

Estimation of biomass of forage sorghum (*sorghum bicolor*) Cv. Samurai-2 using support vector regression

Kahfi Heryandi Suradiradja¹, Imas Sukaesih Sitanggang¹, Luki Abdullah², Irman Hermadi¹

¹Department of Computer Science, Faculty of Mathematics and Natural Science, IPB University, Bogor, Indonesia

²Department of Nutrition and Feed Technology, Faculty of Animal Science, IPB University, Bogor, Indonesia

Article Info

Article history:

Received Aug 15, 2022

Revised Feb 13, 2023

Accepted Feb 20, 2023

Keywords:

Estimated production

Forage sorghum

Machine learning

Sorghum bicolor

Support vector regression

ABSTRACT

One alternative to improve feed quality is to combine the main feed with forages which are more economical in cost but contain high protein sources, such as sorghum. Production estimation is essential because it will determine the sustainability of the feed. This study aimed to estimate the amount of sorghum production using support vector regression (SVR). Several stages of this research are collecting data, preprocessing, modelling, and evaluation. The dataset used and the input for this SVR algorithm model is field observation data. The kernels used in the SVR algorithm modelling are linear, Polynomial, and RBF. Sorghum production estimation using SVR has a performance evaluation value that refers to the root mean square error (RMSE). The result of this research is that the model obtained from the SVR algorithm can estimate sorghum production with performance evaluation values using R², mean absolute error (MAE), mean absolute percentage error (MAPE), and RMSE. The best results on the Polynomial kernel are R²=0.7841, MAE=0.0681, MAPE=0.46641, and RMSE=0.1006. This study shows that the classification model obtained from the SVR algorithm with Kernel Polynomial is the best model for estimating sorghum production.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



Corresponding Author:

Kahfi Heryandi Suradiradja

Department of Computer Science, Faculty of Mathematics and Natural Sciences, IPB University

Street of Agatis, Campus IPB Darmaga Bogor 16680, Indonesia

Email: kahfi.heryandi@apps.ipb.ac.id

1. INTRODUCTION

In the livestock industry, a significant concern is the availability of land, livestock and feed. The main feed for the livestock industry is grass, but the grass has high fibre and low protein content for livestock. The grass needs to be mixed with concentrates such as dregs, corn, and other similar foods to add nutritional value to the feed. It will cause production costs to increase. Abdullah and Suharlina [1], an alternative source of high forage protein but at an economical cost is to combine the main feed with types of legumes such as sorghum. Sorghum has been introduced and cultivated in Indonesia, particularly in dry and marginal areas [2], and it is a universal multipurpose crop for food, fodder, and potential biofuel feedstock [3].

The problem in this study is that to estimate the production of feed biomass for ruminants is sufficient or more or less as a feed production material to combine forage with the main feed. Therefore it is necessary to estimate the biomass of sorghum yields. In the industrial era 4.0, information technology has become necessary in various fields, including agriculture and animal husbandry. One of the uses of this information technology is the application of machine learning algorithm models, namely computer programming to optimize performance using history data [4]. Liakos *et al.* [5], in general, the machine learning methodology involves a learning process to learn from training data in carrying out tasks. It is stated by Ghosal *et al.* [6] in the national strategy for artificial intelligence in Indonesia that increasing forecasting accuracy with machine

learning will help farmers plan agricultural cycle activities. Several previous studies by BPPT [7] and Masjedi *et al.* [8] used machine learning algorithms for research on sorghum plants. Several studies related to predictions in agriculture and animal husbandry are wheat yield prediction [9], crop disease prediction [10] and [11]. One widely used algorithm for forecasting or predicting target values is the support vector machine (SVM), for example, in the medical field [12], analogue circuit [13], education [14], face recognition [15] and also in the agriculture [16]. For solving the SVM regression case, it is modified to the support vector regression (SVR) algorithm [17]. SVR aims to find a hyperplane to predict the training data set and the optimal value of the parameters obtained through the GridSearch method. The grid search method tests a model to find the error value in the classification [18]. The parameters determined by the optimal value are epsilon (ϵ), cost (C), and gamma (γ). In the SVR method, several choices of kernel functions can be used, such as linear, Gaussian, Polynomial, and several other kernels. SVR builds a hyperplane in high dimensional space in linear or nonlinear data and can overcome overfitting [19]. Several studies using SVR in agriculture and animal husbandry, such as soil erosion susceptibility prediction [20], predicting forage quality of warm-season legumes [21], crop model of rice production [22], Water stress detection [23] and also Rumex and Urtica detection in grasslands [24]. In this study, it is hoped that the machine learning SVR algorithm models will be widely used to predict or estimate the amount of sorghum biomass production. This study will look for the best kernel function of the three kernels and the best parameters using the GridSearch method from the SVR model to estimate the biomass of animal feed sorghum production.

