Observation on Polynomial and Radial Basis function in Support Vector Machine (SVM) Tuned Parameters for Agarwood Oil Quality Grading

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ABSTRACT

Agarwood oil is well-known as exorbitant lubricant, extricated from the adhesive of aromatic heartwood. The oil is profoundly request in the market particularly from Asia, Turkey, Iran and India in view of its one of a kind scent. First-class agarwood oil is one of the most overpriced common organic materials in the nature. For this on-going research in classifying quality of the agarwood oil, the observation on Polynomial and Radial Basis Function (RBF) in Support Vector Machine (SVM) tuned Parameters for agarwood oil quality grading. The work involved of feeding abundances (%) as input to SVM network training and quality of the oil as output. The Polynomial and RBF kernels were used during training stage. After that, the development of SVM model was tested using testing dataset. The complete analysis work was achieved using MATLAB R2015a version. The outcome of the finding proved that Polynomial were better than RBF in classifying the agarwood oil. The research advantages to future work and also the utilization for agarwood oil investigate region particularly its quality grouping.
Keywords: Agarwood oil, classification, oil quality, polynomial, RBF, SVM

1. Introduction

Agarwood or *Gaharu* is their popular name for resinous or attaching heartwood from 'wounded or infected' Aquilaria trees, from warm and humid woodland crop which has tremendous rate in global market. Thus, in this time there are rising requirement for these agarwood-based production for the purpose in cure and remedy, cologne also essence. Agarwood can also exchange into structure of product derivatives such as wood chips, powder, and oil.

Reason of high orders of the agarwood is because of its exclusive function and rare aroma which is coming from Asia and the region of Middle East. For instance, it is use as ingredient in making perfumes and also in related religious ceremony. People in Middle East such as Syria, Turkey and Iran, they believed that it is symbol of prosperity and it is also use in marriage solemnity [1].

The agarwood oil is traded through their quality than quantity causing affects values of the product, meaning the good quality is more valuable rather than poor quality. Nevertheless, the features as in the quality is differentiated by durability and the long lasting of the odor, terrestrial origin, resin content also the pureness of the oil itself [2]. Moreover, the dark color and long-lasting aroma is commonly classified as high quality, which is sold on more exclusive price [3]. The price range for high quality of agarwood oils are around USD126 to USD633 per tola (12ml). However, costing for agarwood's wood in the range from USD19 per kg to USD100,000 per kg depends on its features [4]. Lots of studies have been done to empathize the good elements of the agarwood oil [5]. The grading and classification of agarwood is traditionally performed by experienced personnel graders (sensory panels), but this approach had weakness to objectivity and repeatability. Then again, typical human being nose would not accept a large number of sampling, which causing the sense to become fatigue rapidly and results will become inconclusive. Besides, there are also the used of support vector

machines or vector networks, that evaluation of data used for classification or regression and also relapse analysis, which are supervised learning algorithms. This agarwood oil can be classified using kernel methods such as Multilayer Perceptron (MLP), Polynomial, Radial Basis Function (RBF), and Sigmoidal by using support vector machine [6].

Recently, there is high demand for agarwood oil but the supply however is declining and this will automatically cause the price becomes rising along the years. Moreover, the species of agarwood trees is at the edge of endanger especially without any supervision. However, in order to get the solution of this complication, it is discover for agarwood trees be able seeded and cultivated through profit-making and conducted to manage both high quantity and quality [7]. Besides that, the price of the agarwood oil sometimes goes up and down depends to its quality of the oil. From the oil compound, the quality of oil can be measured based on the physical appearance such as color, odor and long-lasting of the fragrance. The human sensory panel are limited and subjective. This technique is non-reliable and definite due to the capability of human nose to take multiple samples in a time. Withal, it is easily exhausted when facing continuous production [8].

To overcome all the problems, several techniques was introduced so that the agarwood oil can be graded fairly and accurately by looking at their chemical properties. The result will be a common standard recognized on grading the agarwood oil.

