The Capabilities of Multiclass Support Vector Machine (MSVM) Training Algorithms in Grading Agarwood Essential Oil

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Agarwood essential has a high economic value around the globe for the use of perfumery, medicinal remedies, incense, and other products in the market. However, there is still no standard grading method. Different countries grade agarwood essential oil differently. Traditionally, the grading expert classifies agarwood essential oil by using the aspect of odor, texture, resin color and intensity. Standard grading method is important to ensure the stability of agarwood essential oil's market value. This paper purposes to proof the capabilities of multiclass support vector machine (MSVM) training algorithms in grading agarwood essential oil. Multiclass support vector machine has been identified to be a very effective tool for classification. The MSVM was constructed utilizing radial bias function as the kernel function using MATLAB2021b. One versus all strategies have been added to improve the ability of SVM to classify more than four different grades. The holdout was chosen as the partition for the model with 80:20% training and testing data ratio. The data consists of 660 samples for each significant chemical compound. There are eleven significant chemical compounds which consists of 10-epi-δ-eudesmol, α-agarofuran, β-agarofuran, δ-eudesmol, dihydrocollumellarin, valerianol, ar-curcumene, β-dihydro agarofuran, α-guaiene, allo aromadendrene epoxide and δ-cadinene. The agarwood essential was graded into five grades (low, medium low, upper low, medium high, and high) and six grades (low, medium low, upper low, medium high, high, and upper high). The findings of this paper show the confusion matrix for five grades and six grades have no mismatch between actual and predicted data. The model's performance evaluation results were recorded, with all criteria, including accuracy, sensitivity, specificity, and precision, achieved 100%. In conclusion, the model has the capabilities to identify significant agarwood essential oil chemical compounds and separate agarwood essential oil grades into five and six with high accuracy using eleven significant compounds based on the classification evaluated on two different grades of agarwood essential oil.

Keywords: Agarwood Essential Oil; Grading Technique; Multiclass Support Vector Machine; Confusion Matrix

The well-known name for the resinous heartwood from "wounded" or "infected" Aquilaria trees, which has a high value in international trade, is "agarwood." Agarwood is traded in numerous products such as wood chips, powder, and oil. The demand for agarwood-based goods for use in incense, perfume, and medicine is rising [1, 2]. Agarwood essential oil is a heavy oil that still holds potential for development. This is proven by the high selling price of high-grade quality agarwood essential oil, which is 1,500 USD per tola (11.7 grammes) [3] and it can reach up to 100,000 USD per kg [4]. One of the products that contribute significantly to the nation's foreign exchange revenues from the export of all essential oils is agarwood essential oil [5].

However, agarwood essential oil classification still lacks a standardized grading system. Currently, a trained human sensory who is familiar with a variety of oil compositions determines the purity of agarwood essential oil. Depending on whether the testers have a good sense for identifying the grades of oil, the method's results can vary. The purity or grade of agarwood essential oil cannot be guaranteed by grading it using a human sensory panel. This method is anticipated to be unreliable because it relies on the human nose, which unable to handle a large number of samples due to quick fatigue, lack of uniformity, and time-consuming process [6, 7].

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The grades of agarwood essential oil have been proposed and verified using a variety of intelligent methods [6, 8-10]. There is now a platform where the grades of agarwood essential oils may be totally identified based on their chemical constituents, allowing reliable results to be measured and agarwood essential oil to be classified according to their many grades (low, medium low, upper low, medium high, high, and upper high grades). Agarwood essential oil has been divided into four grades by previous researchers based on the chemical compounds of the oil [11]. A self-organizing map (SOM) is used to group four classes into low, medium low, medium high, and high grades.

This study aims to demonstrate the effectiveness of Multiclass Support Vector Machine (MSVM) training algorithms for agarwood essential oil. Multiclass support vector machine has been found to be a very effective classification tool. The MSVM was built using MATLAB 2021b and the radial bias function as the kernel function. To enhance SVM's capacity to categories more than four different grades, one versus all methods have been implemented. The partition for the model with an 80:20 training to testing data ratio was chosen as the holdout. There are 660 samples total for each key chemical compounds in the data. There are eleven significant chemical compounds which consists of 10-epi-δ-eudesmol, α-agarofuran, β-agarofuran, δ-eudesmol, dihydrocollumellarin, valerianol, ar-curcumene, β-dihydro agarofuran, α-guaiene, allo aromadendrene epoxide and δ-cadinene. The agarwood essential was graded into five grades (low, medium low, upper low, medium high, and high) and six grades (low, medium low, upper low, medium high, high, and upper high). Hence, this study has built Multiclass Support Vector Machine (MSVM) to demonstrate the effective in classifying the agarwood essential oil into five and six grades.

