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PERFORMANCE EVALUATION OF 7TH GRADE STUDENTS FOR SOCIAL SCIENCE EDUCATION (IPS) UTILISING SUPPORT VECTOR MACHINE (SVM) METHOD

Jatim Kristina[1*)], Puguh Hiskiawan[2)]
[1)]Social Sciences Teacher, SMP Negeri 3 Jember, Indonesia
[2)]Earth Sciences Department, National Central University (NCU), Taiwan

Abstrak: Dalam penelitian ini, metode Support Vector Machine (SVM) digunakan untuk memprediksi kinerja ilmu pengetahuan sosial (IPS) kelas 7 pada tingkat lanjutan berikutnya dan untuk menggambarkan evaluasi rencana pengajaran yang sedang berlangsung bagi guru kelas 7. Model dataset dibangun untuk 192 siswa, yang terdiri dari kognitif dan psikomotor formatif Dataset mengacu pada tiga kategori klasifikasi (Layak, Cakap, dan Mahir) yang digunakan dalam algoritma komputasi untuk pemrosesan menggunakan linear dan non-linear. (Polynomial and gaussian). Hasil penilaian kinerja model SVM memperoleh akurasi (ACC) kinerja 84% (linear), 80% untuk polinomial, dan gaussian (90%). Penilaian *Mathew Correlation Coefficient* (MCC) menggambarkan validasi performansi; 47% untuk linear, 40% dan 20% untuk polynomial dan gaussians. Kesimpulannya bahwa kinerja siswa dapat mengikuti pembelajaran secara optimal di tingkat berikutnya, sementara guru dapat mereplikasikan proses belajar untuk kelas 7 pada ruang kelas di masa depan.
Kata kunci: Support Vector Machine Method, Kelas 7, Ilmu Pengetahuan Sosial

Abstract: In this study, a Support Vector Machine (SVM) method was utilized to predict the 7th grade performance of social science education (IPS) within the following advanced levels and to delineated an evaluation of ongoing teaching plans for 7th grade teachers. The model dataset was built for 192 students, consisting of cognitive and psychomotor formative The dataset refers to three classification categories (Adequate, Qualified, and Skilled) employed in computational algorithms for processing using linear and non-linear (polynomial and gaussian). The SVM model performance evaluation results obtained a performance accuracy (ACC) of 84% (linear), 75% for polynomials, and gaussians (90%), respectively. The *Mathew Correlation Coefficient* (MCC) evaluation described a validated performance of 47% for linear, 40% and 20% for polynomial and gaussians, respectively. In conclusion, student performances can follow the learning optimally at the next level, while teachers can replicate the learning process for 7th grade in future classrooms.
Keywords: Metode *Support Vector Machine, 7th grade, social science education*

A. INTRODUCTION

Primary secondary education serves as an organizer of academic education for students who have completed primary school and are expected to be able to manage quality education to produce knowledgeable, skilled, and creative human resources to support the sustainability of primary to higher education in order to achieve national development (Campbell et al., 2021; Kulgemeyer et al., 2020). The teaching and learning process is deemed successful if it is carried out properly and efficiently and the national education objectives have been met. A student's success or achievement in their learning is frequently considered the success and

*) Correspondence address :
e-mail : jatimkristinamu@gmail.com

greatness of all parties, including the instructor and the student; on the other hand, a student's failure or poor performance in their learning is a sign that the teacher is ineffective as a learning axis (Johnson et al., 2021). Continuous learning is the responsibility of the teacher to evaluate the performance of both students and the basis for future learning (Rolfes et al., 2022).

The foundation of in-depth learning activity observation is the teaching and learning process, which also ensures the success of learning at the following level (Cambra-Fierro et al., 2017). Therefore, a performance evaluation of the sustainability of the learning process for social studies courses at the junior high school level of the seventh grade is conducted in this study. Support vector machine (SVM)-based computer algorithms are used to assess the effectiveness of the learning process. The viability of a planned, systematic process for performance evaluation is the foundation for the choice of this approach. The dataset used to evaluate the outcomes of social studies learning activities was collected over the course of two semesters in the school year (2022–2023) for seventh graders at SMP Negeri 3 Jember.

