cost function based on an ϵ-insensitive loss. The SVR optimization problem is formulated as:

$$\min_{w,b,\mathcal{E}\mathcal{E}^*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\mathcal{E}_i + \mathcal{E}_i^*) \quad (2)$$

Equation 2 is subject to:

$$y_i - (w^T\varphi(x_i) + b) \le \epsilon + \mathcal{E}_i \quad (3)$$

$$(w^T\varphi(x_i) + b) - y_i \le \epsilon + \mathcal{E}_i^* \quad (4)$$

$$\mathcal{E}_i, \mathcal{E}_i^* \ge 0 \quad (5)$$

Where, $\|w\|^2$ is the regularization term to control model complexity, C is the regularization hyperparameter, ϵ denotes the tolerance margin, $\mathcal{E}_i, \mathcal{E}_i^*$ are slack variables (allows violation beyond ϵ). The goal is to find a function that predicts oil yield within an acceptable error range (ϵ) while minimizing model complexity. Since the relationship between shaft speed, cone gap, and moisture content is likely nonlinear, SVR applies the kernel trick to project inputs into a higher-dimensional space:

$$K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j) \quad (6)$$

For this work, the RBF kernel is preferred because it captures complex relationships between oil yield and input parameters. RBF kernel function is defined as:

$$K(x_i, x_j) = \exp\left(-\gamma\|x_i - x_j\|^2\right) \quad (7)$$

The SVR constructs the optimized predictor function based on the kernel function, $K(x_i, x)$ is expressed as follows:

$$\hat{y} = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x_i, x) + b \quad (8)$$

Where, Lagrange multipliers ere denoted as α_i, α_i^* and their values are gotten from the optimization process. This function is used to predict oil yield based on the learned relationship. The summary of the Support Vector Regression (SVR) model's hyperparameters and their values are presented in Table 1.

The study of the 10-ton PKO extractor machine used an empirically collected dataset consisting of 125 records of the four parameters; moisture content of the palm kernel, shaft speed, and cone gap settings as the input parameters while the PKO yield is the output parameter for each combination of the three inputs parameters. The line chart plot of the four parameters are given in Figure 1 to Figure 4. Furthermore, Generative Adversarial Network (GAN) model was used to augment the data to make up 5000 data records and then a data split of 80% (training set) and 20% (validation set) was used with respect to the augmented dataset to train and validate the SVR model. The model prediction performance was evaluated using Mean Square

Error (MSE), Mean Absolute Error (MAE) and R-Squared (R^2).

Table 1 The Hyperparameter settings for the Support Vector Regression (SVR) Model

Hyperparameter	Value	Explanation
Kernel	'rbf'	Radial Basis Function (RBF) kernel for non-linear regression.
C	100	Regularization parameter, controls trade-off between model complexity and error minimization.
Epsilon	0.1	Defines margin of tolerance where no penalty is given in training loss function.
Gamma	'scale'	Kernel coefficient (default 'scale' means 1/(n_features*X.var())).
Shrinking	'true'	Whether to use shrinking heuristic to speed up training.
Tol	1e-3	Tolerance for stopping criterion.
Max_iter	-1	Maximum number of iterations (default -1 means no limit).