2. METHOD

This research methodology has five stages: a preliminary study, data collection, preprocessing, modelling, and model evaluation. Each step in this research flow cycle diagram is as shown in the research flow chart Figure 1. The explanation of each stage of this research carried out is as:

- Data collection: This study uses the sample data taken from direct observations in the sorghum field in the sorghum bicolor block cv. Samurai-2. The research area is Jonggol Animal Science Teaching and Research Unit (JASTRU), Singasari Village, Jonggol District, Bogor City. The dataset was taken at harvest time on March 8, 2021, with as many as 88 plant data with attributes shown in Table 1 and sample data from the field shown in Table 2.

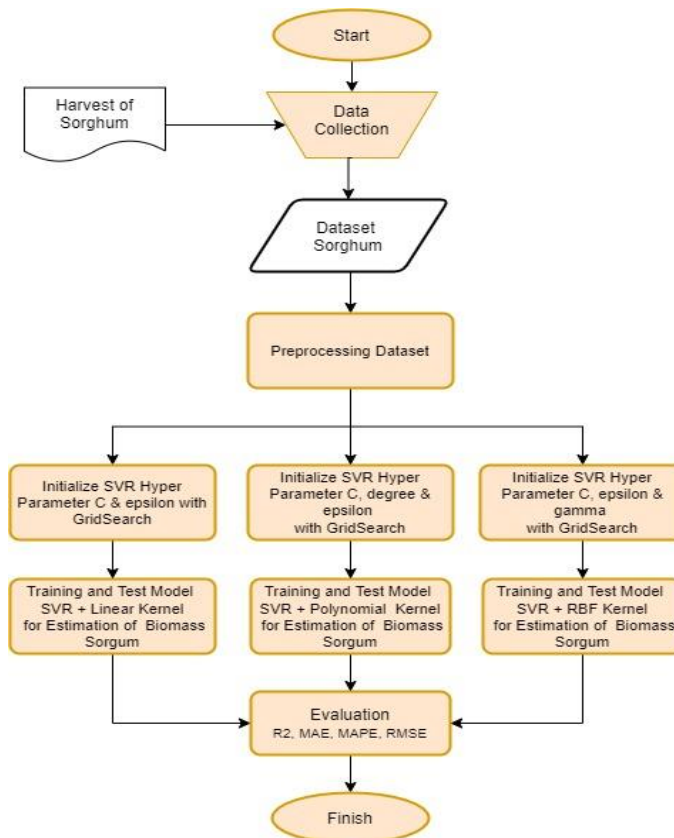


Figure 1. Research steps

Table 1. Dataset sorghum of bicolor cv Samurai-2

No sample	Latitude	Longitude	Stem height	Stem diameter	Leaves	Seed height	Seed width	Biomass
6	-6.46875233	107.01083981	170	14	9	19	4	204
12	-6.46885800	107.01121700	224	25	15	24	5	677
18	-6.46867571	107.01117843	125	11	10	22	4	147
27	-6.46846183	107.01120257	219	16	10	27	7	291
38	-6.46855311	107.01108322	219	23	11	32	9	574
39	-6.46838988	107.01111775	217	20	12	25	5	381
42	-6.46840753	107.01109931	177	19	11	19	4	341
43	-6.46847116	107.01105975	219	20	10	28	6	480
44	-6.46856444	107.01105069	150	15	10	18	3	156
47	-6.46861375	107.01098096	232	19	11	29	6	306
48	-6.46849082	107.01104090	234	22	12	30	8	554
50	-6.46826595	107.01107886	164	15	9	26	5	231
52	-6.46839654	107.01091088	215	16	13	26	5	271
...