An SVM performs order by finding the hyperplane that augments the edge between the two classes. The vectors (cases) that characterize the hyperplane are the help vectors. In spite of the fact that help vector machine is viewed to be twofold direct classifier, it can be adjusted to order information into in excess of two classes [9]. This give rise to a new class of theoretically elegant learning machines that uses central concept of kernel for a number of learning tasks. Moreover, to approach of the kernel function is targeted along definite specification or parameters to be regulated during the training in the support vector machine. Modular framework is the other names for it, solving other scope and works.

To have the adequate large border between the two classes is definition of having excellent and perfect hyperplane for an SVM. Margin or bound meaning the maximum gap of parallel plate to the hyperplane that has no central data points [10]. Linear SVM and non-linear SVM is when they split into these two groups. There were some differential part of elements and arrangement for both groups and it can be seen with the graphical structures for linear and non-linear SVMs. For the Figure 1 and Figure 2, both figure explain more detail on how the SVM works respectively [11].

To evaluate data used for regression or classification analysis, support vector networks or support vector machines is an applicable learning model that are supervised with associated learning algorithms [12].

2. Theoretical Work

2.1 Support Vector Machine (SVM)

An illustration representation for the SVM model as a generalize point in dimensional space, in which the data is detached by the clear hyper plane (also noted as ‘drain’) with an ideal margin. The model classified as linear & non-linear. The margin consists of soft & hard and were introduced by the linear SVM introduced at the same time there are several kernel functions for the non-linear SVM to be tuned for Polynomial, Hyperbolic Tangent & Gaussian Radial Basis Function. SVM classifier maybe estimate by primal, dual, kernel trick and current approach [13]. Class of functions of $T(xx_1,xx_2)$ with the consecutive the characteristics of a linear space S and a function φ that measuring x to S specific example $T(xx_1,xx_2)=<\varphi(xx_1),\varphi(xx_2)>$. The space of S alteration at scalar product which is the calculated from the two vectors. Polynomial also been included into group of functions which positive number n, $T(xx_1,xx_2)=(1+xx_1'xx_2)^n$. For (Gaussian) Radial basis function $T(xx_1,xx_2)=exp(-\|xx_1-xx_2\|^2)$. Lastly, Multilayer Perceptron or sigmoidal,(in MLP) for a positive number of n and a negative number n_1, $T(xx_1,xx_2) = tanh(n_1xx_1'xx_2 + n_2)$ [13], [14].

However, for categorized issues draw near, the objective is to develop the generality margin given that depend on seeking for the loss function and errors allowed to be neglected. So, those two parameters situated within the specified space of the point value [22]. This were shown graphically in both Figure 1.

Support Vector Machines are very in specialized class of methods and symbolized through the uses of these kernels. Computational Learning Theory (COLT) were created by a person or researcher named Vladimir Vapnik with his companion in 1992 at the seminar with the research in paper. In 1960’s, all of those characteristics, were previously exists in machine learning: better boarder hyper planes usage of kernels and analytical clarification of kernels as inner products

in a feature space. Identical optimization methods were used in sparseness techniques and pattern recognition were universally deliberate [15]. Also, introduction to non-separability and the method of slack variable was brought in to avoid noise in the data. All of this feature was not assemble together until 1992 to have the arrangement the maximal margin classifier, the fundamental Support Vector Machine but in 1995, the introduction of soft margin has resurfaced to worldwide [16].