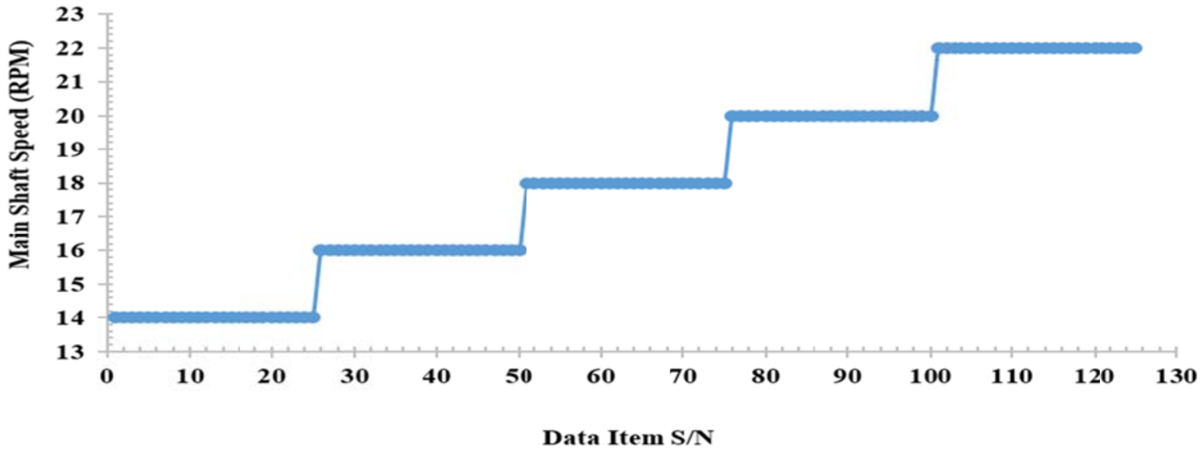

Figure 1 The line chart of the main shaft speed

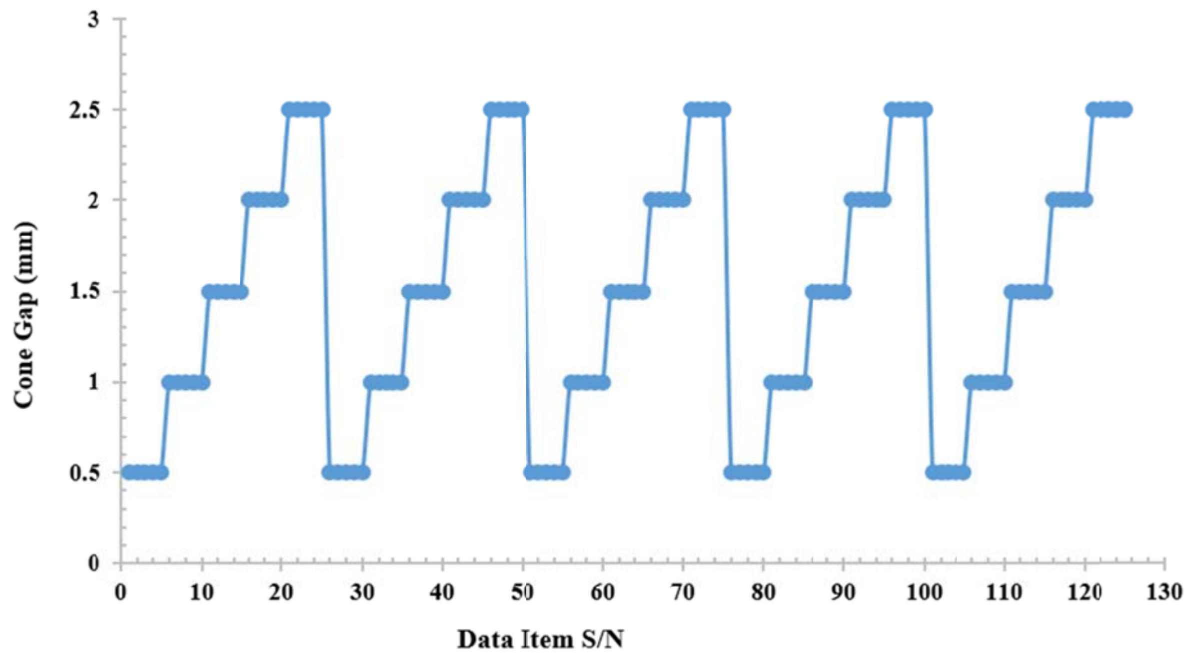

Figure 2 The line chart of the cone gap

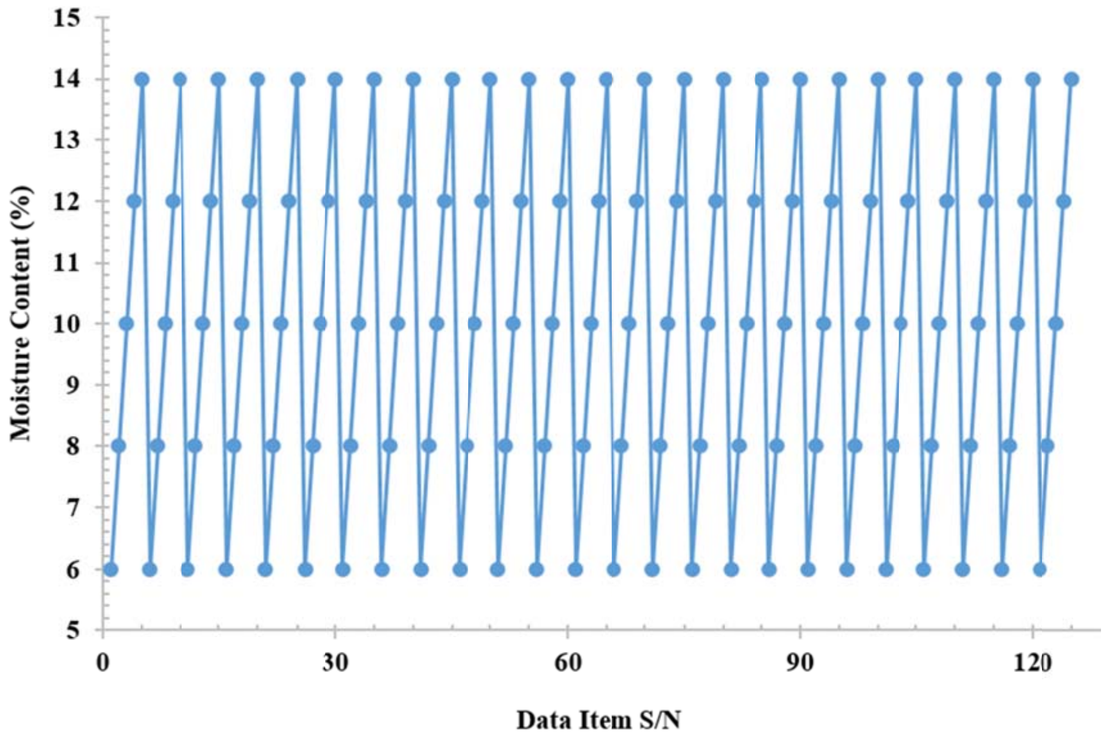

Figure 3 The line chart of the moisture content

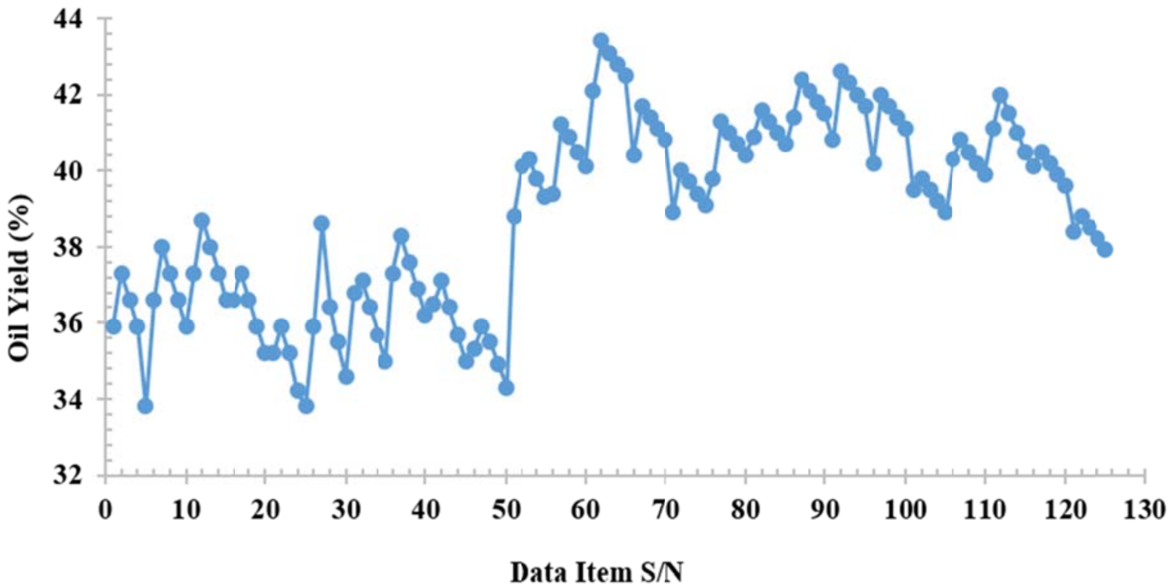

Figure 4 The line chart of the moisture oil yield

3. Results and discussion

The SVR model prediction performance results shown in Table 2 and Figure 5 show that the error metrics over 80 epochs remained constant at 0.084175 for the MAE, 0.007832 for the MSE and 0.992293 for the R^2. The line chart of the actual versus predicted oil yields for the SVR model is shown in Figure 6.

The feature ranking results obtained from SHAP analysis showed that the feature importance value of 0.158 for the moisture content made it the most important feature for the SVR PKO yield prediction. On the other hand, the cone gap had 0.135 feature importance value which made it the least important feature among the three input parameters.

Table 2: The Results of the Error Metrics over 80 Epochs for the SVR model

Epoch	MAE	MSE	R2
0	0.084175	0.007832	0.992293
20	0.084175	0.007832	0.992293
40	0.084175	0.007832	0.992293
60	0.084175	0.007832	0.992293
80	0.084175	0.007832	0.992293
100	0.084175	0.007832	0.992293