Table 2. Attribute dataset sorghum of bicolor cv Samurai-2

No	Attribute	Description
1	NO_SAMPLE	No samples, A and B indicate growing two plant stems in one plant location
2	LATITUDE	Latitude
3	LONGITUDE	Longitude
4	STEM_HEIGHT	Plant stem height in meters
5	STEM_DIAMETER	Plant stem diameter in millimeters
6	LEAVE	Number of leaves
7	SEED_HEIGHT	Sorghum seed length in centimeters
8	SEED_WIDTH	Sorghum seed width in centimeters
9	BIOMASS	Overall weight in grams (target class)

- Preprocess: The attributes of the dataset from field obtained recording as shown in Table 1. The target attribute is WEIGHT, which is the plant's total weight (gram). All selected features are normalized between 0 and 1 before input into the SVR algorithm model.
- Modeling: At this stage, the preprocessed dataset will be input into each SVR algorithm with a different kernel function, namely the SVR algorithm with a linear kernel function, the SVR algorithm with a gaussian kernel function, and the SVR algorithm with a polynomial kernel function. Several parameter values are identified to produce the best results from each kernel function in the modelling and evaluation process. The model validation process uses k-fold cross validation.
- Evaluation: This stage is the output of the modelling process using the validation process. That is to compare actual and predicted values with a low error rate from every kernel function of the SVR. That model selected will be recommended for the prediction of sorghum production. Validation of all kernel functions is using R-Squared, mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE). The achievement of this final stage indicator is that the resulting model has a minimum error value.

3. RESULTS AND DISCUSSION

Data correlation analysis on dataset attributes from collecting selected sorghum research sample data at harvest time, namely STEM_HEIGHT, STEM_DIAMETER, LEAVE, SEED_HEIGHT, SEED_WIDTH, and BIOMASS, there is very high correlation data. Also, data with weak correlation and visually correlation data between these attributes are shown in Figure 2. The highest data correlation was on the seed or panicle width attribute (seed_width) with the seed or panicle length attribute (seed_height), which was 0.92. The number of leaves (leaves) with a length is a weak correlation of a collection of seeds or panicles (seed_height) of 0.35. The preprocessing, modelling, and evaluation stages are carried out using the Python 3.7 programming language. Python using the skit-learn library and several main class packages for vector regression and cross-validation.

In the preprocessing stage, scalar normalization was carried out to convert the value proportionally in each attribute between 0 to 1. The preprocessed dataset is the input of the SVR algorithm with a vector regression package at the modelling stage. The output of the modelling process is validated, and the results are evaluated at the evaluation stage. The standard value of a suitable validation parameter in using the cross-validation method specified to determine accuracy is ten times [25]. The SVR model will construct a hyperplane in high dimensional space in the nonlinear data shown in (1).

$$f(x_i) = (w \cdot x_i) + b \tag{1}$$

Where:

$f(x)$ = predictive value

x = data

w = weight

b = bias value, (also represented by λ)

Estimation for the coefficients w and b through the risk function and with $|w|$ as the normalization of the function to minimize it to produce a function close to flat, E_ϵ is an ϵ -insensitive loss function. The coefficient C value is defined by the user (trade-off) between the thin distance of the f function and the value above the upper limit deviation, which can still be tolerated as shown in (2) [26].

$$R(f(x_i)) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n E_\epsilon(y_i - f(x_i)) \tag{2}$$

$$f(x_i) = \sum_{i \in R} (\alpha_i - \alpha_i^*) K(x_i, x) + b \tag{3}$$

Smola and Schölkopf [27] from (2), determining the parameters w and b become an optimization problem using the Lagrangian. The final equation for determining predictions with SVR is shown in (3), where are the Lagrange multiplier and the selected kernel function. Several kernel functions to handle nonlinear data cases are often used in SVR models, such as linear kernel in (4), polynomial kernel in (5), and Gaussian or Gaussian radial basis function (RBF) kernel in (6).

$$K(x_i, x) = (x, x') \tag{4}$$

$$K(x_i, x) = (\gamma < x, x' > + r)^d \tag{5}$$

Where d is the degree parameter and r is the coefficient.

$$K(x_i, x) = \exp(-\gamma \|x - x'\|^2) \tag{6}$$

Where is the gamma parameter must be greater than 0.