The SVM method, a component of machine learning (ML), falls under the umbrella of artificial intelligence (AI). It is a well-liked method for evaluating predictions and has been widely adopted by working data scientists to forecast the degree of success in a sustainability process (El-Alfy & Abdel-Aal, 2008; Hilmiyah, 2017). The impact of dropouts is minimized in the realm of education by using SVM to predict student achievement (Nurhayati et al., 2015). Learning process to estimate the objectivity of the learning process performance from students' sentiment assessments of lecturers' lessons (Nugroho et al., 2023). Categorization determination for the purpose of allocating student scholarships, allowing beneficiaries to be evaluated for future performance (Lukman, 2016). Performance assessment using the SVM algorithm to forecast when students will graduate (Arifin & Sasongko, 2018). In addition to the sector of education, this ML technique is also applied to the classification of breast cancer patients in the field of health (Resmiati & Arifin, 2021). The SVM approach can be used to anticipate variations in children under the age of five's growth and development (Monika & Furqon, 2018).

Support vector machines are a technique for forecasting the document analysis process that is based on good dataset categorization and can be done supervised or unsupervised (Abbott, 2006; Mathur et al., 2016). Document organization can be accomplished by classifying them. The same category will be used to gather documents with similar content. In this approach, visitors seeking for information can quickly skip through categories that are irrelevant to what they're looking for or don't catch their attention (Rymarczyk, 2018; Sonoda & Murata, 2017). The Support Vector Machine was created in an effort to discover the optimum hyperplane—a function that theoretically separates two classes in the input space—for classification issues involving two groups of documents (as support vectors) (Buscombe & Ritchie, 2018). Data from two courses is shown in Figure 1. The negative class is marked by h_-, whereas the positive class is denoted by h_+. A circle is used to represent data in the negative class. Finding the hyperplane that divides the two groups is how the classification problem's learning process is transformed. Figure 1(a) depicts the alternate hyperplane borders, while Figure 1(b) demonstrates the existence of an ideal hyperplane that lies precisely between the two groups. The fundamental goal of this study is to identify the optimal hyperplane by limiting classification error and maximizing geometric margin, as shown in Figure 1(b) (Cuevas & Galvez, 2019).

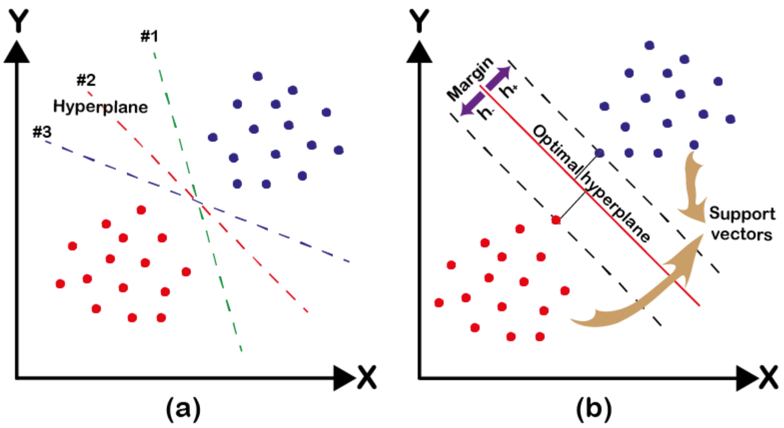

Figure 1. Support Vector Machine (SVM) Illustration (a) Hyperplane Division and (b) Hyperplane Analysis. Source: (personal doc,2023)

Support vector machine classifiers use a function or hyperplane to separate two classes of patterns. SVM tries to find the optimal hyperplane where the two pattern classes can be separated maximally (Kučak et al., 2018). A support vector machine requires merely one C parameter, the kernel parameter, to give a spin to a randomly classified data point. Therefore, the SVM has the weight (w) and the bias (b), which is the global optimum solution of quadratic programming, which is a mathematical formulation of the vector machine support algorithm. This guarantees that enough, once running, will produce a solution that will always be the same for the choice of the kernel and the same parameter (Delen, 2010).

