Classification of Student Learning Styles Using Artificial Neural Networks on Imbalanced Data

Fikri Baharuddin*¹, Ahmad Miftah Fajrin², Felix Handani³

^{1,2,3}Department of Informatics, Faculty of Engineering, University of Surabaya, Surabaya, East Java, Indonesia Email: ^{1*}fikribaharuddin@staff.ubaya.ac.id, ²ahmadmiftah@staff.ubaya.ac.id, ³felix.handani@staff.ubaya.ac.id

(Received: 20 Sep 2024, revised: 11 Oct 2024, accepted: 14 Oct 2024)

Abstract

The transformation of learning activities towards digital form since the COVID-19 pandemic can affect students' learning process. One of the factors that can affect this learning process is the learning style owned by each student. Learning patterns that are not in line with students' learning styles can influence their learning process. This study aims to identify students' learning styles based on data extracted from the Moodle Learning Management System (LMS). The research methods applied in this study include data collection by extracting data from Moodle LMS logs and classifying student learning styles using the Artificial Neural Network (ANN) algorithm. This study uses 310 log extraction data on the Moodle platform. The Isolation Forest algorithm was applied to this study to detect anomalies or outliers in the dataset. The data used in this study also has an unbalanced distribution of data per class. To prevent the performance degradation of the classifier model caused by the imbalance of data distribution, this study uses the SMOTE algorithm for dataset management, the SMOTE Algorithm to solve the problem of data imbalance, and the ANN Algorithm to build a classification model. The model evaluation is carried out by considering the values of accuracy, precision, recall, and F1-Score to identify the reliability level of the produced model. Based on the research, this study produced a classifying model with an accuracy of 96%. The model produced in this study can be used to identify students' learning styles and as a reference for improving the quality of the teaching and learning process.

Keywords: Machine Learning, Imbalanced Data, Learning Style, Artificial Neural Network, SMOTE.

I. INTRODUCTION

Education has undergone significant changes in recent years, along with the development of digital technology. The COVID-19 pandemic is one factor that has accelerated the transition to online distance learning, so more and more educational institutions are using the Learning Management System (LMS) platform. The transformation of learning to digital form has caused changes in learning styles that need to be considered so that the implementation of learning can continue to run optimally. Identifying a student's learning style is important to maximize the learning process. Learning patterns contrary to a person's learning style can increase the risk of learning failure. This learning failure can have several negative impacts on a person, such as decreased interest in learning, decreased achievement index, and the risk of stopping the learning process [1].

Moodle is one of the Learning Management System (LMS) platforms that educational institutions worldwide widely use. Moodle provides a flexible platform and can be designed according to the academic institution's needs. Moodle can collect student behavior and interaction data when using the

LMS platform. The data stored includes information on the time of student access to the system, activities carried out, and the results of the learning evaluation achieved. This data can be extracted for later analysis to identify students' preferences and learning styles. To identify student learning styles, in this study, the Felder-Silverman Learning Style Model (FSLSM) was used with four main learning style domains consisting of input, understanding, preprocessing, and perception. As in research, FSLSM has been used to detect a person's learning style. The domain in FSLSM can be used to identify student learning styles through the data engineering process on student learning data stored in Moodle LMS logs [1].

The Artificial Neural Networks machine learning algorithm is used to classify student learning styles. The use of this machine learning algorithm aims to automate the classification process. By developing an ANN classification model with good performance, the model can automatically predict students' learning styles with good accuracy. The ANN algorithm selection is based on ANN's ability to understand complex data patterns [2], [3] which is better than similar algorithms such as SVM, k-NN, and Logistic Regression. In addition, ANN has a flexible architecture, making it easy to adjust to the case study you want to complete.

Several previous studies have attempted to understand how students interact with Moodle LMS and study the factors that can affect learning effectiveness through this platform. The research [4] analyzed students' study habits using several classification algorithms such as Decision Tree, Naïve Bayes, and K-Nearest Neighbors. The use of Moodle LMS data logs has also been used to analyze learning patterns, as discussed in the study [5]. Several studies [6], [7], [8], [9] FSLSM is an essential reference for mapping student learning styles. Some studies propose improving the methods used to analyze student learning patterns.

This research can help adjust learning more effectively in educational institutions that utilize the Moodle platform. It is an innovative product for education and information technology. In addition, the output of this research can be used as a reference for similar studies in the future to develop technical solutions to improve the quality of learning implementation through the learning management system.

II. RESEARCH METHOD

The method used in this study is a machine learning model development method, as can be observed in Figure 1. Referring to the flow diagram, four main stages dataset load, data pre-processing, model training, and model evaluation need to be passed in this study.

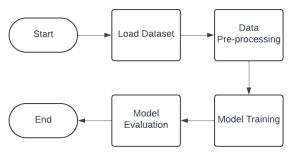


Figure 1. Machine Learning Model Development Workflow

A. Moodle E-Learning

Moodle is one of the most widely used Learning Management Systems today and has been studied and accepted by all parties through the Acceptance Model [10]. Moodle provides a comprehensive educational process through complete learning management, such as material creation, user monitoring, and the assessment process of material [11]. However, learning materials created on Moodle must be well-designed so that users are interested and continue to use the system [12].