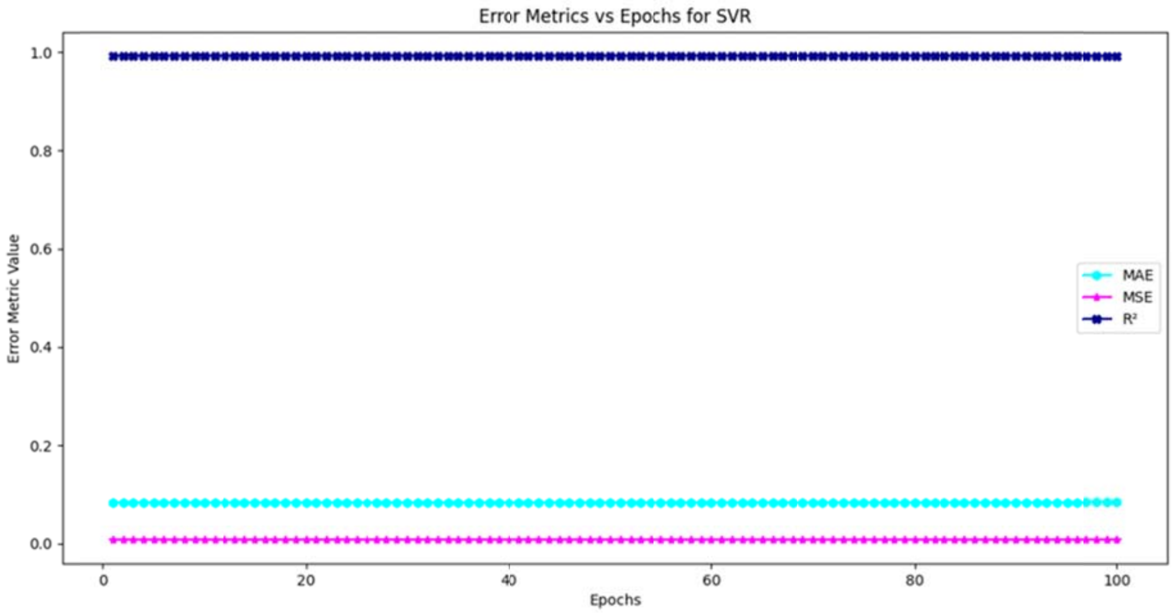

Figure 5 The Plot of the Error Metrics over 80 Epochs for the SVR model

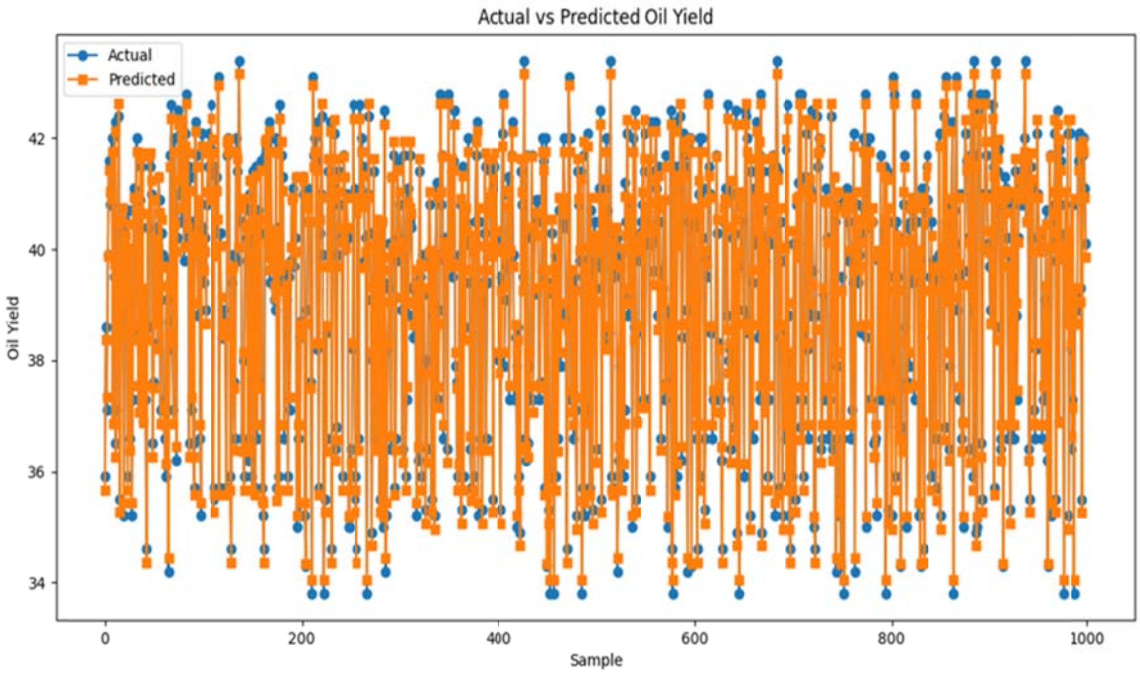

Figure 6 : The Line Chart of the Actual Versus Predicted Oil Yields for the SVR Model