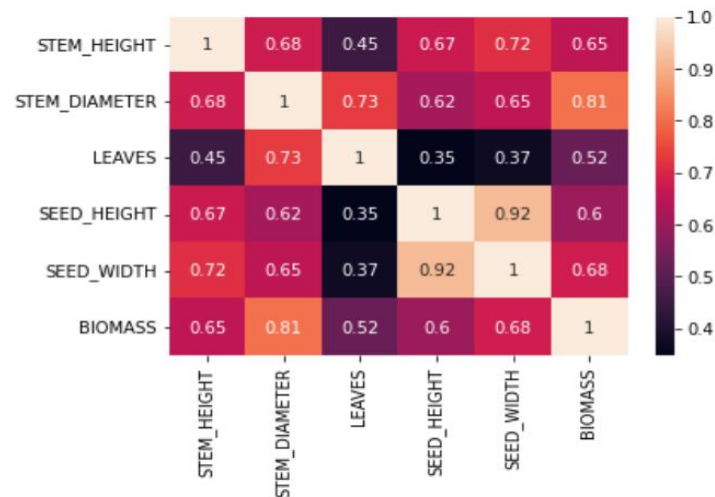


Figure 2. Dataset correlation

The complete grid search process time is very long. Therefore, Hsu and Lin [18] recommends performing the grid search through the loose grid stage for selecting C and values, then proceeding with the finer grid stage to get a value around the C value that has been obtained with the lowest error value previously. The search for parameters C and epsilon on the SVR model in each kernel is done using GridSearch with a combination of parameter values tested, namely $C = 0.01, 0.1, 1, 100, 1000$ and epsilon parameters = $0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10$.

The modelling process with a linear kernel obtained the best parameters for C and epsilon through the GridSearch method were C=1 and epsilon=0.0005, resulting in predictive values compared to real or actual values, as the example shown in Table 3, and graphically visualization is shown in Figure 3. Then the modelling process with a polynomial kernel obtained the best parameters for C, degree, and epsilon through the GridSearch method were C=1, degree=2, and epsilon=0.001, which resulted in predictive values compared to real or actual values as the example shown in Table 4, and graphically visualization is shown in Figure 4.

Table 3. Real data vs. linear predicted biomass

Real/Actual	Linear predicted
0.6251	0.5577
0.2691	0.3145
0.2912	0.4388
...	...
0.4714	0.4446

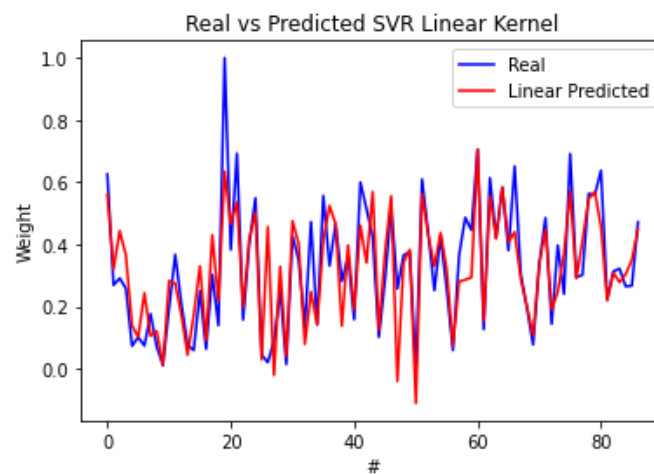


Figure 3. Graph of real data vs. linear predicted biomass

Table 4. Real data vs. polynomial predicted biomass

Real/Actual	Polynomial Predicted
0,6251	0,5725
0,2691	0,2869
0,2912	0,4175
...	...
0,4714	0,4734

Furthermore, the modelling process with the RBF kernel obtained the best parameters for C, epsilon, and gamma through the GridSearch method were C=100, epsilon=0.01, and gamma=0.1, which resulted in prediction values compared to real or actual values as the example shown in Table 5 and graphically visualization is shown in Figure 5.