THEORETICAL WORK

Support Vector Machine (SVM), which is an implementation of the supervised learning paradigm, focuses on the fundamental concepts of classification and regression. Support vector machine was developed by Vapnik and Chervonenkis [12-14]. SVM has proved to be an efficient method for addressing actual binary classification problems. SVM has been shown to be more efficient than other supervised learning methods [13, 14]. SVM can be classified as either linear or non-linear. Nonlinear SVM classify data differently than linear support vector machines [10, 13, 14]. The linear SVM is used when data classifications can be separated linearly using a hyperplane; the non-linear SVM is used for non-linearly separable data that cannot be separated linearly using a hyperplane [13, 14]. Training the SVM decision function involves locating a recurrent hyperplane that maximizes the margin or distance between the support vectors of the two classes [12-15]. In other words, even with few input data, SVM and other methods have quite different classification capabilities. This classification

method improves generalization performance and lowers classification errors in the training set of data. SVM has a significant advantage since they only use a tiny subset of the initial data set—often just a few support vectors—when they acquire models. For instance, a set of support vectors representing a specific classification model was created using the initial data set [12-14].

Kernel function and parameter effects have a substantial impact on SVM performance. A polynomial kernel is a mapping that can be used to learn non-linear models. The polynomial kernel, a kernel function widely used with SVM and other kernelized models, represents the similarity of vectors (training data samples) in a feature space over polynomials of the original variables, allowing the learning of non-linear models [14]. SVM has been applied to many different types of classification tasks, such as text classification [16, 17], picture classification [18, 19], cancer classification [20, 21], character recognition in writing [22, 23], face recognition [24, 25], classification of plants [26, 27], and many more.

On the other hand, the binary SVM method can be extended to multiclass cases typical of remote sensing. Typically, this is achieved by decomposing the multiclass problem into a series of binary analyses that can be addressed by a binary SVM using one of the multiclass methods, such as the One Versus All (OVA) strategy [28].

The majority of multiclass classification methods now in use are either based on or reduced to binary classifiers. Using several binary classifiers that have been trained to distinguish between various groupings of objects is the basic idea underlying this data. The classification uses a variety of voting methods [28-31]. One-versus-all [28, 32], and one-versus-one [29, 33] strategies, the error correcting output codes (ECOC) approach [30, 31], and the single-machine approach [34] strategies are generally used in modern multiclass machine learning approaches.

A heuristic method for using binary classification algorithms for multi-class classification is called "One vs. All" [31, 34]. It entails breaking up the multi-class dataset into various binary classification problems. A binary classifier is trained for each binary classification problem, and the model with the highest confidence is used to make predictions [34].

It is crucial to assess the categorization model's effectiveness after construction and testing to see if it achieves the set objectives. Key performance measures like sensitivity, specificity, precision and accuracy are used to achieve this [7, 10]. Evaluation is important to determine how well the model works on newly acquired and previously unexplored data, offering insightful information for further optimization and modification.

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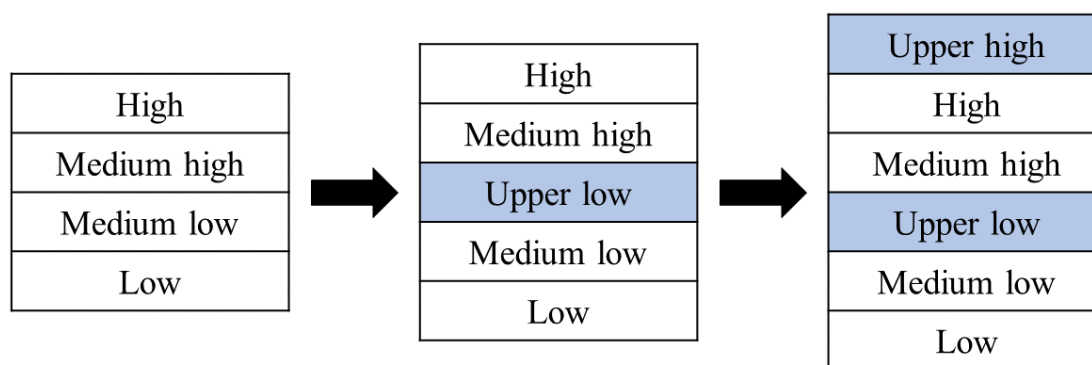
METHODOLOGY