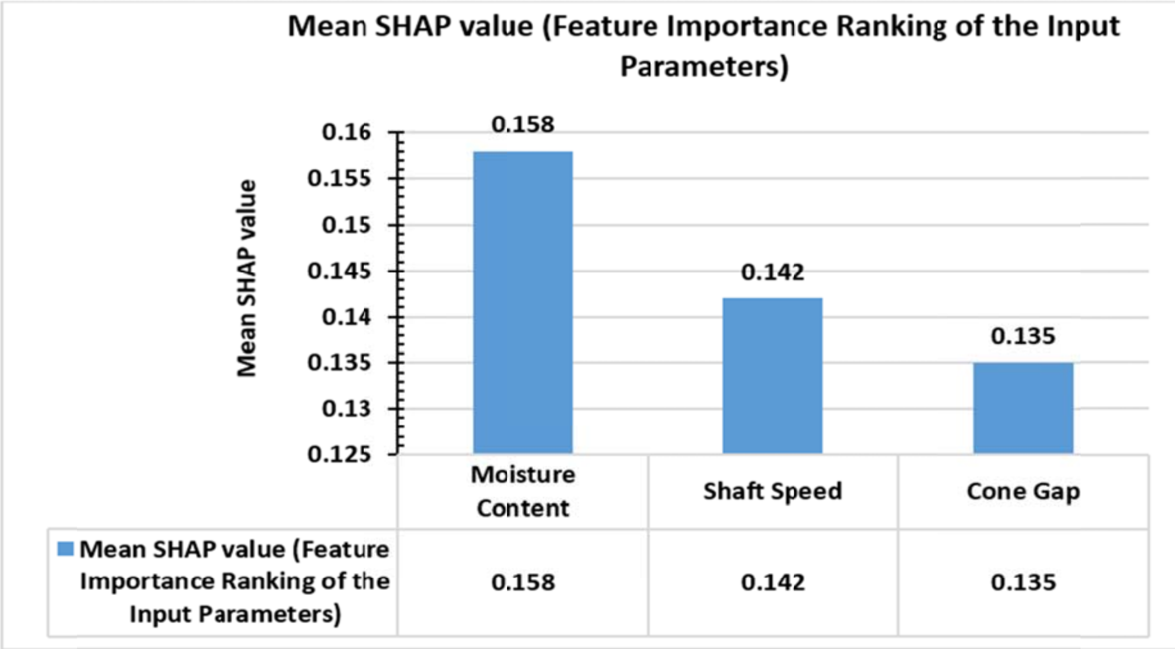

Figure 7: Average impact of the inputs on the SVR model output

The SVR model predictions for the PKO yield are presented in Figure 8 to Figure 12 for different input parameters configurations and the results showed that the optimal PKO yield of 42.7 % occurred in Figure 11 with shaft speed of 20 rpm, cone gap of 1.5 mm and moisture content of 8 %. A closer examination of the optimal configuration using the graphical approach shown in Table 3 and Table 4, as well as in Figure 13 and Figure 14 show that the exact optimal PKO is 43.6 % and it occurred at main shaft speed of 18.4 rpm with cone gap of 1.5 mm. Essential the SVR got the exact cone gap setting but it deviated from the exact optimal PKO yield by 2.06% and from the exact main shaft speed by 2.17%.

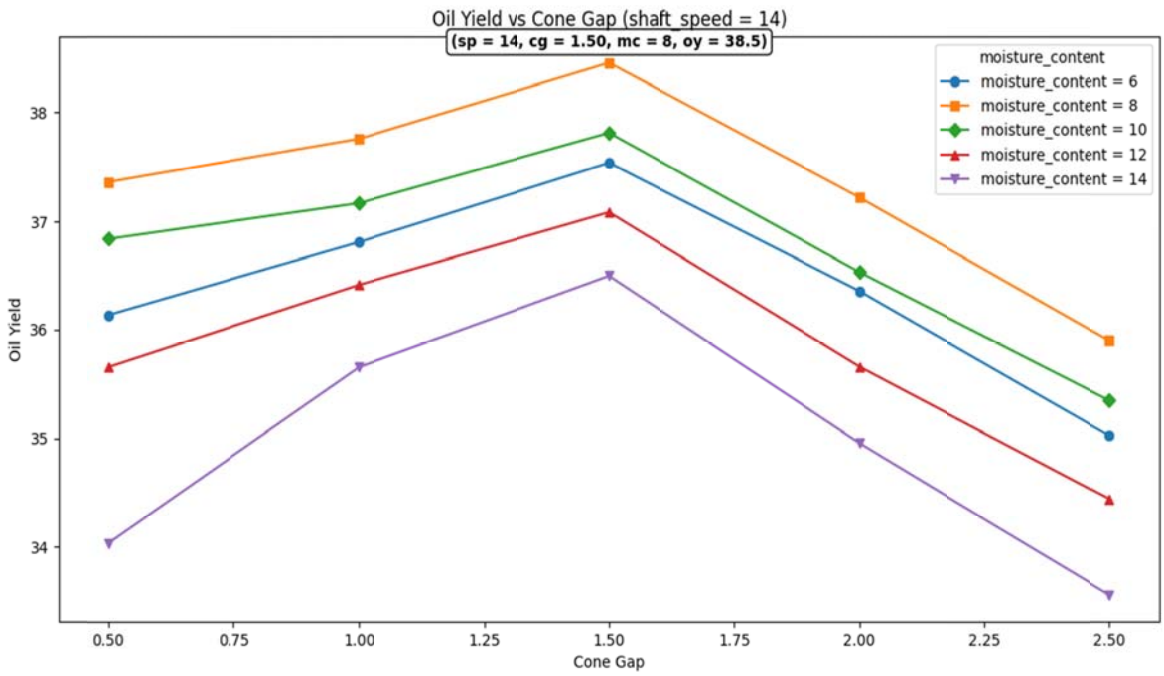

Figure 8: Oil yield versus cone gap at shaft speed = 14rpm and varying moisture content