Table 5. Real data vs. linear Gaussian RBF biomass

Real/Actual	RBF Predicted
0.6251	0.5813
0.2691	0.2846
0.2912	0.3591
...	...
0.4714	0.4767

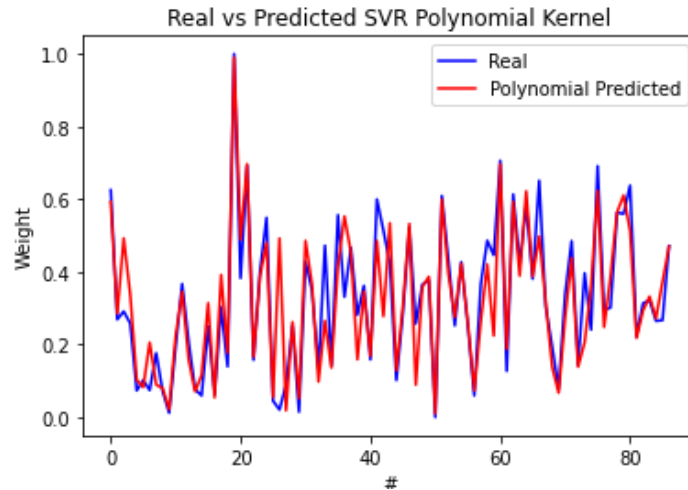


Figure 4. Graph of real data vs. polynomial predicted biomass

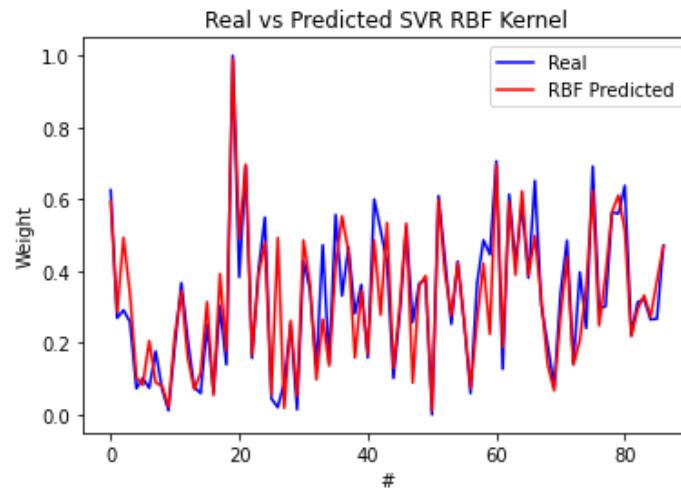


Figure 5. Graph real data vs Gaussian RBF predicted biomass

Measurement of accuracy and measurement of the error value between the predicted value and the real or actual value at the evaluation stage for each model result for each kernel uses the R-squared accuracy measurement method in (7) [28].

$$R^2 = 1 - \frac{SSE}{SSEM} \tag{7}$$

Meanwhile, for measuring the error value between the predicted value and the real or actual value at the evaluation stage for each model result, each kernel uses the MAE error measurement method [29] in (8), MAPE in (9), and RMSE in n (10) [28].

$$MAE = \frac{1}{n} \sum_{i=1}^n (y^{\wedge} - y) \tag{8}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n (y^{\wedge} - y) \times 100 \tag{9}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y^{\wedge} - y)^2} \tag{10}$$

The predicted value and the real or actual value of the modelling results from each kernel are entered into the MAE, MAPE, and RMSE measurement equations to produce error measurement values, shown in Table 6.

Table 6. Metric comparison result

	Linear Kernel	Polynomial Kernel	Gaussian RBF Kernel
R-squared	0.6861	0.7841	0.7751
MAE	0.0836	0.0681	0.0715
RMSE	0.1173	0.1006	0.1055
MAPE	55.1891	46.641	48.7648

SVR with Polynomial Kernel has the smallest MAE, MAPE, and RMSE error measurements compared to the linear kernel and the Gaussian RBF kernel. Likewise, with the R-squared value of the polynomial kernel compared to the linear kernel and Gaussian kernel, the polynomial kernel has the largest R-squared value, so based on the research that has been done that the Polynomial Kernel is a good Kernel on the SVR method for estimating the production of forage sorghum (sorghum bicolor) cv. Samurai-2.