The SVM method, which involves a training procedure, is referred to as a semi-eager learner's classification methodology. A support vector machine keeps a little amount of the training data for later use; some of the data that is still kept is a support vector. Whenever the same parameter is used for classification, support vector machines generate a classification model whose solution is global optimum, which means that support vector machines always availability the same model and solution with the greatest possible margin. The data used in the training process and the prediction are bigger than the real dimensions, which demands advanced training computing and prediction (Zabriskie et al., 2019). A large data set SVM required a significant quantity of memory for the allocation of the kernel matrix. The usage of the nucleus matrix has another advantage, notably the performance of data sets with large dimensions, but the quantity of data will be slightly faster as the size of the data in the new dimensions reduces significantly (Korkmaz & Correia, 2019).

In this study, linear and non-linear SVMs (polynomial and gaussian) were used. Linear SVM is a linear function where each dataset is expressed in terms of (*xi*, *yi*) in which *i* = 1,2, …, N and $x_i = \{x_{i1}, x_{i2}, \dots, x_{iq}\}^T$ is the feature attribute for the *i*-th class training dataset. By labeling {-1} for the first class and {+1} for the second class, then to predict all test datasets using the formula

$$y = \begin{cases} +1\ jika\ \ w.a + b\ > 0 \\ -1\ jika\ w.b + b < 0 \end{cases} \quad \dots \dots (1)$$

Where w = weight, a = hyperplane distance in the first-class outer dataset, and b = hyperplane distance in the second-class outer dataset. So that the hyperplane margin (d) is given between the two hyperplanes of the two classes, as follows (Vaculík et al., 2013):

$$\|w\|\ x\ d = 2\ atau\ d = \frac{2}{\|d\|} \dots \dots .(2)$$

As a result, the linear SVM function is based on K (*x*, *y*) = *x.y*, however the classification problem of most data samples is not linearly separated, therefore when a linear support vector machine is employed, the results obtained are not suitable and result in poor classification results. The kernel approach can be applied to transform a linear support vector machine into a non-linear support vector machine. The input data is transformed to a higher-dimensional feature space applying this method. It is expected that the input data mapped to the feature space will be linearly separated with the objective to determine the best hyperplane. This method is dissimilar from typical classification approaches, which minimize the initial dimension to simplify the computing process and improve prediction accuracy (Anguita et al., 2012). Polynomial nonlinear SVM $K(x, y) = (x.y + c)^d$ and a Gaussian RBF $K(x, y) = \exp\left(\frac{-\|x-y\|^2}{2.\sigma^2}\right)$ in which x, y are training dataset pairs and σ is a constant parameter.

This study is aimed at evaluating grade 7 students' semester-by-semester social science education so that the findings can be used to forecast social science education at the next level and also so that social studies teachers can use the study's findings as a foundation for future grade 7 learning. To consistently improve social science education, these issues must be addressed in great detail. In this study, the SVM approach was implemented utilizing three computational algorithmic methodologies. Gaussian SVM, polynomial SVM, and linear SVM are the three SVM approach methodologies. The three methods will be used as a point of reference and for comparison when looking at the dataset that was used to get findings in line with the support vector machine (SVM) method's performance evaluation (Ninaus et al., 2019; Pratama et al., 2018).

B. METHOD

B.1. DATASET PREPARATIONS

Datasets were collected employing classroom research procedures, particularly observation cycles. Two cycles of social studies (IPS) learning observation were conducted in this project, in the odd and even semesters of the 2022-2023 school year. The goal of implementing this strategy is to follow the 7th grade social studies (IPS) curriculum pattern, which includes systematic teaching and learning procedures. Two sorts of assessments are carried out each cycle or semester, namely cognitive assessment and psychomotor evaluation. Cognitive evaluation in the form of giving independent and group assignments to generate the transfer of knowledge from teachers to the students. Whereas psychomotor assessment fosters creativity and curiosity in social studies learning through skill exercises, the consequences of treatment and observation yield data for each individual student. The number of datasets perceived is 192 learners with an assortment of assessments, reaching more than 2000 datasets. The outcomes of student assessments are labelled as ADEQUATE, QUALIFIED, or SKILLED (Kulgemeyer et al., 2020; Obey Al Farobi, 2021). The ADEQUATE label indicates that students have adequate learning performance in acquiring learning, nevertheless the QUALIFIED label implies that students are capable to think critically in receiving social study education. Students in the SKILLED category showed uniqueness and a strong interest in social studies (Huang et al., 2011; Williams, 2021)

B.2. IMPLEMENTATIONS

The SVM method computational algorithm using linear and non-linear algorithm techniques (polynomial and gaussian) is implemented to carry out the research flowchart by comparing performance results through analysis and evaluation. Figure 2 depicts the research flow chart schematic.