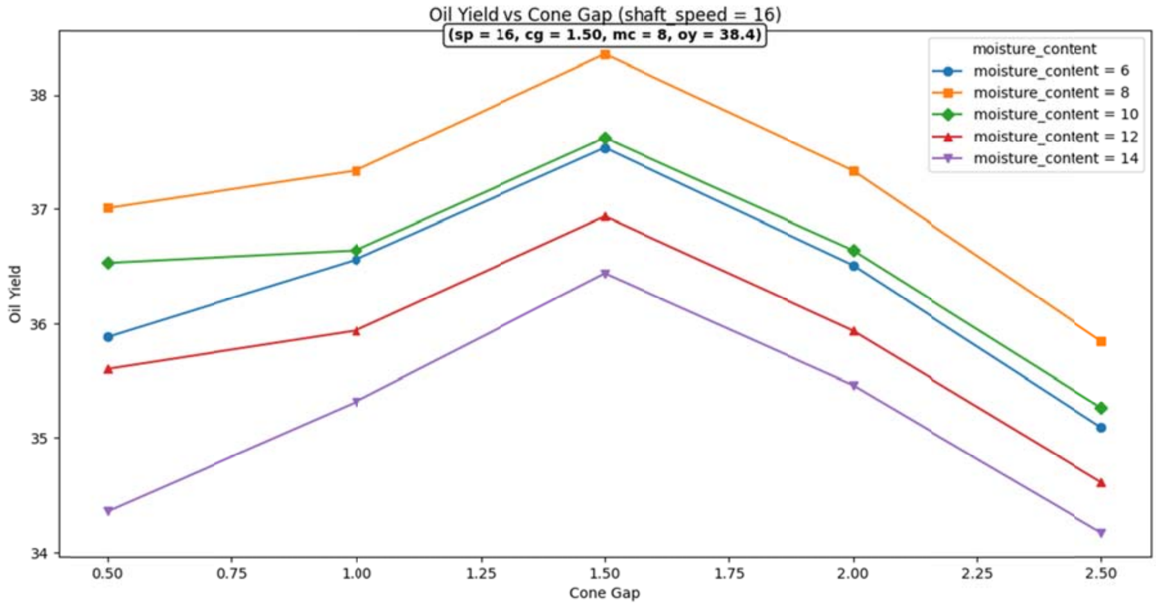

Figure 9: Oil yield versus cone gap at shaft speed = 16rpm and varying moisture content

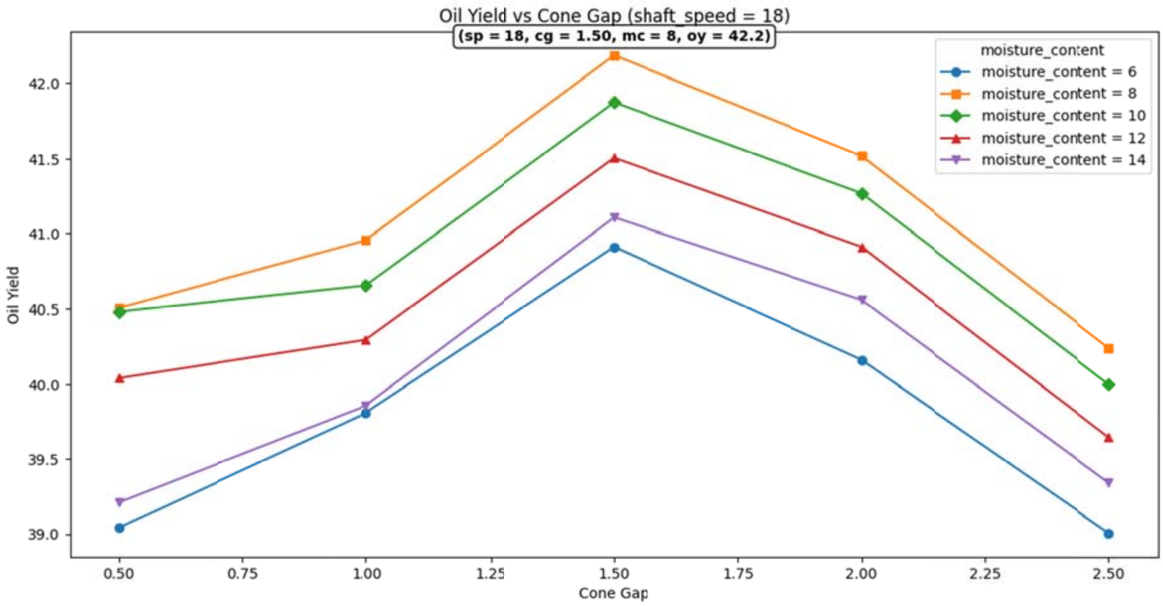

Figure 10: Oil yield versus cone gap at shaft speed = 18rpm and varying moisture content

