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Support vector machine performance: simulation and rice phenology application

Hengki Muradi[1,2], Asep Saefuddin[1], I Made Sumertajaya[1], Agus Mohamad Soleh[1], Dede Dirgahayu Domiri[3]
[1]Department of Statistics and Data Science, School of Data Science, Mathematics, and Informatics, IPB University, Bogor, Indonesia
[2]Research Center for Data Science and Information, National Research and Innovation Agency (BRIN), Bandung, Indonesia
[3]Research Center for Geoinformatics, National Research and Innovation Agency (BRIN), Bandung, Indonesia

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ABSTRACT

In the case of classification, model accuracy is expected to result in correct predictions. This study aims to analyze the performance of two kinds of support vector machine (SVM) methods: the support vector machine one versus one (SVM OvO) method and the generalized multiclass support vector machine (GenSVM) method. This method will compare to the generalized linear model, namely the multinomial logistic regression (MLR) method. Simulations were conducted using SVM OvO and GenSVM methods to get an overview of the parameters affecting both methods' performance. Furthermore, the three classification methods are implemented in the case of modelling the rice phenology and tested for performance. Simulation results show that, however, the SVM OvO and GenSVM machine learning methods are sensitive to the choice of model parameters. The empirical study results show that the SVM OvO and GenSVM methods can produce satisfactory model accuracy and are comparable to the MLR method. The best rice phenology model accuracy was obtained from the SVM OvO model, where 79.20 ± 0.21 overall accuracy and 70.69 ± 0.29 kappa were obtained. This research can be continued by handling samples, especially when class members are a minority, and can also add random effects to the SVM model.

Corresponding Author:

Hengki Muradi
Department of Statistics and Data Science, School of Data Science, Mathematics, and Informatics
IPB University
Bogor, Indonesia
Email: hengkimuradis3@gmail.com

1. INTRODUCTION

The support vector machine (SVM) is a supervised, non-parametric classification method that has demonstrated strong performance in producing high-accuracy models. It effectively addressing common modelling challenges such as multicollinearity, nonlinearity, and overfitting [1], [2]. Due to its robustness and versatility, SVM has been widely applied across diverse scientific fields, including pattern recognition [3], remote sensing [4], [5], as well as medical applications such as cancer and tumor diagnosis [6], [7].

The SVM method was initially developed for binary classification cases. Developing SVMs for multiclass cases is difficult because the outputs are not on a calibrated scale and are difficult to compare [8]. In the case of multiclass classification, the SVM method was developed using primary binary classification, such as the one versus one (OvO), directed acyclic graph support vector machines (DAGSVM), and one versus all (OvA) methods. The OvO method is sometimes better than the DAGSVM and OvA methods

[9], [10]. In the multiclass classification of complex remote sensing data, the OvO SVM method remains comparable to the quantum multiclass support vector machine (QMSVM) and OvA methods [11]. A multiclass classification method that is not based on binary classification was also developed in [12], namely a multiclass classification method using a simplex approach. The advantage of this simplex method is that it can produce classifications without ambiguity in the prediction space and allows geometric interpretation. This method is called the generalized multiclass support vector machine (GenSVM) method. The GenSVM method is claimed to have quite a competitive performance compared to the SVM OvO, SVM OvA, DAGSVM classification methods and several other multiclass classification methods [12]. Multiclass classification can also be done using the multinomial logistic regression (MLR) method. This method is based on the generalized linear model (GLM) [13]. The MLR method can accurately define the relationship between groups of explanatory variables and response variables, identify the influence of each variable, and predict the classification of each case [14].

This study aims to analyze the performance of two types of SVM methods: the SVM OvO method based on binary classification and the GenSVM method based on non-binary classification. This method will compare to the GLM, namely the MLR method. Furthermore, the three classification methods are implemented in the case of modelling rice phenology and tested for performance. The SVM method can be applied for modelling rice phenology [4], [5], as can the MLR method [15], but specifically, there has been no research that applies the GenSVM method for modelling of rice phenology and comparing the three methods to get the best model.

This study also develops the input model where, in previous studies, some researchers only used one input variable, such as a single VH polarization [4], [16], [17] and VH/VV polarization index [18], [19]. In this study, we will use both VV and VH polarization, as well as polarization indices such as ratio polarization index (RPI), normalized different polarization index (NDPI), and average polarization index (API) [20]. In addition, a re-classification scenario on the rice phenology class was also tested to obtain the best rice phenology model.

2. MULTICLASS CLASSIFICATION METHOD

2.1. Support vector machine

In the case of binary classification, let $y \in \{-1,1\}$ and a set of predictors$\{x_1, x_2, \dots, x_p\}, x_i \in \mathbb{R}^n$. The most optimal barrier is needed to separate the negative and positive classes, called a hyperplane. The hyperplane equation can be stated in (1) [21], [22]:

$$w_0 + w_1x_1 + \cdots + w_px_p = 0 \tag{1}$$

In many real-world applications, the relationships between variables are non-linear. The main feature of SVM is its ability to map problems into a higher dimensional space using a process known as the kernel trick so that non-linear relationships become linear [1]. In (2) can be transformed by the function $\phi(.)$ to become [3]:

$$\xi_i \geq 0, y_i(\boldsymbol{w}^T\phi(x_i) + w_0) \geq 1 - \xi_i, i = 1,2, \dots, p \tag{2}$$