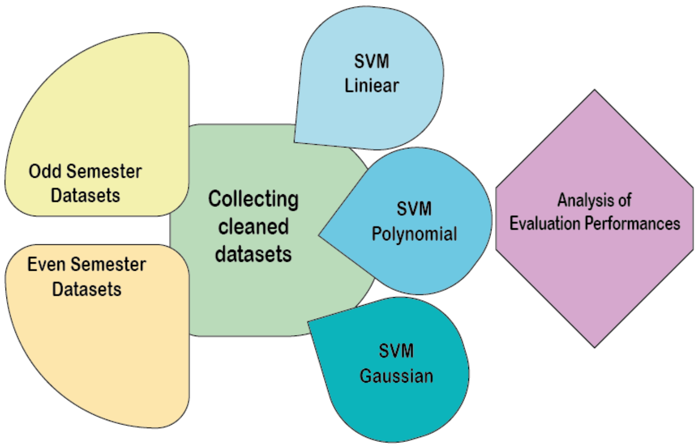

Figure 2. The research flowchart schematic. Source: (personal doc,2023)

Table 1. Confusion matrix research

	Actual Label		
Predicted Label	Adequate (A)	AQ	AS
	QA	Qualified (Q)	QS
	SA	SQ	Skilled (S)

Source: (Grandini et al., 2020)

A confusion matrix, which is a matrix configuration description that attempts to predict evaluation results based on agreed-upon class groupings, was implemented to analysis the results of SVM evaluation performances. Table 1 illustrates label groups for three classes (ADEQUATE (A), QUALIFIED (Q), and SKILLED (S)).

A skewed dataset set may result in inaccurate results and underrepresentation in the evaluation. Dataset design is for actual datasets; therefore, performance results need to be evaluated in order to demonstrate the configuration of the prediction labels. The accuracy score computes the percentage (default) or count (normalize=false) of correct predictions. The function returns the subset accuracy in multilabel classification. The subset accuracy is 1.0 if the entire set of predicted labels for a sample strictly matches the true set of labels; otherwise, it is 0.0, where $\hat{y}_i$ is the predicted value of the *i*-th sample and y_i is the corresponding value estimated over samples and L(x) is the indicator function (Krähenbühl & Koltun, 2011).

$$ACC\ (y,\ \hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} L(y_i - \hat{y}_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

The Mathew Correlation Coefficient (MCC) or phi coefficient (φ) can be deployed for assessing the quality of labels and can indicate the proportion of correct predictions between categories with judgements, where MCC is essentially a correlation coefficient value between {-1} and {+1}. A coefficient of {0} denotes flawless prediction, a coefficient of {+1} average random prediction, and a coefficient of {-1} inverse prediction (Chicco & Jurman, 2020).

$$MCC = \frac{c \times s - \sum_k^K p_k \times t_k}{\sqrt{(s^2 - \sum_k^K p_k^2) \times (s^2 - \sum_k^K t_k^2)}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Where $t_k = \sum_i^K C_{ik}$ is the number of times label *k* truly occurred, $p_k = \sum_i^K C_{ki}$ the number of times label k was predicted, $c = \sum_k^K C_{kk}$ the total number of datasets correctly predicted, and $s = \sum_i^K \sum_j^K C_{ij}$ the actual number of datasets. The dataset optimization characteristic curve, or receiver operating characteristic curve (ROC), is a graph that suggests the classification model's performance over all classification levels. A larger X-axis value in a ROC curve demonstrates a higher average number of predictions than expected. A higher Y-axis value indicates that the results are more absolute means than predicted. The ROC curve's evaluation performances are reported by employing micro and macro averages. The micro-average simply computes the mean of the multilabel metrics, giving each label equal weight. Micro-averaging may be utilized to highlight the performance of infrequent labels in problems where their contributions are still indispensable. The assumption that all labels are equally important, on the other hand, tends to be false, so micro-averaging will excessively emphasize the typically low performance of an infrequent class, whereas the macro-average of the ROC curve gives each dataset an equal contribution to the overall metric (except as a result of dataset weight). Instead of summing the metric per sample, this accumulates the dividends and divisors that comprise the per-dataset metrics to compute an overall quotient. In multilabel environments, such as multiclass classification, while a majority label is to be ignored, macro-averaging may be more appropriate (Fawcett, 2006).