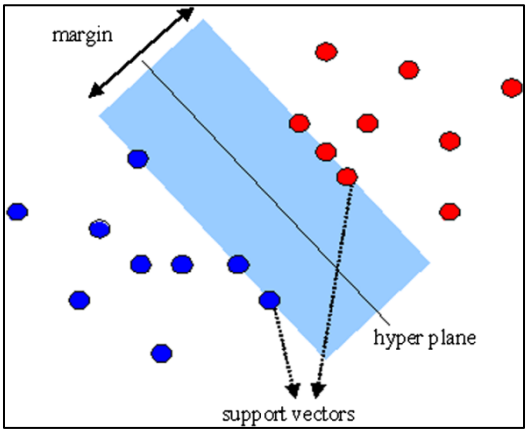

Figure 1. Support vector machine [22]

Support Vector Machine could use into the case of regression. The feature space is affected by the linear learning machine is the one who responsible in designing great spatial kernel. This situation due to the non-linear function which makes the utmost margin algorithm to be distinguished by SVM as it is hold all the crucial element for the transition. The parameters that does not rely on the dimensionality of component space controlled the capacity of the system [16].

A. Polynomial

The basic function of Polynomial is not featuring of input samples to regulate their resemblance, yet combinations of these. Such merger were named as interaction features for the regression analysis. The polynomial regression will be similar for the feature space of the kernel itself if the combinatorial blowup number of parameter to be recognized [17]. The mathematical equation for Polynomial is represented in (1) below. The features will correlate with logical conjunction of the input, if and only if the input are binary-valued as in Booleans. Despite its limited district performance, the polynomial kernel is a universal kernel function and directional. Going through this paper, to get the verification of the kernel function to be exact and has good execution other than the certain previous research paper stated [18].

Polynomial:

$$K(x, x_i) = [\gamma * (x \cdot x_i) + coef]^d \quad (1)$$

The dimension of mapping function grows with the value of the dimensionality of a kernel function. The order of two vectors in such low dimensional zone or dimensional space will affected the outcome of the output result and this is because of the dot product in mathematical equation in Polynomial kernel. The role of magnitude vector will be manipulating the magnitude of the output result [19].It will make more accessible to grade the sample with more advance dimensionality, but simultaneously the computational complexity rising. Complex classifiers have good performance, the classification certainty for training data is quite uplifted. For the fresh sampling it will have poor quality of achievement that is not appropriate fitting.

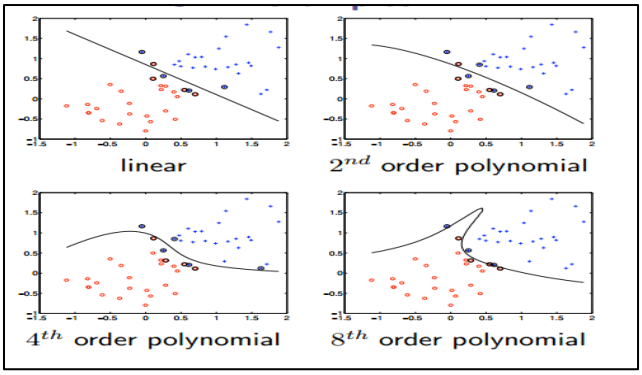

Figure 2. Polynomial features [7]

B. Radial Basis Function (RBF)

This kernel uses normal arc which the value depends on the distance from the origin, $(X) = \emptyset(||X||)$ or or preferably on the distance from some any middle point. It also can be explained in a simple single-layer type of artificial neural network named radial basis function, with function radial basis function taking on the part of the activating the functions of network [20]. A radial function requires for function $\emptyset$ that fulfilled the property $\emptyset(X) = \emptyset(||X||)$. The normal is generally Euclidean distance, although other distance functions are also possible. Sums of radial basis functions are typically used to approximate given functions[14]. This estimation process can also be interpreted as a simple kind of neural network; In 1988, David Broomhead and David Lowe works can be shown it was developed by Michael J.D. Powell seminal works in 1977 [21]. It can be dividing into six category which are Gaussian that popular as bell arc form: $\emptyset(x) = e^{-(\varepsilon x)^2}$, multiquadratic: $\emptyset(x) = \sqrt{1 + (\varepsilon x)^2}$, inverse quadratic $\emptyset(x) = \frac{1}{1+(\varepsilon x)^2}$, inverse multiquadratic: $\emptyset(x) = \frac{1}{\sqrt{1+(\varepsilon x)^2}}$, polyharmonic spline have two equation that is $\emptyset(x) = x^k, k = 1,3,5, \ldots$, and $\emptyset(x) = x^k \ln(x), k = 2,4,6,8 \ldots$, and lastly thin plate spline: $\emptyset(x) = x^2 ln(x)$[14]. Figure 2 shows initial and component space of Radial Basis Function in support vector machine as in [26] separable classification with Radial Basis kernel function in difference space. Left: Original space, right: feature space.