Since the desired space $\phi(.)$ is unknown, solving the problem (2) subject to constraint (2) becomes more complicated. To overcome this problem, the dual of SVM is presented as (3) [3], [23]:

$$\begin{aligned}
&\min_{\mathbf{u}} \textstyle\sum_{i=1}^{N} u_i - \frac{1}{2}\sum_{i=1}^{p}\sum_{j=1}^{p} u_i\, u_j y_i y_j K(x_i, x_j) \\
&\textstyle\sum_{i=1}^{p} u_i y_i = 0 \\
&0 \leq u_i \leq c, i = 1, \dots, p
\end{aligned} \tag{3}$$

Where $u = (u_1, u_2, \dots, u_p)$ is the Lagrange multiplier and $K(x_i, x_j)$ is a symmetric kernel function with a nonnegative value. Kernel functions consist of linear, polynomial, and radial basis function (RBF) kernel functions [8].

For the case of multinomial classification, SVM methods have been used, such as the OvO and OvA methods. Both of these methods are based on binary classification, and in several tests, the OvO method is more competitive and easier to apply than the OvA method. The one-against-one method builds $k(k+1)/2$ classifiers, which are trained one by one for the two classes. For training data from class$-i$ and class$-j$, the best solution is the solution to the problem as in (4) [9]:

$$\min_{w^{ij},w_0^{ij},\xi^{ij}} \frac{1}{2}(w^{ij})^T w^{ij} + C\sum_t \xi_t^{ij}$$
$$(w^{ij})^T\phi(x_t) + b^{ij} \geq 1 - \xi_i^{ij}, \text{jika } y_t = i$$
$$(w^{ij})^T\phi(x_t) + b^{ij} \leq -1 + \xi_i^{ij}, \text{jika } y_t \neq \mathrm{I}$$
$$\xi_i^{ij} \geq 0 \tag{4}$$

Several methods for further testing are used after all $k(k+1)/2$ classifiers have been built. One way is to use a voting strategy proposed by Friedman (1996), which is called the "Max wins" strategy [9], [24]. In the "max win" algorithm, each classifier gives one vote for the class of its choice, and the final result is the class with the most votes [24]. The performance of the SVM multiclass classification method also depends on kernel selection. The multiclass SVM classification method uses the OvO method [25] with RBF kernel [3], [5].

A multiclass classification method that is not based on binary classification was also developed by Burg and Groenen [12], namely the GenSVM method. The GenSVM method is a flexible and general multiclass SVM method that uses simplex coding to formulate the multiclass SVM problem as a single optimization problem, which reduces to a binary SVM when k=2. The complete loss function of GenSVM is as (5) [12]:

$$L_{MSVM} = \frac{1}{n}\sum_{k=1}^{K}\sum_{i\in G_k}\rho_i\left(\sum_{j\neq k} h^p\left(q_i^{(kj)}\right)\right)^{1/p} + \lambda\, tr\, \mathrm{W}'\mathrm{W}$$
$$\lambda > 0, \rho_i = \frac{n}{n_k K}, i \in G_k, G_k = \{i : y_i = k\} \tag{5}$$

The predicted class labels only correspond to the closest simplex vertices as measured by the squared Euclidean norm as in (6):

$$\hat{y}_{n+1} = Arg_k Min\, \|\mathbf{s}'_{n+1} - \mathbf{u}'_k\|^2, k = 1,2,\dots,K \tag{6}$$

The GenSVM algorithm is available in the Gensvm package in the R program. GenSVM can be used for linear and nonlinear multiclass SVM classification. In general, linear classification will be faster, but depending on the dataset, higher classification performance can be achieved using nonlinear kernels [26].

2.2. Multinomial logistic regression

In this study, we carried out classification using the analytical classification method, namely MLR. The method is a non-parametric classification method [6], part of the family of GLM methods. It is used when the response variable has more than two categories [13]. Suppose $y \in \{1,2,\dots,j\}$ and a set of predictors $\{\{x_1, x_2, \dots, x_p\}, x_i \in \mathbb{R}^n$, the MLR equation in probability form can be expressed as (7):

$$\pi_j(\mathrm{x}) = P(y = j|\mathrm{x})\frac{\exp\left(\alpha_i + \beta_j'\mathrm{x}\right)}{1+\sum_{h-1}^{j-1}\exp(\alpha_h \beta_h' \mathrm{x})} \tag{7}$$

The MLR model parameters can be estimated using the maximum likelihood method. The MLR method performs well and is competitive with the random forest classification method [13].

2.3. Model accuracy measurement

Model accuracy is measured from overall accuracy (OA) statistics and kappa statistics (κ) as shown in (8) and (9) [27].

$$OA = \frac{\sum_{i=1}^{k} n_{ii}}{|T|} \tag{8}$$

$$\kappa = \frac{OA - p_e}{1 - p_e} \tag{9}$$

Where n_{ii} is the number of points predicted correctly, $p_e = \sum_i n_{i\cdot} n_{\cdot i}/n$ number of points tested, $n_{i.} = \sum_j n_{ij}$, $n_{.i} = \sum_i n_{ij}$ and n the number of items that have to be classified. OA provides a simple measure of the proportion of correct classifications, while Kappa adds important information by taking into account the possibility of random agreement, thereby providing a fairer evaluation in cases of imbalanced class distributions [28], [29]. The combination of OA and Kappa has been shown to complement each other in image classification research, thereby improving the reliability of model assessment [30].