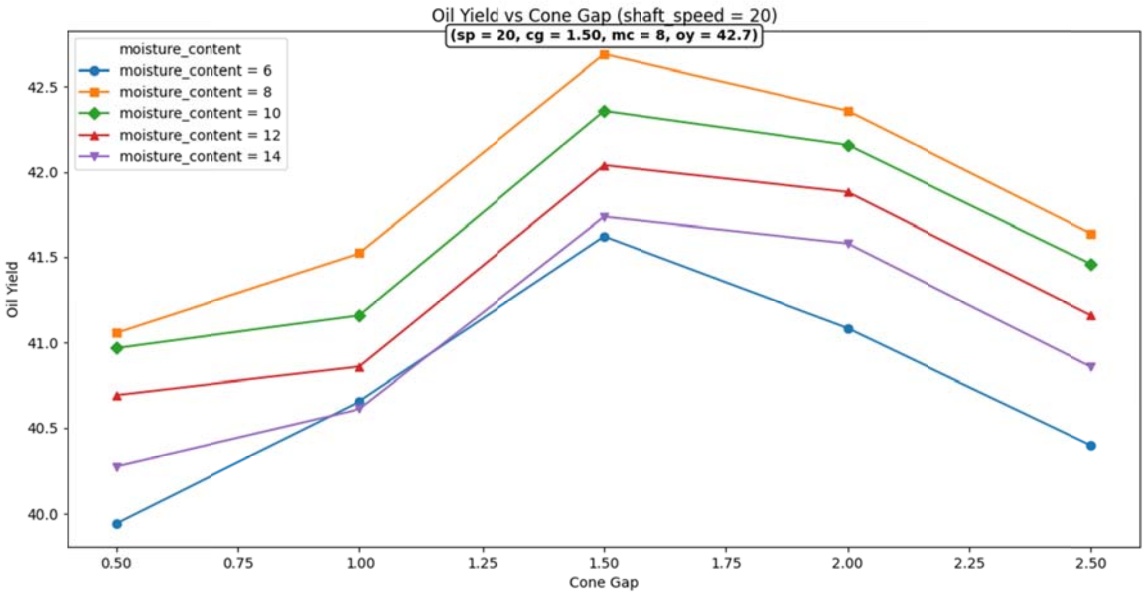

Figure 11: Oil yield versus cone gap at shaft speed = 20rpm and varying moisture content

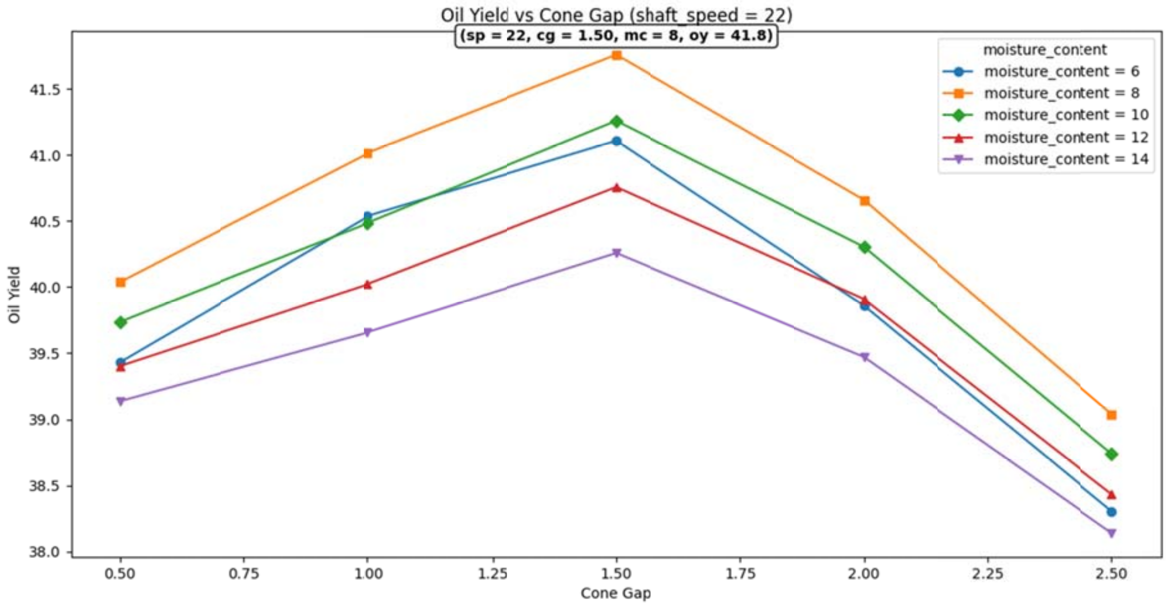

Figure 12: Oil yield versus cone gap at shaft speed = 22rpm and varying moisture content

Table 3 PKO Yield versus Main Shaft Speed for Cone Gap of 1.5 mm and Moisture Content of 8%

Main Shaft Speed (RPM)	Cone Gap(mm)	Moisture Content (%)	Oil Yield (%)
14	1.5	8	38.7
16	1.5	8	38.3
18	1.5	8	43.4
20	1.5	8	42.4
22	1.5	8	42