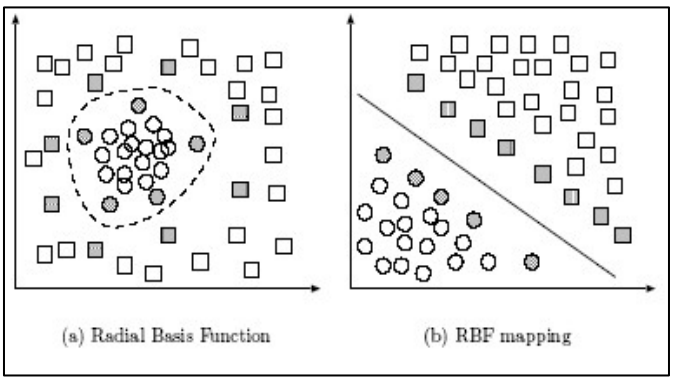

Figure 3. Radial basis function [10]

3. Methodology

For this paper, 96 input and output data of agarwood oil were used, consists of good and bad condition were gathered from the Forest Research Institute Malaysia (FRIM), Malaysia and Bio Aromatic Research Centre of Excellent, University of Malaysia Pahang, Malaysia. The previous researcher [1] already done conducted sampling preparation and compounds evaluation. Next, the data has been through pre-processing stage, associate the involvement of data randomisation, normalization and data divided into 2 datasets; training and testing. RBF and Polynomial kernel parameters were tuning in SVM classifier to grading the agarwood oil compounds from high and low qualities.

Figure 4 shows the flowchart of experimental set-up performs in this paper. It consists of agarwood oil raw data which are input and output data collection [4]. The scope in this study is an extension to the experiment which covers data pre-processing, SVM model development, testing the developed SVM model until it can be accepted once it passes several performance criteria. At the pre-processing stage, the data is randomized and normalized before it divided into training and testing dataset with the portion of 80% and 20%, respectively [22]. After that, the Polynomial and RBF were tuned during SVM model development in which the model is developed using training dataset.

Figure 4. Block diagram of experimental set-up

The matrix which the matrix row designated the target/real class and the matrix column show the targeted class referring to the confusion matrix as in Table 1 [13]. The matrix comprises of four parameters which are false negatives *(fn)*, false positives *(fp)*, true negatives *(kn)* and true positives *(kp)* or or, the matrix form can be indicated as $\begin{bmatrix} kp & fn \\ fp & kn \end{bmatrix}$. The confusion matrix table is preferred as suggested by [7] that can refer to Table 1. *kp* is the data exactly grouped data to the low quality, *kn* is the data exactly correctly data to the high quality. *fp* is the data misclassified to the low quality and *fn* is the data misclassified to the high quality.

Table 1. A Confusion matrix[13]

Data Group	Group as Low Quality	Group as High Quality
Low	True positive *(kp)*	False negative *(fn)*
High	False positive *(fp)*	True negative *(kn)*

All the results yielded from the SVM model using both kernels were tested into the model was accepted once it passed the performance criteria as confusion matrix, accuracy (ACR), sensitivity (SNS), specificity (SPC) and precision (PRC) [23].