This study utilizes Python 3.6 and TensorFlow 1.13.1 to run the programmed algorithms based on CUDA 10.0 and cu-DNN 7.5. Calculation of datasets use computer with specifications on i7-3.00 GHz and RTX 2080Ti.

C. RESULT AND DISCUSSION

C.1. RESULT

The evaluation of 7th grade social studies learning by computational algorithms using cognitive and pycnomorphic datasets with an immense quantity of data SVM incorporates both linear (no kernel) and non-linear (kernel) evaluation techniques, especially polynomial and gaussian and also accompanied with ACC and MCC values.

Table 2. Analysis evaluation performances utilize confusion matrix

Cycle:	SVM Technique:	A [%]	Q [%]	S [%]	A≡Q [%]	Q≡S [%]	S≡A [%]	ACC [%]	MCC [%]
Odd Sem	Linear	5.78	49.71	28.32	7.38	8.36	0.45	83.74	47.14
	Polynomial	4.05	55.49	13.87	16.24	16.24	2.12	80.43	40.27
	Gaussian	4.62	50.29	28.32	8.67	8.01	0.09	90.24	20.22
Even Sem	Linear	12.72	32.37	33.53	13.87	6.62	0.89	83.51	46.25
	Polynomial	10.40	34.10	30.06	16.18	7.24	2.02	79.85	39.72
	Gaussian	2.89	32.37	34.10	23.70	6.83	0.11	89.82	19.85

Source: (computational results, 2023)

The intention of measuring and observing this evaluation is to further clarify the confusion matrix and algorithm evaluation, which represents the distribution of multilabel denoting the performance of students in seventh grade at SMP Negeri 3 Jember, as shown in Table 2.

The ROC curve corresponds to the results of the performance evaluation analysis using the confusion matrix with the assessment of evaluation results using the ACC and MCC variables, demonstrating that the performance of grade 7 students in social studies learning for two learning cycles in the 2022-2023 school year can be observed and investigated by means of Figure 3 (Zimmer, 2022).