The use of Moodle in an institution is essential with an analysis related to technological developments and system usage behavior by users [13]. User behavior on Moodle can be seen in a log. The log can track the behavior patterns of users who have certain tendencies such as discipline in opening material in the form of text, video to how to communicate on forums [14]. Teachers such as lecturers who use Moodle need to pay attention to student interaction when using Moodle because students are valuable assets [15].

B. Felder and Silverman Learning Styles Model (FSLSM)

The FSLM model is a modeling framework initiated by [16]. The FSLMS model was developed by considering factors that affect the suitability of the delivery of learning materials and the level of student understanding. Learning patterns are measured by evaluating the effectiveness of students in understanding the learning material. Meanwhile, the teaching pattern is developed by considering factors affecting the success rate in conveying the core of learning to students. FSLSM can describe in detail its characteristics, can be easily translated into a framework, and can be used as a framework for research [17].

Improving the success of the student learning process can be done by identifying their learning style. One way to identify student learning styles is to use Felder and Silverman Learning Styles (FSLSM) [6], [7], [8]. FSLSM can be analyzed using logs obtained on Moodle. The learning style domains contained in the study [16] can be observed in Table 1.

Table 1. FSLSM Learning Style Domain

Preferred Learning Style			
sensory intuitive	perception		
visual auditory	input		
inductive	organization		
active reflective	processing		
sequential	understanding		

C. Dataset

The dataset used in this study is obtained from the data extraction results on the Moodle E-Learning platform used at "X" University. The data used is students' learning log data from several courses under the informatics department. The data used in this study amounted to 327 data. The data used has attributes, as can be observed in Table 2. The dataset labeling was based on research [18] using the FSLSM learning style domain, where data labeling based on FSLSM domains is carried out by considering student statistical data in accessing learning materials, quizzes, and other assessments on the Moodle LMS platform. This research dataset is public and can be accessed through [19]

Feature	Description		
RESULT	An attribute to show the total		
ASSIGNMENT	assignment that a student has done.		
VALUES	An attribute to show the percentage of a		
ASSIGNMENT	student's completion of a student's		
	assignment to the total assignment given		
	by the teacher.		
RESULT QUIZ	An attribute to show the total quiz that a		
	student has done.		
VALUES	An attribute to show the percentage of a		
QUIZ	student's completion of a student's		
	assignment against the total quiz given		
	by the teacher.		
RESULT PDF	An attribute to show the total PDF		
	material that a student has accessed.		
VALUES PDF	An attribute that shows the percentage		
	of a student's activity toward the total		
	PDF material provided by the teacher.		
RESULT PPT	An attribute to show the total PPT		
	material that a student has accessed.		
VALUES PPT	An attribute to show the percentage of		
	activity of a student towards the total of		
or	the PPT material given by the teacher.		
CLASS	Labels to categorize students' learning		
	styles based on aspects of FSLSM		

Table 2. Features of the Dataset

D. Data Pre-processing

The pre-processing methods used in this study include handling missing values, handling outliers, class balancing, standard scaling, and split data. Handling missing values eliminates data that contains "null" or empty data from the dataset. Data containing this "null" element can degrade the model's performance, so it needs to be cleaned from the dataset to be used. The handling outlier aims to check for anomalies in the dataset to be used. Anomalies in datasets, also called outliers, can affect the performance of a classification model. Therefore, it is crucial to manage outliers properly [20]. This study uses the Isolation Forest algorithm to recognize anomalies in the dataset. Referring to research [21] (Liu et al., 2, the Isolation Forest (iForest) algorithm works by performing three processes. The process begins with a random selection of data features to identify whether there are significant character differences. Identification of data that has anomalies can be made based on the results of calculating the anomalous score from the data on other data. The iForest algorithm can be used to detect outlier and noise data [22], [23], [24].

E. Synthetic Minority Over-sampling Technique (SMOTE)

The SMOTE method is applied to overcome the problem of data imbalance between classes, which can cause a decrease in the model's performance. SMOTE is a preprocessing method that is widely used to balance datasets with an unbalanced distribution of data per class, as in research [25], [26], [27], [28], [29], [30].

Referring to the SMOTE algorithm that can be seen in Table **3**, the SMOTE method works by creating synthesis data obtained from the results of the feature distance calculation using the formula (1). The result of the distance calculation is then added with $bias(\lambda)$ to produce new data that is not the same as observable in equation (2). The newly generated synthetic data is combined with the initial dataset to create a balanced dataset. Thus, the total data in the minority class will be equalized with the total data in the minority class. This balanced data will then be used in the model training stage.