The overall capability of a classifier is defined of the accuracy, ACR. It can be written as [24]:

$$ACR = \frac{kp + kn}{kp + fn + fp + kn} \quad (2)$$

The capability of a classifier to classify low quality defined the sensitivity, SNS. The interpretation for sensitivity as follows [24]:

$$SNS = \frac{kp}{kp + fn} \quad (3)$$

The specificity, SPC interpreted as practicable of the partitioned detects negative tag [24]:

$$SPC = \frac{kn}{kn + fp} \quad (4)$$

The group matching between measured high-quality data and the predicted high-quality produce by SVM is called, precision, PRC. The mathematical equation for PRC is [24]:

$$PRC = \frac{kp}{kp + fp} \quad (5)$$

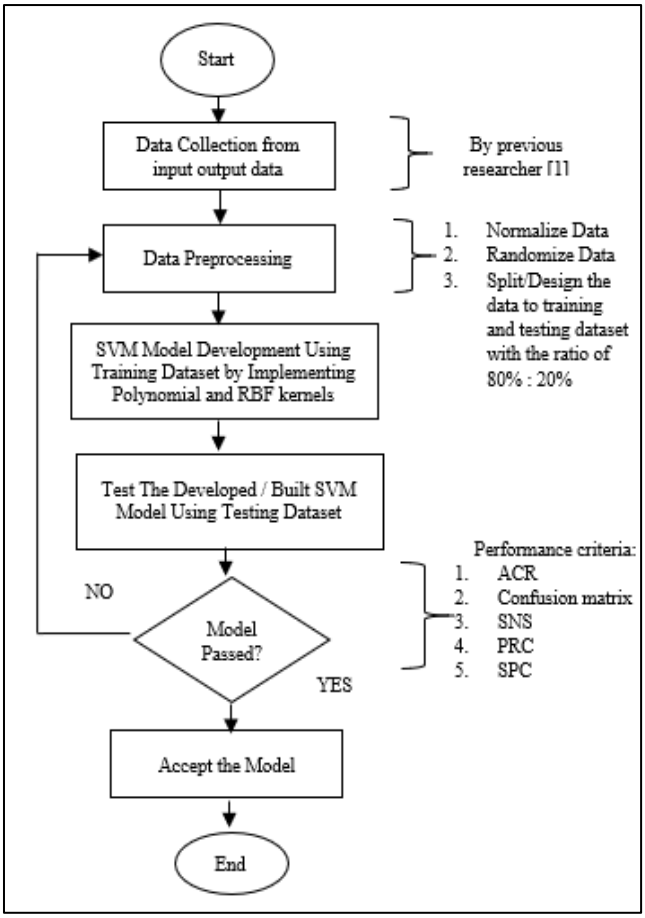

Figure 5. Flowchart of the SVM model development

4. Results and Discussion

4.1 Support Vector for Polynomial

The result from SVM obtained 12 support vectors from training for Polynomial and it is shown in Table 2. From the table, it shows the result obtained from seven compound which is Compound 1 (C1) to Compound 7 (C7). For Compound 1 (C1), the lowest value is -0.74 which is in vector 1 and the highest value in Compound 1 (C1) is 2.83 in vector 8. Next, the lowest value in Compound 2 (C2) is -0.76 and the highest value is 2.36 in vector 10. For Compound 3 (C3), the lowest value is -1.13 and the highest value is 2.72 also in vector 10. Compound 4 (C4) contain the lowest value at vector 1 and 5 which is -1.38 while the highest is 1.59 at vector 12. For Compound 5 (C5), the lowest value is -0.31 and the highest value is -0.24. Compound 6 (C6) obtain lowest value, -0.38 and highest value is 0.11. Last but not least, the lowest value -0.37 and the highest value is 0.76.