Data Preparation

A total of 660 samples of agarwood essential oil were collected from Forest Research Institute Malaysia (FRIM) [6]. The eleven significant chemical compounds are 10-epi-δ-eudesmol, α-agarofuran, β-agarofuran, δ-eudesmol, dihydrocollumellarin, valerianol, ar-curcumene, β-dihydro agarofuran, α-guaiene, allo aromadendrene epoxide and δ-cadinene. More information about data collection is available in previous studies [11, 35]. Bio-Aromatic Research Centre of Excellence (BARCE) utilizes gas chromatography-mass spectrometry (GC-MS) and standard operating procedure (SOP) to extract chemical compounds from samples. The study was conducted using MATLAB version R2021b.

Experimental Set-Up

Agarwood essential oil has been divided into four classifications by the original data from [11]: low, medium low, medium high and high. This study intends to categorize agarwood essential oil into five grades: low, medium low, upper low, medium high and high. It also aims to categorize it into six grades: low, medium low, upper low, medium high, high, and upper high. Figure 1 shows the data extraction from four grades to five and six grades. The multiclass support vector machine model was done to assess and see how each grade can be categorized. To evaluate the performance of the SVM classification model, its accuracy, sensitivity, specificity, and precision for classifying the test data are examined, and its effectiveness is then assessed by comparing it to that of other classification models. It is considered to have good high accuracy for categorizing the characteristics of agarwood essential oil if the accuracy is not less than 80%. The accuracy, sensitivity, precision, and specificity performance criteria for the model must all be met for the SVM algorithm to be accepted and considered successful.

According to Figure 2, the experiment begins by loading the input and output data into the MATLAB workspace. All the data samples underwent data pre-processing, which included normalizing the data, randomly arranging the data, and finally dividing the data into training and testing data in 80%:20% ratio. The standard template using SVM as method, classification as the type of analysis and 'radial bias function' as kernel function parameter. Then, to make sure the classification successful, multiclass classification method based on binary classifiers was used. Then, in the multiclass classification, the One versus all (OVA) strategies have been chosen as multiclass method of machine learning. Next, all 528 of training data were involved during the development of the SVM model but 132 of testing data were held for analyzing the model by following the performance measure criteria as standard pass evaluation for SVM model.