4. CONCLUSION

In this study, to obtain an SVR model for estimating the biomass of animal feed sorghum, we tried the SVR model with a combination of linear kernel, polynomial kernel, and gaussian RBF kernel. Each of our kernels looks for the best parameters using the GridSearch method function. The result is that the SVR model using the Polynomial Kernel kernel function with parameters $C=1$, $\text{degree}=2$, and $\text{epsilon}=0.001$ has the lowest error value and the highest coefficient of determination. Thus, SVR with a polynomial kernel function can be recommended to estimate the biomass of sorghum bicolor cv Samurai-2. The prospect of developing research results and implementing further research in the future can use other kernels such as Splines, B-Splines, and others.

ACKNOWLEDGEMENTS

We want to thank the Ministry of Research and Technology/National Research and Innovation Agency for funding this research through funding for doctoral dissertation research according to contract number 1/E1/KP.PTNBH/2021, dated March 8, 2021, and RISPRO LPDP Ministry of Finance in supplying sorghum plants as research objects.




REFERENCES

- [1] L. Abdullah and Suharlina, "Herbage yield and quality of two vegetative parts of indigofera at different times of first regrowth defoliation," *Media Peternakan*, vol. 33, no. 1, pp. 44–49, 2010, doi: 10.5398/medpet.v33i1.1246.
- [2] D. Astuti, B. Suhartanto, N. Umami, and A. Irawan, "Productivity, nutrient composition, and hydrocyanic acid concentration of Super-2 forage sorghum at different NPK levels and planting spaces," *Tropical Animal Science Journal*, vol. 42, no. 3, pp. 189–195, Dec. 2019, doi: 10.5398/tasj.2019.42.3.189.
- [3] P. S. Rao, C. G. Kumar, B. V. S. Reddy, A. B. V. S. Reddy, P. S. Rao, and C. G. Kumar, *Characterization of Improved Sweet Sorghum Cultivars*. India: Springer India, 2013.
- [4] E. Alpaydin, *Introduction to Machine Learning*, 2nd ed. The MIT Press, 2009.
- [5] K. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: a review," *Sensors*, vol. 18, no. 8, p. 2674, Aug. 2018, doi: 10.3390/s18082674.
- [6] S. Ghosal *et al.*, "A Weakly Supervised deep learning framework for sorghum head detection and counting," *Plant Phenomics*, vol. 2019, Jan. 2019, doi: 10.34133/2019/1525874.
- [7] BPPT, "Indonesia's artificial intelligence national strategy 2020-2045" (in Indonesian). [Online]. Available: <https://ai-innovation.id/server/static/ebook/stranas-ka.pdf>.
- [8] A. Masjedi, N. R. Carpenter, M. M. Crawford, and M. R. Tuinstra, "Prediction of sorghum biomass using uav time series data and recurrent neural networks," in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, Jun. 2019, vol. 2019-June, pp. 2695–2702, doi: 10.1109/CVPRW.2019.00327.
- [9] X. E. Pantazi, D. Moshou, T. Alexandridis, R. L. Whetton, and A. M. Mouazen, "Wheat yield prediction using machine learning and advanced sensing techniques," *Computers and Electronics in Agriculture*, vol. 121, pp. 57–65, Feb. 2016, doi: 10.1016/j.compag.2015.11.018.
- [10] A. S. C. D. S. Mokashi and P.M.Ghodke, "Crop disease prediction using data mining method," *Ijirmps*, vol. 6, no. 5, pp. 2014–2015, 2018.
- [11] U. Ayub and S. A. Moqurrab, "Predicting crop diseases using data mining approaches: Classification," *Proceedings - 2018, IEEE 1st International Conference on Power, Energy and Smart Grid, ICPESG 2018*, pp. 1–6, 2018, doi: 10.1109/ICPESG.2018.8384523.
- [12] N. M. Ali, N. A. A. Aziz, and R. Besar, "Comparison of microarray breast cancer classification using support vector machine and logistic regression with LASSO and boruta feature selection," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 20, no. 2, p. 712, Nov. 2020, doi: 10.11591/ijeecs.v20.i2.pp712-719.