3. METHOD
3.1. Simulation study

The simulation steps taken can be seen in Figure 1. The simulation study is conducted to obtain an overview of the parameter settings in the SVM OvO and GenSVM methods. In the SVM OvO method, the cost (C) and gamma (γ) parameters are thought to influence model performance. Similarly, with the GenSVM method, the parameters kappa (κ) and lambda (λ) are thought to influence the performance of the resulting model. In package e1071 in the R programme, the parameters C and γ in the SVM OvO method can be used by default [25], but it is also possible to modify them. Then, in the gensvm package [26], the parameters κ and λ can use the default settings but can also be modified. Meanwhile, the MLR method does not require parameter settings because, in the maximum likelihood method, the MLR model parameters can be determined without involving the initial value of the model parameters.

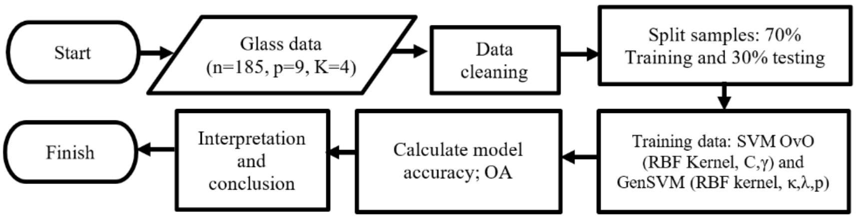


Figure 1. Simulation steps

The simulation data used in this research is glass data accessed from the kknn R package, which consists of n=185, the number of predictors is nine, and the number of classes is 4 [31]. In this simulation, all predictors are included in the model. In the SVM OvO method, CV=10-fold and RBF kernel settings are used, while the C and γ parameters used are set to the value $C \in \{2^0, 2^1, 2^2, 2^4, 2^6, 2^8, 2^{10}, 2^{12}, 2^{14}, 2^{16}\}$ and the value $\gamma \in \{2^{-6}, 2^{-4}, 2^{-2}, 2^{-1}, 2^0, 2^2, 2^3, 2^4, 2^5, 2^6\}$ [9]. The GenSVM method is set with parameter values $\kappa \in \{-0.9, -0.5, 0.5, 1.5, 2.0, 2.5, 3.0, 4.0, 4.5, 5.0\}$, $\lambda \in \{2^0, 2^1, 2^2, 2^4, 2^6, 2^8, 2^{10}, 2^{12}, 2^{14}, 2^{16}\}$, and $p \in \{1.0, 1.1, 1.2, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2.0\}$.

3.2. Simulation results

The simulation results show differences in the accuracy of the SVM OvO model in each cost parameter experiment and the gamma parameter experiment. The simulation results show that the SVM OvO method's performance depends on the cost value and gamma parameters. The effect of the cost parameter value on the performance of the SVM OvO method is presented in Figure 2. Meanwhile, the effect of gamma parameters is presented in Figure 3. In the case of glass data classification, it shows that the accuracy of the SVM OvO model reaches 100% when cost= 2^{14}. Therefore, researchers can adjust the cost parameter values. By default, package e1071 provides a parameter value of cost=1.

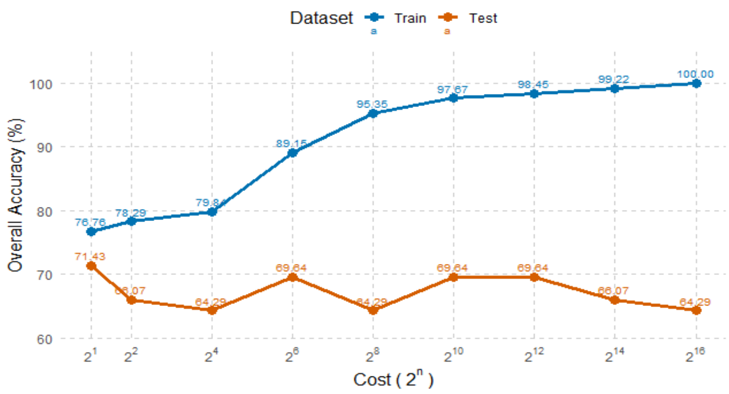


Figure 2. Simulation results of the SVM OvO method: cost parameters

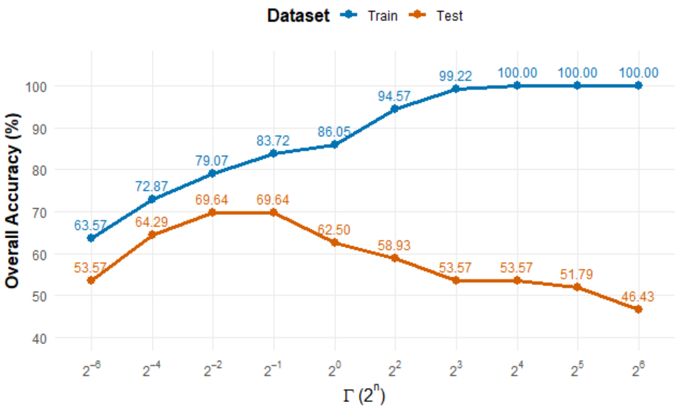


Figure 3. Simulation results of the SVM OvO method: gamma parameter

The simulation results of several gamma parameter settings also show that the accuracy of the OvO SVM model increases as the gamma parameter increases. The accuracy of the OvO SVM model reaches optimal when gamma $=2^4$. Based on this simulation, it can be seen that the performance of the SVM OvO classification method is very dependent on the cost and gamma parameters, wherein the simulation carried out, the SVM OvO model achieved the best accuracy when setting the cost parameter $=2^{14}$ and the gamma parameter $=2^4$. The simulation results show that the kappa, lambda, and p parameters influence the GenSVM model. The effect of the kappa parameter on the performance of the GenSVM method is presented in Figure 4, the effect of the lambda parameter on the performance of the GenSVM method is presented in Figure 5, and the effect of the p parameter on the performance of the GenSVM method can be seen in Figure 6.