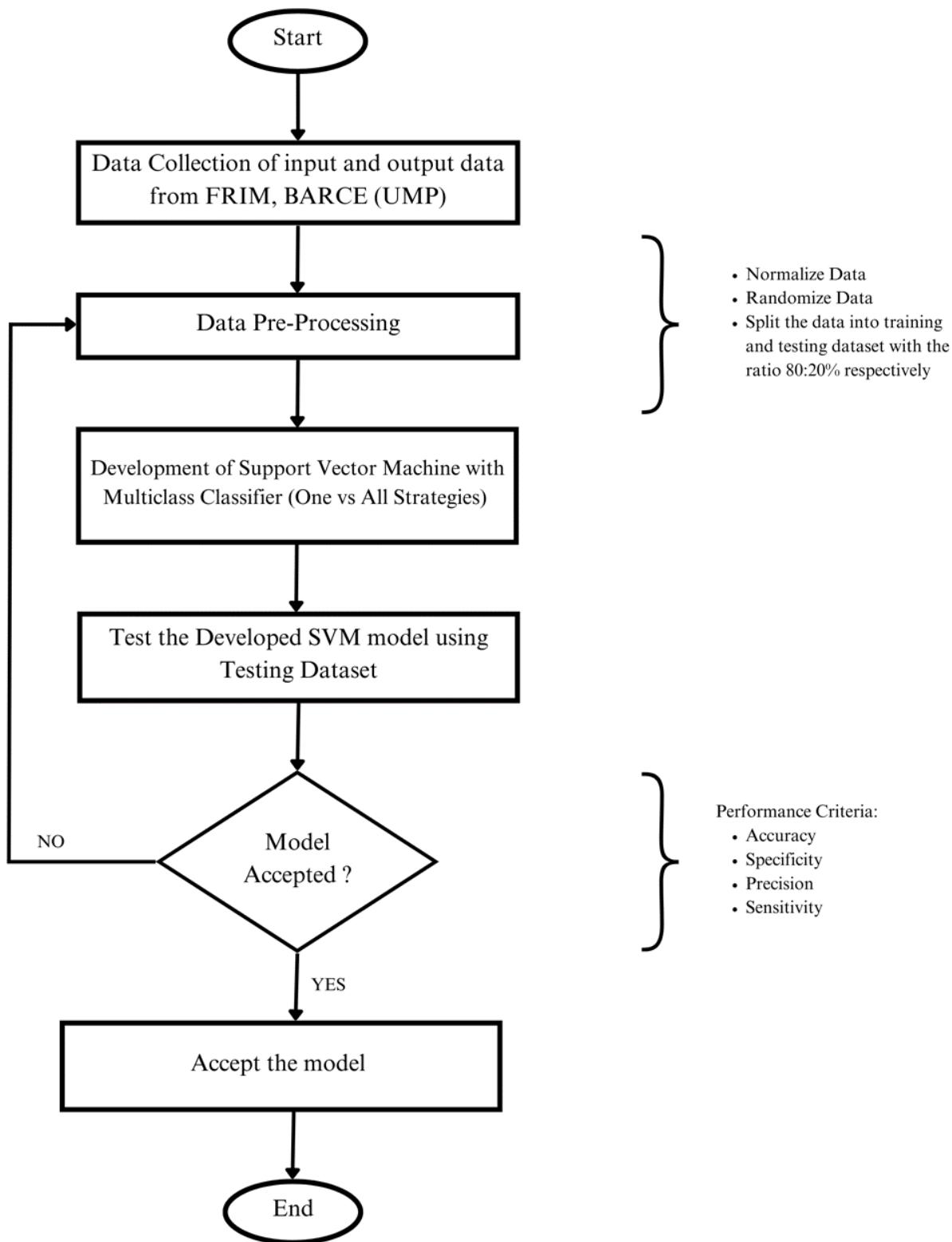**Figure 1.** Data extraction from four grades to five and six grades.

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Figure 2. Detail experiment of Multiclass Support Vector method.

RESULTS AND DISCUSSION

The capabilities of multiclass support vector machine training techniques in grading agarwood essential oil were discussed in length in this section. The performance of the data samples over multiple different grades was then assessed, and an MSVM classification model was developed. The evaluation process' results are summarized and discussed in the steps that follow to determine the model's success and effectiveness.

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Classification of Agarwood Essential Oil using Multi-class Support Vector Machine

The MSVM algorithm was developed using agarwood essential oil data samples with eleven chemical compounds: 10-epi-δ-eudesmol, δ-eudesmol, β-agarofuran, valerianol, β-dihydro agarofuran, δ-cadinene, α-guaiene, α-agarofuran, allo aromadendrene epoxide, ar-curcumene, and dihydrocollumellarin with respect to multiple different grades – four, five and six of agarwood essential oil. The model was developed using using 80% of the data samples (training data set). The model was tested using 20% of the data, also known as testing dataset.

Figure 3 shows the confusion matrix of four grades that has been done in previous study [11]. The distribution of testing data shows that Class '1' for low grade contributes for 31.8% which consists of 42 data samples, Class '2' for medium low grade contributes for 13.6% which consists of 18 data samples, Class '3' for medium high grade contributes for 4.5% which consists of 6 data samples and Class '4' for high grade contributes for 50.0% which consists of 66 data samples. From the confusion matrix of four grades in Figure 3, there is no mismatch between predicted and true class. Table 1 shows the summary of number of samples for four grades according to its grades: low, medium low, medium high and high with 660 data samples. A total of 330 data points for grade high, 30 data points for grade medium high, 90 data points for grade medium low, and 210 data points for grade low. The model's performance criteria evaluation result was recorded, with all criteria, including accuracy, sensitivity, specificity, and precision, achieved 100% is shown in Table 2.
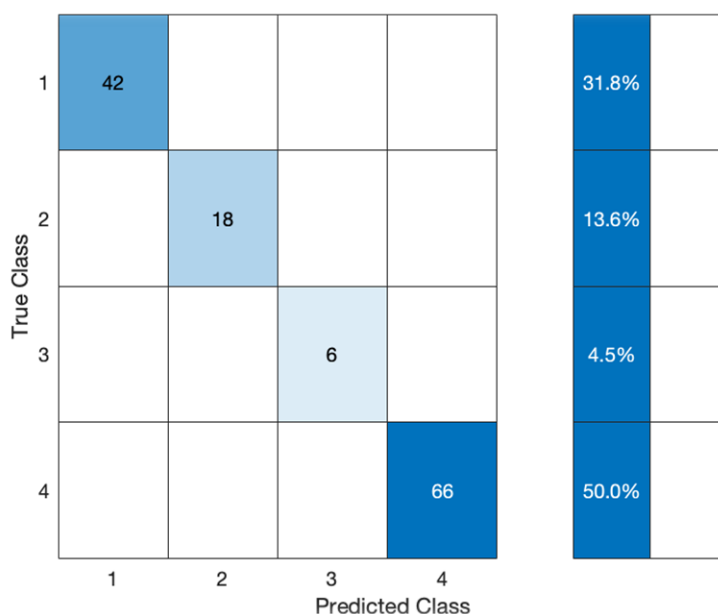