- [13] B. S. Patro and S. K. Mandal, "A multi output formulation for analog circuits using MOM-SVM," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 7, no. 1, pp. 90–96, Jul. 2017, doi: 10.11591/ijeecs.v7.i1.pp90-96.
- [14] O. C.-Atalaya *et al.*, "Quadratic vector support machine algorithm, applied to prediction of university student satisfaction," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 27, no. 1, p. 139, Jul. 2022, doi: 10.11591/ijeecs.v27.i1.pp139-148.
- [15] C. Annubaha, A. P. Widodo, and K. Adi, "Implementation of eigenface method and support vector machine for face recognition absence information system," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 26, no. 3, p. 1624, Jun. 2022, doi: 10.11591/ijeecs.v26.i3.pp1624-1633.
- [16] N. S. B. M. Said, H. Madzin, S. K. Ali, and N. S. Beng, "Comparison of color-based feature extraction methods in banana leaf diseases classification using SVM and K-NN," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 24, no. 3, pp. 1523–1533, 2021, doi: 10.11591/ijeecs.v24.i3.pp1523-1533.
- [17] B. E. Boser, V. N. Vapnik, and I. M. Guyon, "Training algorithm margin for optimal classifiers," *Perception*, pp. 144–152, 1992.
- [18] C.-C. C. C.-W. Hsu and C.-J. Lin, "A practical guide to support vector classification," *BJU international*, vol. 101, no. 1, pp. 1396–1400, 2008, [Online]. Available: <http://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf>.
- [19] A. K. Lagat, "Support vector regression and artificial neural network approaches: case of economic growth in East Africa community," *American Journal of Theoretical and Applied Statistics*, vol. 7, no. 2, p. 67, 2018, doi: 10.11648/j.ajtas.20180702.13.
- [20] T. V. Dinh, H. Nguyen, X.-L. Tran, and N.-D. Hoang, "Predicting rainfall-induced soil erosion based on a hybridization of adaptive differential evolution and support vector machine classification," *Mathematical Problems in Engineering*, vol. 2021, pp. 1–20, Feb. 2021, doi: 10.1155/2021/6647829.
- [21] G. S. Baath *et al.*, "Predicting forage quality of warm-season legumes by near infrared spectroscopy coupled with machine learning techniques," *Sensors*, vol. 20, no. 3, p. 867, Feb. 2020, doi: 10.3390/s20030867.
- [22] Y. Su, H. Xu, and L. Yan, "Support vector machine-based open crop model (SBOCM): Case of rice production in China," *Saudi Journal of Biological Sciences*, vol. 24, no. 3, pp. 537–547, Mar. 2017, doi: 10.1016/j.sjbs.2017.01.024.
- [23] D. Moshou, X.-E. Pantazi, D. Kateris, and I. Gravalos, "Water stress detection based on optical multisensor fusion with a least squares support vector machine classifier," *Biosystems Engineering*, vol. 117, no. 1, pp. 15–22, Jan. 2014, doi: 10.1016/j.biosystemseng.2013.07.008.
- [24] A. Binch and C. W. Fox, "Controlled comparison of machine vision algorithms for Rumex and Urtica detection in grassland," *Computers and Electronics in Agriculture*, vol. 140, pp. 123–138, Aug. 2017, doi: 10.1016/j.compag.2017.05.018.
- [25] I. H. Witten, E. Frank, and M. A. Hall, *Data Mining: practical machine learning tools and techniques*. Elsevier, 2011, doi: 10.1016/C2009-0-19715-5.
- [26] S. Haykin, "Neural networks and learning machines," *Pearson Prentice Hall New Jersey USA 936 pLinks*, vol. 3, p. 906, 2008, doi: 978-0131471399.
- [27] A. J. Smola and B. Schölkopf, "A tutorial on support vector regression," *Statistics and Computing*, vol. 14, no. 3, pp. 199–222, Aug. 2004, doi: 10.1023/B:STCO.0000035301.49549.88.
- [28] J. S. Damji, B. Wenig, T. Das, and D. Lee, *Learning Spark: Lightning-Fast Data Analytics*, 2nd editio. O'Reilly Media, 2020.
- [29] A. Jierula, S. Wang, T. M. Oh, and P. Wang, "Study on accuracy metrics for evaluating the predictions of damage locations in deep piles using artificial neural networks with acoustic emission data," *Applied Sciences (Switzerland)*, vol. 11, no. 5, pp. 1–21, Mar. 2021, doi: 10.3390/app11052314.