Table 2. Support vectors for polynomial

Vectors	C1	C2	C3	C4	C5	C6	C7
1	-0.74	-0.76	0.67	-1.38	-0.31	-0.38	-0.37
2	-0.67	-0.67	-0.53	1.57	-0.28	-0.06	-0.36
3	-0.55	-0.72	-0.99	-1.04	-0.30	-0.32	-0.33
4	-0.63	-0.16	-1.13	-0.78	-0.30	-0.24	0.76
5	-0.72	-0.75	0.67	-1.38	-0.30	-0.27	-0.33
6	0.47	0.68	-0.35	1.17	-0.28	-0.29	-0.29
7	-0.69	-0.74	-0.04	-1.37	-0.27	-0.25	-0.37
8	2.83	-0.64	-0.55	-0.09	-0.30	-0.33	-0.36
9	0.41	1.04	0.72	0.77	-0.28	-0.29	-0.32
10	1.38	2.36	2.72	-1.09	-0.24	0.11	-0.29
11	-0.70	-0.75	-0.02	-1.36	-0.27	-0.34	-0.34
12	-0.71	-0.58	-0.58	1.59	-0.26	-0.24	-0.26

C1 = β-agarofuran,
C2 = α-agarofuran,
C3 = 10-epi-ϒ-eudesmol,
C4 = ϒ-eudesmol,
C5 = longifolol,
C6 = hexadecanol
C7 = eudesmol.

4.2 Support Vector for Radial Basis Function (RBF)

Table 3 tabulated 29 support vectors from training dataset. For Compound 1 (C1), the lowest value is -0.74 and the highest is 2.97 in vector 22. Compound 2 (C2) has the lowest value in vector 1 and 2 that is -0.76 and the highest value is 2.36 in vector 24. Next, the lowest value in Compound 3 (C3) is -1.20 and the highest value is 2.76. For Compound 4 (C4), the lowest value is -1.38 and the highest value is 1.94. Compound 5 (C5) has the lowest value in vector 1 to 6 for the same value that is -0.31, the highest value is 3.44 in vector 14. The lowest value in Compound 6 (C6) also has same position vector 1 until vector 5 and the value is -0.38 and the highest value is 3.66. Lastly, for Compound 7 (C7) the lowest value is -0.37 and the highest value is 3.45.

Table 3. Support vector for RBF

Vectors	C1	C2	C3	C4	C5	C6	C7
1	-0.74	-0.76	0.67	-1.38	-0.31	-0.38	-0.37
2	-0.74	-0.76	-0.48	1.94	-0.31	-0.38	-0.37
3	1.11	1.59	0.55	0.97	-0.31	-0.38	-0.37
4	-0.55	-0.76	-0.99	-1.04	-0.31	-0.38	-0.37
5	-0.19	1.25	0.84	-0.45	-0.31	-0.38	-0.37
6	-0.69	-0.23	-1.14	-0.79	-0.31	-0.34	0.72
7	0.46	0.78	-0.33	1.20	-0.27	-0.09	-0.34
8	-0.55	-0.72	-0.99	-1.04	-0.30	-0.32	-0.33
9	-0.47	-0.62	-1.16	-0.72	3.39	3.66	3.19
10	2.82	-0.76	-0.55	-0.11	-0.28	-0.36	-0.37
11	-0.72	-0.75	0.67	-1.38	-0.30	-0.27	-0.33
12	-0.54	-0.75	-0.99	-1.04	-0.29	-0.38	-0.37
13	-0.69	-0.74	-0.04	-1.37	-0.27	-0.25	-0.37
14	-0.52	-0.65	-1.20	-0.67	3.44	3.18	3.31
15	-0.72	-0.73	0.67	-1.37	-0.28	-0.27	-0.36
16	1.15	1.99	2.76	-1.13	-0.27	-0.09	-0.32
17	-0.54	-0.71	-0.99	-1.02	-0.29	-0.36	-0.37
18	-0.28	-0.74	0.70	0.28	-0.27	-0.26	-0.28
19	-0.72	-0.72	-0.02	-1.37	-0.30	-0.31	-0.37
20	-0.72	-0.71	-1.19	-0.71	3.39	3.40	3.45
21	-0.69	-0.64	-0.59	0.33	-0.29	-0.30	-0.35
22	2.97	-0.73	-0.56	-0.14	-0.30	-0.29	-0.32
23	-0.66	-0.60	0.66	-1.36	-0.26	-0.21	-0.36
24	1.38	2.36	2.72	-1.09	-0.24	0.11	-0.29
25	-0.55	-0.75	-0.99	-1.02	-0.31	-0.36	-0.37
26	-0.70	-0.75	-0.02	-1.36	-0.27	-0.34	-0.34
27	-0.74	-0.61	0.66	-1.35	-0.30	-0.21	-0.35
28	1.49	2.33	2.63	-0.99	-0.28	-0.29	-0.31
29	-0.31	1.19	0.85	-0.45	-0.28	-0.14	-0.27