Figure 3. Confusion Matrix of Four Grades.

Table 1. Summary of number of samples for four grades.

Grades	Number of Samples	Percentage
Low	210	31.80%
Medium Low	90	13.60%
Medium High	30	4.50%
High	330	50.00%

Table 2. Performance criteria of four grades.

Accuracy	Sensitivity	Specificity	Precision
100%	100%	100%	100%

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Figure 4 shows the confusion matrix of five grades. The MSVM model was developed using the same data samples as four grades. The distribution of testing data shows that Class '1' for low grade contributes for 13.6% which consists of 18 data samples, Class '2' for medium low grade contributes for 22.7% which consists of 30 data samples, Class '3' for upper low grade contributes for 18.2% which consists of 24 data samples, Class '4' for medium high grade contributes for 13.6% which consists of 18 data samples and Class '5' for high grade contributes for 31.8% which consists of 42 data samples. From the confusion matrix of five grades in Figure 4, there is no mismatch between predicted and true class. Table 3 shows the summary of number of samples for five grades according to its grades: low, medium low, upper low, medium high and high with 660 data samples. A total of 210 data points for grade high, 90 data points for grade medium high, 120 data points to grade upper low, 150 data points for grade medium low, and 90 data points for grade low. The model's performance criteria evaluation result was recorded, with all criteria, including accuracy, sensitivity, specificity, and precision, achieved 100% is shown in Table 4.
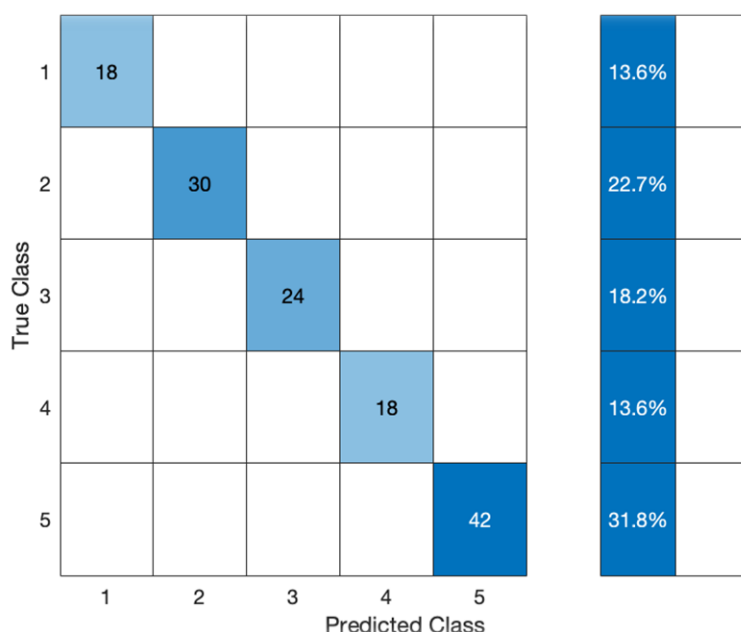

Figure 4. Confusion Matrix of Five Grades.

Table 3. Summary of number of samples for five grades.

Grades	Number of Samples	Percentage
Low	90	13.64%
Medium Low	150	22.73%
Upper Low	120	18.18%
Medium High	90	13.64%
High	210	31.82%

Table 4. Performance criteria of five grades.