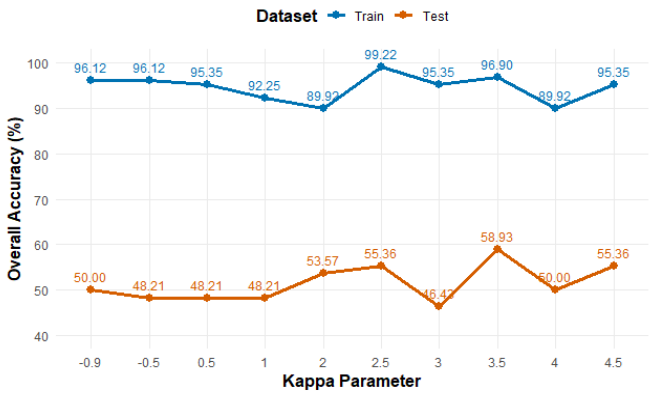


Figure 4. Simulation results of the GenSVM method: kappa

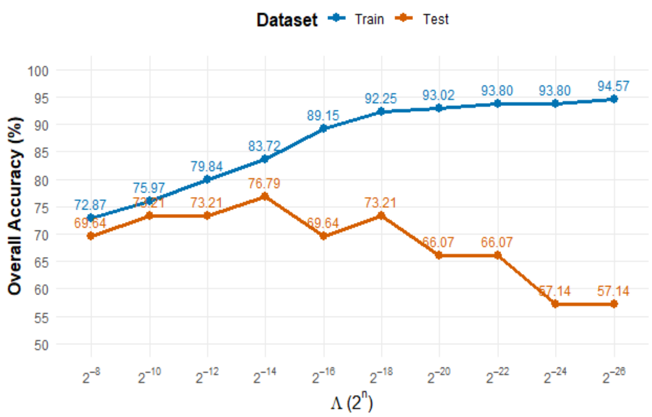


Figure 5. Simulation results of the GenSVM method: lambda

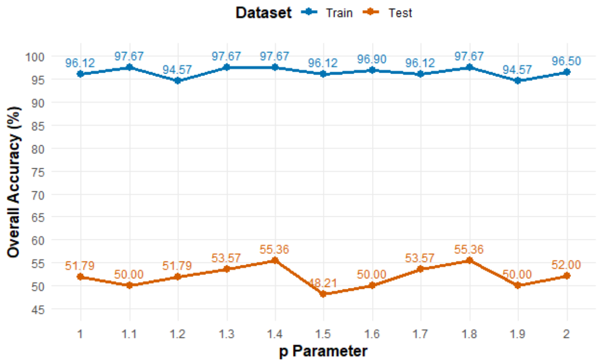


Figure 6. Simulation results of the GenSVM method: parameter p

The performance of the GenSVM method fluctuates with several variations of the kappa parameter and reaches optimal performance when the kappa parameter is set to 2.5 or 4.0. The performance of the GenSVM method becomes more optimal when the lambda parameter is increasingly reduced and will reach optimal when the lambda parameter is set to 2^{-16}. Meanwhile, the performance of GenSVM fluctuates when simulating several parameter values, where this method will achieve optimal performance when setting the parameter p=1.7.

In this simulation, setting the parameters of the SVM OvO and GenSVM models greatly impacts the performance of both models. However, setting model parameters such as cost and gamma should also consider the impact on the possibility of overfitting. For example, when the cost=2^{16} and gamma parameters are default, the accuracy of the SVM OvO model on training data increases to 100%. However, when predicted on testing data, the accuracy of SVM OvO drops to 64.29%. Similarly, when the gamma parameter is 2^4 and the cost parameter is set by default, the model's accuracy in the training data reaches 100%. However, when predicted on the testing data, the accuracy of SVM OvO decreases to 53.57%.

Similarly, in the GenSVM method, when the kappa parameter=2.5, the model accuracy in the training data reaches 99.22%, but when predictions are made on the testing data, the accuracy of the GenSVM model drops to 55.36%. This shows that the SVM OvO method is sensitive to changes in cost and gamma parameter values. The GenSVM method also depends on setting kappa, lambda, and p parameters. In other words, the SVM OvO and GenSVM machine learning methods are sensitive to the selection of model parameters. For this reason, the hyperparameter process is essential. Hyperparameters are key factors in developing machine learning models, including SVM and GenSVM, because they determine the model's behavior before training. Selecting the correct hyperparameters can prevent overfitting, improve performance on test data, and make the model more stable. Hyperparameter tuning can be done using the tune function in the e1071 package [25].