BIOGRAPHIES OF AUTHORS






Kahfi Heryandi Suradiradja    completed an Associate Degree in information technology from the Bandung Institute of Technology Polytechnic, a bachelor's degree in Computer Science from Padjadjaran University, a master's degree in Software Engineering from Eresha (Pamulang University) and is currently pursuing a doctoral degree in Computer Science at IPB University. He has handled various projects in the fields of telecommunications, banking, mining and government. He has also served as a technical consultant at Sybase Inc, Indonesian Subsidiary, software engineers at SDI Tech, general manager R&D at PT. Collega Inti Pratama (Telkom Group), technical director at PT. Fortuna Mediatama and finally CEO and founder at PT. Mahardika Caraka Indonesia. His research interests include machine learning and intelligent systems. He can be contacted at email: kahfi.heryandi@apps.ipb.ac.id.






Imas Sukaesih Sitanggang    is a Professor at IPB University. He holds a doctoral degree in Computer Science, a master's degree in Computer Science at the University of Indonesia and a bachelor's degree in Computer Science at IPB University. His research areas are in the fields of data mining, data warehousing and spatial data processing. He is the recipient of an award from the Coordinating Ministry for Political, Legal and Security Affairs of the Republic of Indonesia for his innovations in developing the application of the Forest and Land Fire Prevention Patrol Information System in Indonesia. She can be contacted at email: imas.sitanggang@apps.ipb.ac.id.



Luki Abdullah    is a Professor at IPB University, his highest study is a doctor degree in plant nutrition expertise at the University of Gottingen, Germany and also a Master of Science Agriculture in the field of forage plant science also at the University of Gottingen, Germany and a bachelor's degree in animal nutrition at IPB University. He served as Dean of the Faculty of Animal Husbandry, Bogor Agricultural University (IPB) for two consecutive periods, namely the period 2007-2011 and 2011-2015. His research results are many in the fields of animal nutrition, feed crop science, and livestock plant nutrition which are included in the Innovation Indonesia's Most Prospective version of the Bussiness Innovation Center supported by the Ministry of Research and Technology of the Republic of Indonesia. The results of his research are quite popular and are widely published in the mass media, especially related to Indigofera feed. He is also trusted as Secretary General of the Indonesian Animal Husbandry Higher Education Leadership Forum (FPPTPI) for the period 2011-2014. In the professional field, he was one of the founders and was the General Chair of the Indonesian Animal Feed Plant Scientists Association (HITPI) which was founded in 2011 in Bali. He can be contacted at email: labdull@apps.ipb.ac.id@apps.ipb.ac.id.



Irman Hermadi    completed his bachelor's degree in Computer Science from IPB University, master's degree from King Fahd University of Petroleum & Minerals and doctoral degree at The University of New South Wales. He has over 22 years of academic, research, and professional experience in the field of computer science, specifically in computational intelligence, software engineering, software testing, information system, knowledge management system, and information technology/system audit. He has been delivering various lectures, conducting research, and supervising research (undergraduate, master, and doctoral students) in these areas, and provided several industrial-scale professional consultations on information and communication technology (ICT) projects. My involvement in the projects includes, but are not limited to: business analyst, project manager, system analyst, knowledge engineer, system designer, database analyst, database designer, software developer, and software tester. He can communicate effectively and efficiently with other civitas academics, colleagues, stakeholders, users, managerial staff, customers, and executives. This experience enriches him with some pedagogical expertise, the ability to conduct research independently, and professional knowledge and practice. His achievements were reflected in the positions held, supervised undergraduate/graduate students, received awards, research publications, and completed ICT projects. He can be contacted at email: irman.hermadi@apps.ipb.ac.id.