C1 = β-agarofuran,
C2 = α-agarofuran,
C3 = 10-epi-ϒ-eudesmol,
C4 = ϒ-eudesmol,
C5 = longifolol,
C6 = hexadecanol
C7 = eudesmol.

Figure 6 shows the coding used in MATLAB that starts with the load of the data that contains the input-output from GC-MS into the MATLAB workspace. The input and output data in Figure 6 consist of training dataset and testing dataset that are called as inptrain, outtrain, inptest and outtest.

```
xdata = dataAnn(:,1:7);
group = dataAnn(:,8);
P = cvpartition (group, 'Holdout', 0.20);

inptrain = xdata(P.training,:);
outtrain = group(P.training);
inptest = xdata(P.test,:);
outtest = group(P.test);
```

Figure 6. The MATLAB script for load the data and arrange the data in MATLAB

Figure 7 shows the coding for RBF tuned in SVM kernel. The analysis used 'SVM train' to implement this function of RBF. After that, the model is tested by using the coding of 'SVM classify'. For Polynomial, the same principle used as in RBF coding. The word 'RBF' is changed to 'Polynomial'. Refer to Figure 8 for more details.

```
SVMStruct = svmtrain(inptrain,outtrain,
'kernel_function','rbf');

outtestpredicted = svmclassify(SVMStruct,inptest);

% svmStruct = svmtrain(xdata(P.training,:),
group(P.training),'ShowPlot',true);

% C = svmclassify(SVMStruct,xdata(P.test,:),
'showplot',true);

errTest = outtest - outtestpredicted;

mseTest = mse (errTest);

errRate = sum(outtest~=outtestpredicted)/P.TestSize;

conMat = confusionmat(outtest,outtestpredicted);
```

Figure 7. The coding for RBF

```
SVMStruct = svmtrain(inptrain,outtrain,
'kernel_function','polynomial');

outtestpredicted = svmclassify(SVMStruct,inptest);

% svmStruct = svmtrain(xdata(P.training,:),
group(P.training),'ShowPlot',true);

% C = svmclassify(SVMStruct,xdata(P.test,:),'showplot',true);

errTest = outtest - outtestpredicted;

mseTest = mse (errTest); %manual calculation for mse

errRate = sum(outtest~=outtestpredicted)/P.TestSize;

conMat = confusionmat(outtest,outtestpredicted);
```

Figure 8. The coding for polynomial

Figure 9 shows the command line in MATLAB to find the confusion matrix as suggested by [7], [13]. It also displays the coding to obtain performance criteria used in which accuracy (ACR), sensitivity (SNS), specificity (SPC), and precision (PRC).

```
tp = conMat(1,1);
fp = conMat(2,1);
fn = conMat(1,2);
tn = conMat(2,2);

acc = ((tp+tn)/(tp + tn + fp +fn))*100;
sens = ((tp)/(tp +fn))*100;
spec = ((tn)/(fp +tn))*100;
prec = ((tp)/(tp +fp))*100;
```