3.3. Empirical application

In the empirical application study, the modeling of rice phenology using sentinel-1 satellite image data was tested. The steps of the empirical study are presented in Figure 7. In Figure 7, it can be seen that in the initial stage, we extracted sentinel-1 image data to produce VV and VH polarization and their derivatives, namely RPI, NDPI, and API. We adjusted this data with field survey data in the form of rice growth phase information to produce tabulated data. We checked the tabulated data to ensure no missing values or extreme outliers. We conducted a rice phenology reclassification scenario to obtain the optimal number of rice classes in the rice phenology model. Ten repetitions of the scenario were performed on the training and testing data to observe the consistency of the SVM model's performance. The OvO SVM, GenSVM, and MLR models were trained using the training data. Parameter and kernel tuning were also performed on the OvO SVM and GenSVM models to obtain the optimal parameters and kernels. The model's performance on the training and testing data was measured using OA and kappa statistics.

3.3.1. Research data

The research data were from the rice phase team at the remote sensing research center of the Indonesian National Research and Innovation Agency. Sentinel-1 satellite data were extracted using the Google Earth Engine platform, while field data were obtained from survey activities conducted in the rice fields of PT. Sang Hyang Seri is in the administrative area of Subang Regency, West Java Province, Indonesia Figure 8. Sentinel-1 SAR GRD image data with acquisition modes interferometric wide swath (IW) accessed during the first planting season of 2021-2022 from the Google Earth Engine platform. Sentinel-1 data has gone through the preprocessing stage of thermal noise removal, radiometric calibration, and terrain correction to be ready for use [32].

Extraction of sentinel-1 image data produces polarization VV, VH, and a polarization index VH/VV, called the RPI, NDPI, and API. The polarization values VV, VH, RPI, NDPI, and API polarization index are intensities ranging from 0 to 1. All are predictors of the rice phenology model.

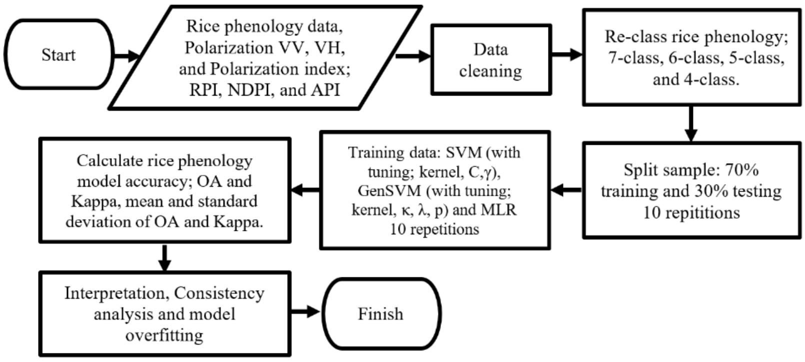


Figure 7. Steps of empirical study of SVM, GenSVM, and MLR methods

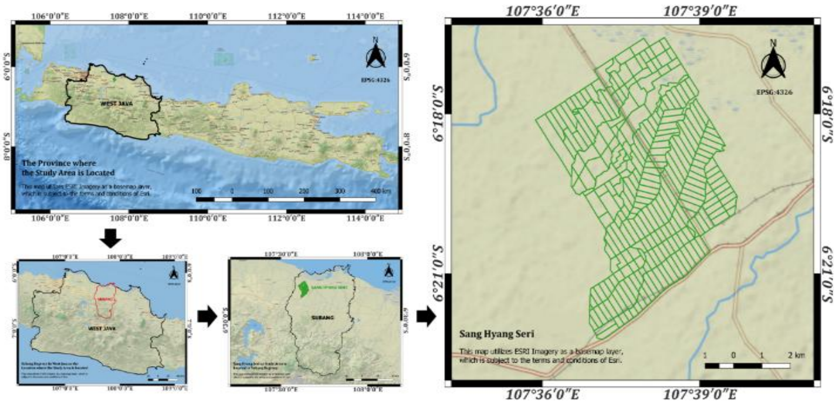


Figure 8. Research area

3.3.2. Rice phenology model

The rice phenology classes used in this study consisted of 7 classes, namely the water phase (<0 DAP), early vegetative phase (0-20 DAP), vegetative-1 phase (21-40 DAP), vegetative phase-2 (41-64 DAP), generative-1 phase (65-90 DAP), generative-2 phase (91-120 DAP), and fallow phase (>120 DAP). Recluse scenarios were also tested on the model to accommodate possible changes in model accuracy [15]. The reclass scenario consists of 7-class scenario, 6-class scenario, 5-class scenario, and 4-class scenario Table 1. Each scenario represents a different level of aggregation, where classes that have similarities or relevance are combined to simplify the classification problem. This experiment aims to identify the number of classes that provide the best performance in the SVM model, considering the balance between model complexity and generalization ability. Selecting the correct number of classes can help reduce overfitting and improve model interpretability, resulting in classification results that are more reliable and easier for end users to understand.

The rice phenology model was constructed using VV, VH, RPI, NDPI, and API predictors. Several modelling schemes considered the number of rice phenology classes and the number of model predictors. In the rice phenology model with one predictor, the performance of VH polarization [4], [17] and RPI polarization index was tested [20]. In classification models with two predictors, the performance of the VV+VH and VH+RPI predictors has been tested. In classification models with three predictors, the performance of the VV+VH+RPI predictors has been tested [33].

The risk of overfitting problems in the model was tested by dividing the sample into 70% for training and 30% for testing. Model accuracy is measured from training and testing data to show the difference between the estimated OA and kappa parameters. The stability of the model is tested by doing ten repetitions of training and ten repetitions of testing. Data processing uses the packages caret [34], GenSVM packages [26], and nnet [35] in R programming.