Accuracy	Sensitivity	Specificity	Precision
100%	100%	100%	100%

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Figure 5 shows the confusion matrix of six grades. The MSVM model was developed using the same data samples as four and five grades. The distribution of testing data shows that Class '1' for low grade contributes for 13.6% which consists of 18 data samples, Class '2' for medium low grade contributes for 22.7% which consists of 30 data samples, Class '3' for upper low grade contributes for 18.2% which consists of 24 data samples, Class '4' for medium high grade contributes for 13.6% which consists of 18 data samples, Class '5' for high grade contributes for 18.2% which consists of 24 data samples and Class '6' for upper high grade contributes for 13.6% which consists of 18 data

samples. From the confusion matrix of six grades in Figure 5, there is no mismatch between predicted and true class. Table 5 shows the summary of number of samples for five grades according to its grades: low, medium low, upper low, medium high, high and upper high with 660 data samples. A total of 90 data points for grade upper high, 120 data points for grade high, 90 data points for grade medium high, 120 data points to grade upper low, 150 data points for grade medium low, and 90 data points for grade low. The model's performance criteria evaluation result was recorded, with all criteria, including accuracy, sensitivity, specificity, and precision, achieved 100% is shown in Table 6.
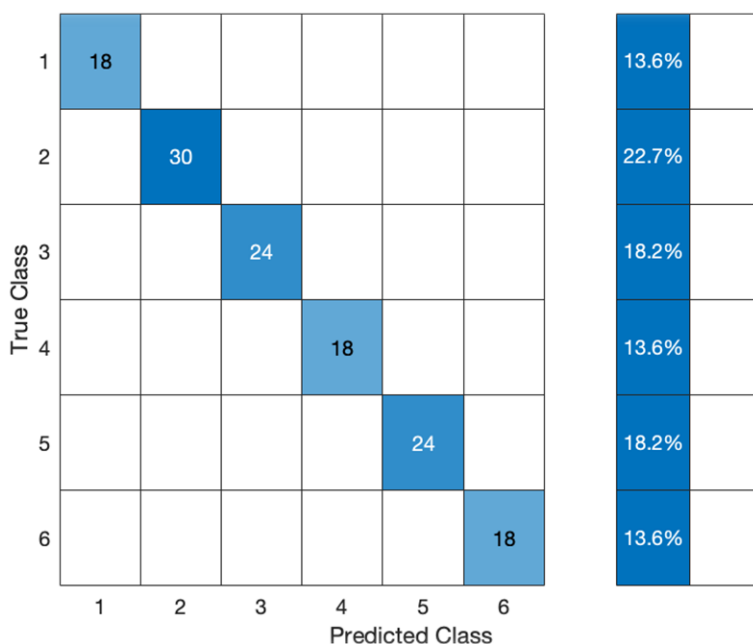

Figure 5. Confusion Matrix of Six Grades.

Table 5. Summary of number of samples for six grades.

Grades	Number of Samples	Percentage
Low	90	13.64%
Medium Low	150	22.73%
Upper Low	120	18.18%
Medium High	90	13.64%
High	120	18.18%
Upper High	90	13.64%

Table 6. Performance criteria of six grades.

Accuracy	Sensitivity	Specificity	Precision
100%	100%	100%	100%

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CONCLUSION

The outcomes of developing the MSVM classification model with multiple different grades were thoroughly addressed. The MSVM model successfully categorised and validated the grade of agarwood essential oil into six classes based on these findings: low, medium low, upper low, medium high, high and upper high. The grades were divided into classes using the 4x4 Confusion Matrix table before the performance criteria evaluation was taken. No misclassifications were present in the training or testing confusion matrix for four, five and six grades, demonstrating that the expected and actual classification processes were correctly aligned during testing. Because there were no mismatch during the model testing procedures for four, five and six grades, the success was further demonstrated by reaching 100% accuracy, specificity, sensitivity, and precision. The research presented in this study demonstrates the MSVM classification model's capabilities for accurately classifying agarwood essential oil into four, five and six grades. In order to increase the uniqueness of the classification of agarwood essential oil and progress its chemical analysis, future research should examine the classification of agarwood from diverse species, including those from other producing countries. The standardised agarwood essential oil classification approach created in this study shows considerable promise for adoption and implementation on a global scale.

ACKNOWLEDGEMENTS

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