Figure 9. The coding for confusion matrix

The result of confusion matrix for both kernels Radial Basis Function (RBF) and Polynomial were shown in Table 4 and Table 5 respectively. Refer to Table 4, the number of samples in the low-quality group for RBF were rightly classified to 4 and the number of samples in the high-quality group for RBF is 1. It appears that 1 of the sample were misclassified to the low-quality group and another 14 samples were rightly grouped as high quality. Table 5 represents the confusion matrix for Polynomial, the number of samples in the low quality were 4 and all of them were rightly classified to the low-quality group. For the high-quality group, all of the 15 samples were successfully classified to the high-quality group. None of the samples were misclassified. This can be stated that Polynomial performed better than RBF to do classifying of the agarwood oil.

Table 4. Confusion table for RBF

Data Group	Group as Low	Group as High
Low	4	0
High	1	14

Table 5. Confusion table for polynomial

Data Group	Group as Low	Group as High
Low	4	0
High	0	15

In the Table 6, the data that had been tabulated precisely reveal for SNS, for Polynomial and Radial Basis Function (RBF), both are 100%. For the training and testing datasets, the accuracy for RBF is 94.74 % and Polynomial is 100%. It revealed that accuracy of Polynomial is higher than RBF. The specificity for both kernels is, Polynomial yielded 100% and RBF yielded 93.33. This supports that Polynomial is better than RBF. Polynomial remains better than RBF when the accuracy result of its precision is 100% and RBF is 80%. The increasing degree in Polynomial in which this study, degree of 3 were used. It helps the kernel to have better performance during their training network. For RBF kernel, the adjustment of C and gamma are crucial and the value of C and gamma are used by default. Due to these factors, it is confirmed that Polynomial is better than RBF to classify the agarwood oil. Figure 10 shows that the result through graphical by line graph for more explanation and understanding.

Table 6. RBF and polynomial observation in SVM.

Performance Criteria (%)	Radial Basis Function (RBF)	Polynomial
ACR	94.74	100.00
SNS	100.00	100.00
SPC	93.33	100.00
PRC	80.00	100.00
MSE	0.0526	0.0000

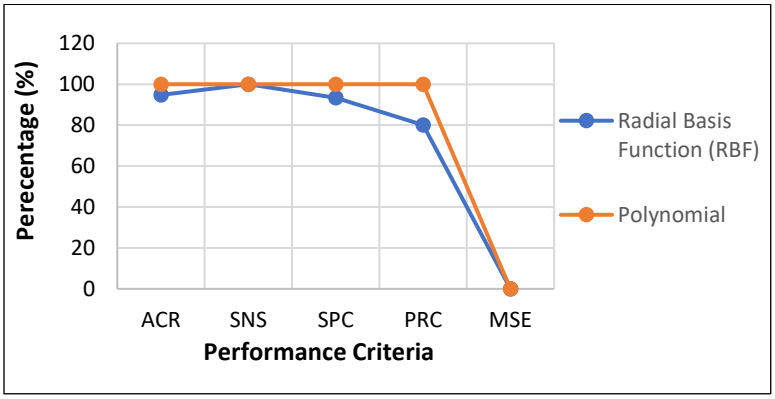

Figure 10. Graphical observation for RBF and polynomial in SVM.

5. Conclusion

The observation on Polynomial and Radial Basis Function (RBF) in Support Vector Machine (SVM) tuned parameters for agarwood oil quality grading has been presented in this research. It has proven by sufficient and appropriate finding during experiment and analytical work. The approach was selected because it provides efficient and capability in grading the agarwood oil quality. The usage of Support Vector Machine (SVM) was to model the data as part of analysis. This analysis showed that Polynomial performs better than the RBF. The accuracy of Polynomial and RBF yielded 100% and 94.74%, respectively, which are very significant and benefits for future work related to agarwood oil quality classification.

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