Table 1. Scenario of modelling

Modelling scenario	Phenology class (Y)	Days after planting (DAP) of paddy
7-class	Y= 1, Water	1. < 0 DAP
	2, Early-vegetative	2. 0-20 DAP
	3, Vegetative-1	3. 21-40 DAP
	4, Vegetative-2	4. 41-64 DAP
	5, Generative-1	5. 65-90 DAP
	6, Generative-2	6. 91-120 DAP
	7, Fallow	7. > 120 DAP
6-class	Y= 1, Water	1. < 0 DAP
	2, Vegetative-1	2. 0-40 DAP
	3, Vegetative-2	3. 41-64 DAP
	4, Generative-1	4. 65-90 DAP
	5, Generative-2	5. 91-120 DAP
	6, Fallow	6. > 120 DAP
5-class	Y= 1,Water	1. < 0 DAP
	2, Vegetative-1	2. 0-40 DAP
	3, Vegetative-2	3. 41-64 DAP
	4, Generative-1	4. 65-90 DAP
	5, Generative-2	5. 91-120 DAP
4-class	Y= 1, Vegetative-1	1. 0-40 DAP
	2, Vegetative-2	2. 41-64 DAP
	3, Generative-1	3. 65-90 DAP
	4, Generative-2	4. 91-120 DAP

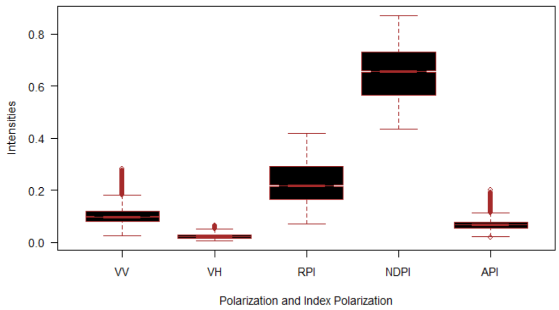
4. RESULTS AND DISCUSSION

Upper extreme data is detected in both datasets, which occurred in the fallow phase. This extreme data is reduced when the data is reduced to the RPI and NDPI polarization indices. Figure 9 shows the boxplots of polarization parameters and indices across rice growth phases. This extreme data is still visible in the API Figure 9(a). In Figure 9(b), it can be seen that the VV polarization fluctuates from the water phase to the fallow phase. The scatter boxplot shows that VH polarization has a positive trend from the early vegetative phase to the fallow phase Figure 9(c). Therefore, VH polarization consistently increases trends from the early vegetative phase to the early ripening phase after the plant reaches its maturity phase [36]. The RPI polarization index has a unique pattern and can describe the pattern of rice growth phases Figure 9(d). However, the VH polarization has better accuracy individually than the RPI polarization index. Meanwhile, the NDPI polarization index has the opposite pattern to RPI Figure 9(e), which can be used to describe the quantity of water in rice fields. Finally, the API polarization index appears to fluctuate, similar to the VV polarization Figure 9(f).

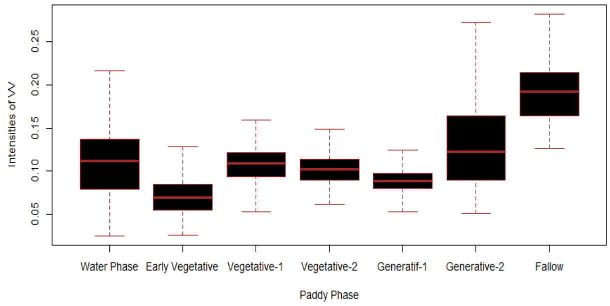
The performance of the three methods increases as the number of classes in the rice phenology is reduced and reaches optimal performance in the 4-class scenario. Non-rice classes, such as water and fallow, still need to be classified correctly by the three methods. This could be because there are very few members of both classes compared to members of other rice classes. Therefore, addressing the class imbalance problem can improve the model's accuracy [37], [38]. Table 2 presents the results of modelling the growth phase of rice using the SVM OvO, GenSVM, and MLR methods.

The SVM OvO method in the initial scenario, namely the 7-class rice phase, achieves optimal performance and, at the same time, does not experience overfitting problems when the parameters are set to cost=28 and gamma=1/6. In the 4-class rice phenology scenario, the SVM OvO method achieved optimal performance with the parameter settings of cost=28 and gamma=1/2. This result indicates that the performance of SVM OvO is highly dependent on parameter selection, thus requiring careful tuning in each class scenario. The GenSVM method achieves optimal performance when the parameters kappa=0.2, lambda=2-36, and p=1. This method does not require different settings for all rice phenology class scenarios.

In the case of the rice phenology classification model, the accuracy of the classification model from the SVM OvO, GenSVM, and MLR methods will be optimal when all predictors are included in the model. The results in Table 2 show that the OvO SVM method consistently provides the highest performance compared to GenSVM and MLR in all class number scenarios. In the 4-class case, SVM achieved an OA of 79.20% on the training data and 78.57% on the testing data, with kappa values of 70.69% and 69.83%, respectively. These accuracies are much higher than MLR's, which only achieved an OA of 76.86% on the training data and 77.24% on the testing data. Meanwhile, GenSVM showed quite competitive performance, and in some cases, the results were close to those of SVM, although generally still slightly below. These findings confirm that the SVM OvO approach can better accommodate the complexity of data with non-linear relationships, while MLR is limited to linear relationships, resulting in lower performance.