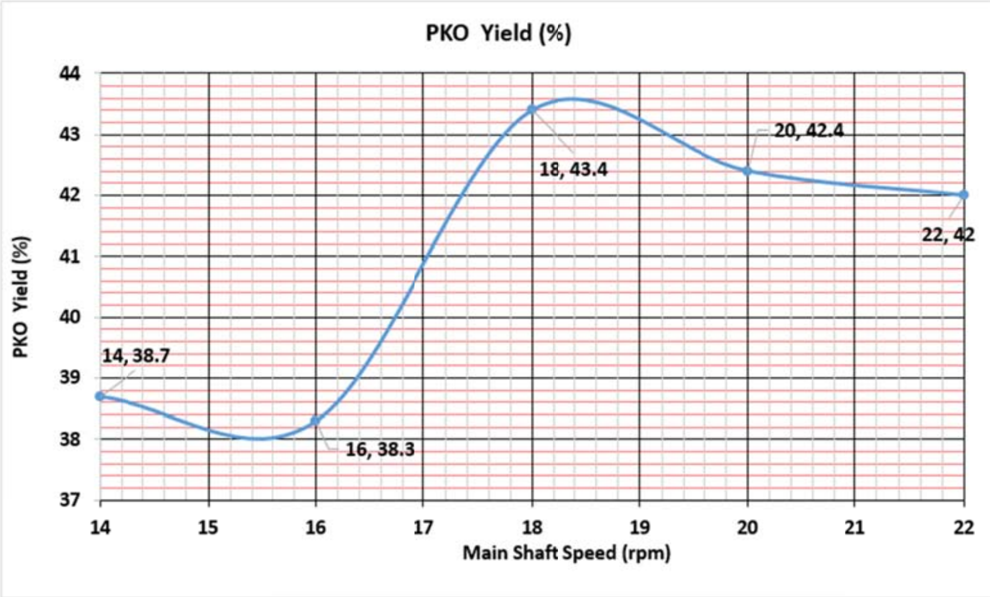

Figure 13 Scatter Plot with line for PKO Yield Versus Main Shaft Speed for Cone Gap of 1.5 mm and Moisture Content of 8%

Figure 13 Scatter Plot with line for PKO Yield Versus Main Shaft Speed for Cone Gap of 1.5 mm and Moisture Content of 8%

Table 4 PKO Yield Versus Cone Gap (mm) for Main Shaft Speed of 18 rpm and Moisture Content of 8%

Main Shaft Speed (RPM)	Cone Gap(mm)	Moisture Content (%)	Oil Yield (%)
18	0.5	8	40.1
18	1	8	41.2
18	1.5	8	43.4
18	2	8	41.7
18	2.5	8	40

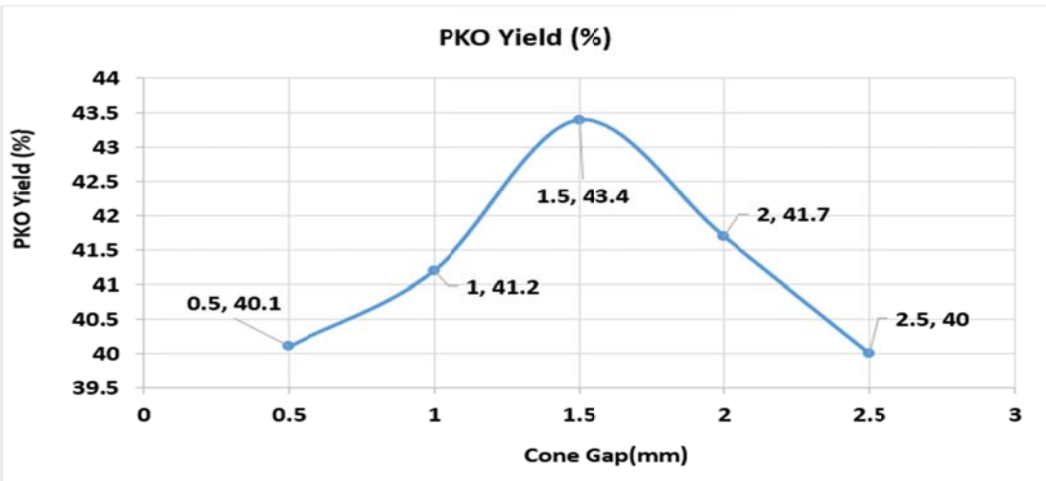

Figure 14 Scatter Plot with line for PKO Yield Versus Cone Gap (mm) for Main Shaft Speed of 18 rpm and Moisture Content of 8%

Figure 14 Scatter Plot with line for PKO Yield Versus Cone Gap (mm) for Main Shaft Speed of 18 rpm and Moisture Content of 8%

4. Conclusion

Support Vector Regression (SVR) model is presented for application in the prediction of palm kernel oil (PKO) output of a 10 ton extractor machine. The machine has input parameters such as the main shaft speed and the cone gap while the palm kernel parameter considered is the moisture of the kernel. These three parameters were used in the prediction of the PKO yield with emphasis on identifying the input parameter configuration that gives the optimal PKO yield. The results showed that the SVR was able to predict the optimal point with about 2 % deviation from the exact point.

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