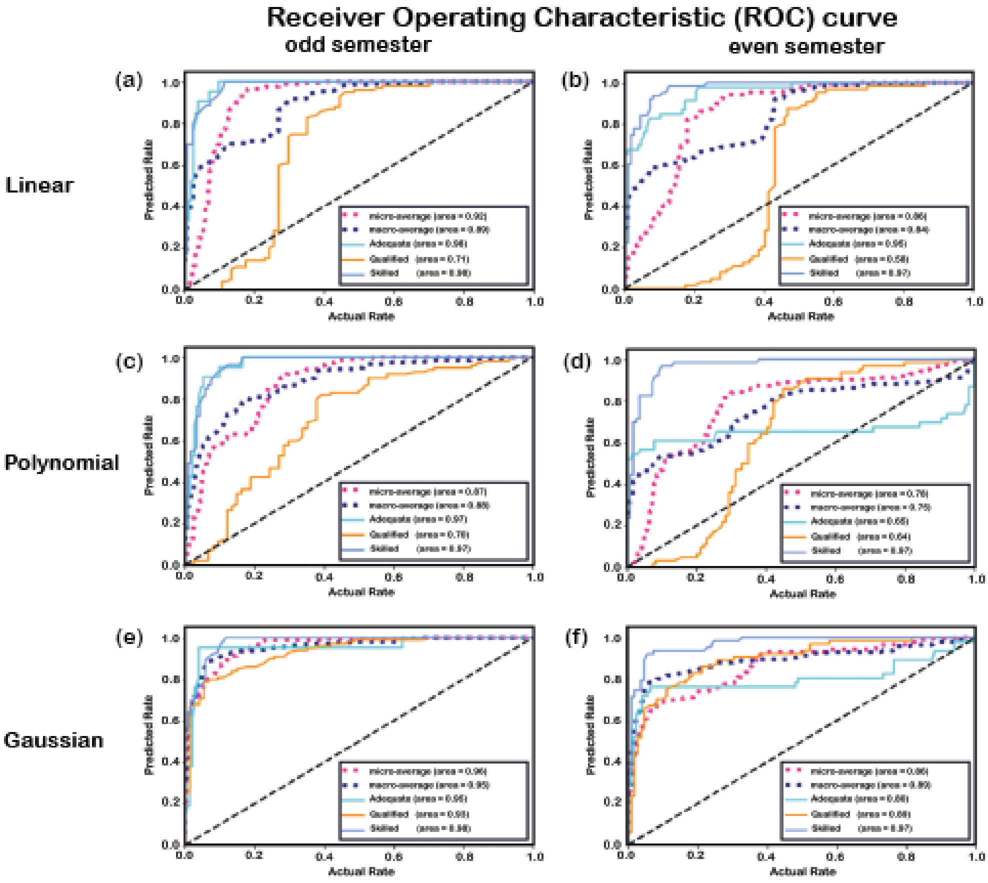

Figure 3. ROC curve observations for evaluation performances.
Source: (computational results,2023)

C.1. DISCUSSION

The accuracy value (ACC) obtained in the calculation and observation of the linear SVM algorithm is 84%, which is quite consistent with the results obtained, although not high, while the MCC gets a significant value slightly below 47%, which means that the evaluation results can be used as evaluation results (Grandini et al., 2020). In general, social studies learning in the odd semester is better than in the even semester (Fig. 3a), which is indicated by the smaller value of the adequate label; however, the achievement of students labelled as skilled in the even semester shows a better distribution than the odd semester (Fig. 3b).

The distribution characteristics of the 7th grade social studies education evaluation performance results of polynomial SVM have similarities with the performance results of linear SVM evaluation, but the accuracy value (ACC) of polynomial SVM is nearly 80% and MCC is achieved quite well at 40%, which is where the data distribution experiences ambiguity from non-linear increases that are linear in nature so that there is no curvature in the performance evaluation results (Cuevas & Galvez, 2019). Even semesters dominate the asynchronization of the dataset in the algorithmic process (Fig. 3e), whereas odd semesters generate results exhibiting variability in each label (Fig. 3c). Furthermore, it can be observed in the SVM polynomial ROC curve results that there is a disparity between the ROC curve results. In general, the SVM polynomial evaluation performance results have ambiguity in the final process of the dataset, but in the process of processing the dataset, the SVM polynomial conveys reliable findings based on the ACC and MCC results. This is due to the algorithm's stability in processing the dataset (Lary et al., 2018).

The results of measuring the performance of social studies learning adopting non-linear gaussian SVM are quite satisfactory, as the accuracy value (ACC) reaches 90% and MCC reaches 20%, or an increase of more than 20 points compared with the previous technique. The label distribution of social studies learning evaluation performance in grade 7 reveals significant improvements as compared to the odd semester. This is due to the gaussian SVM provide a more rigorous and integrated data concentration, resulting in good and clear data appropriateness (Zhang et al., 2019). The distribution results of the social studies learning performance evaluation, on the other hand, contradict the ROC curve, alongside the odd semester (Fig. 3e) demonstrating greater data consistency than the even semester (Fig. 3f). The situation in question is associated with a data distribution that is too near and tight. The micro and macro averages are more ultimate in the odd semester than in the even semester, but the curves reveal results that are in accordance with the performance evaluation of 7th grade social studies learning in general.

Overall, the findings of the performance of 7th grade social studies learning at SMP Negeri 3 Jember applying support vector machines (SVM) were appropriate. However, SVM Gaussian is better furnished to generate results that can be used continuously as part of recommendations for students to continue learning social studies at a higher level. Meanwhile, the gaussian SVM results can be used as a future reference for the 7th grade social studies learning pattern.

D. CONCLUSION

The results of research and discussion show good results and can be used properly as a performance evaluation of 7th grade social studies learning. The results of linear SVM have provided results in accordance with polynomial SVM, while gaussian SVM has improved performance evaluation results. The gaussian SVM has succeeded in increasing the accuracy (ACC) by 20 points from both the SVM and MCC by 20%.

Recommendations based on the findings of the evaluation of social studies learning using the SVM learning method show that students can progress to the next level of social studies learning. Those on the label ADEQUATE, on the other hand, receive a comprehensive record, those on the label QUALIFIED, a motivational message, and those on the label SKILLED, additional admiration. SVM evaluation findings for social studies teachers in 7th grade can be used as a beginning point and reference for future teaching patterns in social studies in grade 7.

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