(a)



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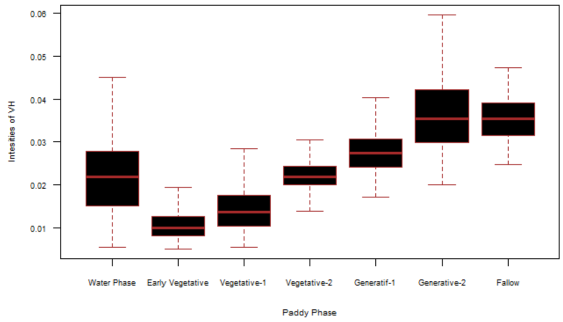

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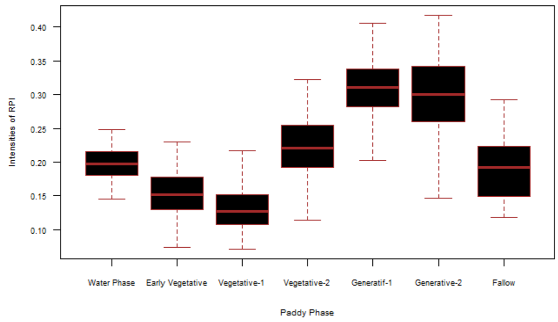

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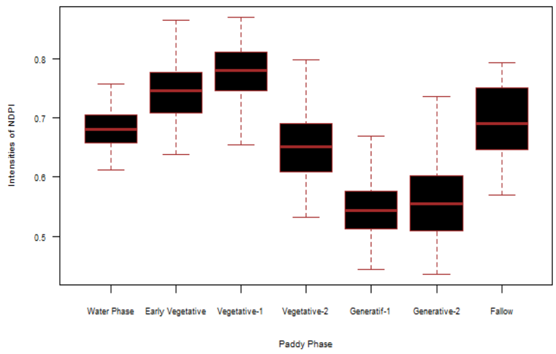
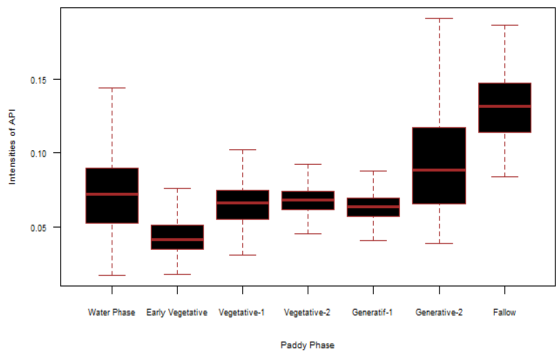


(e)



(f)

Figure 9. The boxplot of (a) VV, VH, and RPI, (b) VV based on rice phase, (c) VH based on rice phase, (d) RPI based on rice phase, (e) NDPI based on rice phase, and (f) API based on rice phase

Table 2. Result of modelling

Modelling scenario	Method	Training		Testing	
		OA	Kappa	OA	Kappa
7-class	SVM OvO (CV=10, cost=2^8, gamma=1/6)	67.37±0.15	58.75±0.33	66.56±0.37	57.35±0.77
	GenSVM(kappa=0.2, lambda=2^{-36}, p=1)	65.84±0.17	56.37±0.19	65.56±0.41	56.12±0.31
	MLR	60.78±0.18	50.12±0.31	60.20±0.28	49.36±0.35
6-class	SVM OvO (CV=10, cost=2^6, gamma=1)	70.60±0.09	58.52±0.24	69.30±0.22	55.46±0.62
	GenSVM (kappa=0.2, lambda=2^{-36}, p=1)	70.37±0.16	57.37±0.22	69.87±0.35	56.23±0.49
	MLR	65.48±0.12	50.29±0.19	64.97±0.22	49.14±0.35
5-class	SVM OvO (CV=10, cost=2^2, gamma=1/6)	71.54±0.08	61.40±0.12	71.13±0.18	60.87±0.23
	GenSVM (kappa=0.2, lambda=2^{-36}, p=1)	70.94±0.14	60.73±0.20	70.48±0.23	59.91±0.32
	MLR	66.24±0.08	52.98±0.11	65.98±0.23	52.45±0.32
4-class	SVM OvO (CV=10, cost=2^8, gamma=1/2)	79.20±0.21	70.69±0.29	78.57±0.43	69.83±0.59
	GenSVM (kappa=0.2, lambda=2^{-36}, p=1)	78.01±0.15	68.96±0.21	78.01±0.31	69.12±0.46
	MLR	76.86±0.17	67.34±0.23	77.24±0.40	69.93±0.54

This study also observed the possibility of overfitting in the model. Ten replications were performed on both the training and test data to assess this. The analysis showed that the performance difference between the training and test data was relatively small for all three methods, namely SVM, GenSVM, and MLR. This condition indicates that the model did not experience significant overfitting and could generalize the test data well. In addition, the relatively small standard error value of the average repetition results (<1%) indicates the stability of the model's performance in ten repetitions. This stability provides additional evidence that the performance of SVM, especially with the OvO approach, is quite consistent and reliable in modelling highly complex data such as the rice growth phase. However, the accuracy of the OvO SVM model still needs to be improved through further optimization so that results of rice growth phase classification become more precise.

The results of this study indicate that the rice growth phase model based on sentinel-1 image data still produces misclassification. Misclassification mainly occurs in the water and follow-up phases. This is because the number of sample points in these two phases is not comparable to the other phases. This situation can cause the model to make misclassifications, especially when the class distribution is unbalanced, so the SVM method can be ineffective in determining class boundaries [39]. To overcome this unbalanced problem, a sampling strategy can be applied to balance the size of each rice phase class, such as the synthetic minority oversampling technique (SMOTE) method and its derivative methods [37]. The application of class balancing methods, such as SMOTE and its variants, was not carried out in this study because it was outside the scope of the study. However, this approach has the potential to be applied in future studies to overcome class imbalance issues and improve the accuracy of rice growth phase classification models. Misclassification can also occur due to problems occurring in one rice cropping cycle, such as problems with pest attacks, drought, and floods, so the rice phenology is disrupted. Damaged rice is usually replaced with new rice plants, so the field data used in the sample differs from the latest real field data.

Furthermore, this research can be continued by developing a model that considers random effects, such as the planting season. In Indonesia, there are two main planting seasons, namely the rainy and dry seasons, which can affect the dynamics of rice phenology [40]. In Indonesia, there are two main growing seasons, namely the rainy and dry seasons, which can affect the dynamics of rice growth. The research in [41], [42] shows that adding random effects to machine learning models can improve performance. By including the planting season as a random effect, the model is expected to be able to capture natural variations between seasons so that rice phenology phase predictions become more robust and accurate. In subsequent research, adding random effects to the multiclass SVM classification model can be used as an alternative to improve the performance of the rice phenology model.

5. CONCLUSION

The SVM OvO and GenSVM methods can produce rice phenology model accuracy, which is reasonably satisfactory and comparable to the MLR method. In the case of rice growth phase classification, the accuracy of the classification model from the SVM OvO, GenSVM, and MLR methods will be optimal when all predictors are included in the model. The models produced by the three methods show good stability and no visible overfitting problems. However, it should be noted that the SVM OvO method is sensitive to changes in the value of the cost and gamma parameters. The GenSVM method also depends on the kappa, lambda, and p parameter settings. The accuracy of the rice phenology model using sentinel-1 satellite image data is most optimal in the 4-class scenario through SVM OvO modelling. In future research, sampling handling tests can be carried out, for example, using the SMOTE method to increase the small number of class members. In addition, future research can be carried out by adding random effects to the SVM model that can accommodate fixed effects and random effects in the model to reduce misclassification caused by fixed and random effects.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration. he following are the contributions of each author to this paper.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Hengki Muradi	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓
Asep Saefuddin	✓	✓						✓	✓	✓	✓	✓		✓
I Made Sumertajaya	✓	✓			✓				✓	✓	✓	✓		✓
Agus Mohamad Soleh	✓	✓	✓						✓	✓		✓		✓
Dede Dirgahayu Domiri				✓		✓	✓		✓	✓	✓	✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this paper.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [HM], on request.

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BIOGRAPHIES OF AUTHORS

Hengki Muradi is a researcher at data and information science research center of Indonesia's National Research and Innovation Agency. The research topic is related to developing machine learning methods for modeling and classification for modeling rice growth phases. He is a first-degree graduate of the FMIPA mathematics study program at the University of Bengkulu and a second-degree graduate of the FMIPA mathematics master's program at the University of Indonesia. He has recently completed his doctoral program in Statistics and Data Science at IPB University. He can be contacted at email: hengkimuradis3@gmail.com.

Asep Saefuddin is a Professor of Statistics at the Department of Statistics, School of Data Science, Mathematics, and Informatics, IPB University, Bogor. He completed his undergraduate education at the Statistics Department of IPB, undergraduate education at the master program of the Biostatistics Guelph University of Canada, and undergraduate education at the doctoral program of the Biostatistics Guelph University of Canada. He has expertise in biostatistics, quantitative genetics, and research methods. He has published hundreds of papers in national and international journals of global repute. He can be contacted at email: asaefuddin@gmail.com.

I Made Sumertajaya is Professor at the Department of Statistics, School of Data Science, Mathematics, and Informatics, IPB University, Bogor. He completed his undergraduate and postgraduate education at the Statistics Department IPB. He has expertise in experiment design, statistical modelling, and multivariate analysis. He has published dozens of papers in national and international journals of global repute. He can be contacted at email: imsjaya.stk@gmail.com.

Agus Mohamad Soleh is an Assistant Professor at the Department of Statistics, School of Data Science, Mathematics, and Informatics, IPB University, Bogor. He completed his undergraduate education in the Statistics study program of IPB Bogor, undergraduate education in the Master of Informatics study program of Bandung Institute of Technology, and undergraduate education in the doctoral study program of statistics at IPB. He has expertise in computational statistics and data management. His research interests include machine learning, statistical computation, and statistical modelling He can be contacted at email: agusms@apps.ipb.ac.id.

Dede Dirgahayu Domiri is a researcher of remote sensing and GIS at the Geoinformatics Research Center of the National Research and Innovation Agency. The research focuses on the use of remote sensing data for monitoring rice and plantation phases. He completed undergraduate education majoring in agrometeorology, Faculty of Mathematics and Natural Sciences, IPB. His master's education in land evaluation, soil science, and doctoral program in the Natural Resources & Environment Management Study Program was completed at the IPB. He can be contacted at email: dede004@brin.go.id.