Table 3. SMOTE Algorithms

SMOTE Algorithm				
Input	- Dataset X	Dataset X (Original unbalanced		
	dataset)			
	- N (genera	ted synthesis data)		
	- K (numbe	r of nearest neighbors)		
Output	- Dataset D	(Balanced Dataset)		
Algorithm				
1. Separ	ating datasets into m	inority and majority-class		
data				
	in minority ():			
3 L	ooking for neighbors	as many as K;		
4 s	electedNeighbors = k	a nearest neighbors from		
rando	mly selected x data;			
5. End l	or			
6. For n	eighbor in selectedI	Neighbors:		
7. d	istance = $\sqrt{\sum_{d=1}^{n} (2)}$	$x_i^d - x_{ij}^d \Big)^2 (1)$		
	$_{new} = x_i + \lambda (x_{ij} -$	x_i) (2)		
9. <i>L</i>	$ = D + x_{new}$			
10. End l	or			
11. return	D'			

F. Artificial Neural Networks

Artificial Neural Network (ANN) is one of the machine learning methods. ANNs work using interconnected neurons and send signals to simulate the human neural learning process using complex algorithms [2]. The ANN algorithm is used to obtain learning prediction results based on the input features that have been described previously. The ANN algorithm can be observed in Table 4.

Table 4. ANN Algorithm

Artificial Neural Networks Algorithm				
1.	Determination of learning rate (α) and number of			
	iterations (epoch)			
2.	Initialization of the weight value (W) and the			
	refractive value (b)			
3	For each iteration(epoch):			
4	For each data training(X,y)			
5	Linear output calculation			
6.	Calculation of activation functions using weights			
	and bias			

Arti	Artificial Neural Networks Algorithm			
7.	Prediction output calculation			
8.	Loss/error rate calculation			
9.	Calculation of error value changes to weights			
	and bias			
10.	Update weight values and bias			
11.	End For			
12.	If(stop condition == true)			
13.	break			
14.	Save the best model			
15.	End If			
16.	End For			
17.	Return best model			

Table 6. Model Evaluation Metric			
Metrics	Formula		
Accuracy	$A_{couracu} = TP + TN$		
Ассигису	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$		
Precision	$Precision = \frac{TP}{TP}$		
	$Precision = \frac{TT}{TP + FN}$		
Recall	$Recall = \frac{TP}{TP + FN}$		
	TP + FN Precision		
F-Score	$F - Score = 2 \times \frac{Precision}{Precision}$		
	Recall		

One of the uses of ANN is to predict learning styles for eLearning applications [3]. The use of ANN for learning style prediction is carried out by using interactive videos and can recognize learning types from teachers and students [31]. Predicting learning styles and providing feedback that can be processed are essential parameters in the eLearning domain.

A survey conducted on the use of ANN for learning styles resulted in the conclusion that student behavior analysis is very important so that it can be prevented, such as dropout problems in students [32]. ANN has a high prediction to assess student graduation based on the correlation of viewing learning videos in online courses [33]. ANN is also used to predict student categories, namely bad, medium, and good for their academic achievement [34].

G. Model Training

The Artificial Neural Network (ANN) algorithm creates the classifier model. The model was trained using the hyperparameter configuration, as can be observed in Table 5.

Value
dam
.001
2
parse Categorical Cross
ntropy
0
layers
28 neurons
4 neurons
.4

 Table 5. Hyperparameter Configuration in the ANN Model

H. Model Evaluation

The model is evaluated using evaluation metrics consisting of accuracy, precision, recall, and F-Score metrics. Metric evaluation involves several attributes, namely True Positive(TP), True Negative(TN), False Positive(FP), and False Negative(FN). The calculation formula for each metric can be observed in Table **6**.

III. RESULTS AND DISCUSSION

The dataset used in this study was first filtered using the Isolation Forest algorithm, which aims to separate the noise or outlier from the data used in the modeling process. Implementing the Isolation Forest algorithm successfully detected as many as 17 data classified as outliers. The data classified as outliers is omitted from the dataset. The dataset used in this study also has an unbalanced class composition, as can be observed in Figure 2.

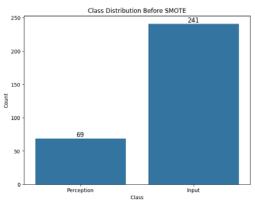


Figure 2. Amount of Data per Class

After applying the SMOTE method, the dataset was successfully balanced with an output of 241 data for each class, as shown in Figure 3.

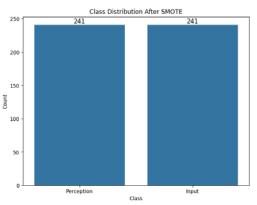


Figure 3. Amount of Data per Class after SMOTE

The balanced dataset is then transformed into a more standard form using the standard scaling method. The data processed through several methods is then separated into two partitions: the training data partition and the test data partition. The data division was done by applying a 60:40 composition, with 60% used for training data. Of the total 482 data in the dataset, 289 were used as training data, and 193 were used as test data.

The model is created according to the hyperparameter configuration described earlier. The model was trained in 30 epochs as described in the hyperparameter configuration and produced the best model results, as can be observed in Table 7. The callback implementation stores the best model state during training. In addition, early stopping is implemented to stop the training automatically if accuracy increases or loss levels do not decrease three times.

Aspect	Value
Epoch	29
Accuracy	0.988439
Loss	0.031415
Validation Accuracy	0.974138
Validation Loss	0.056495
Training Time	45s

Based on Table 4, the best model produced in this study was obtained in the 29th epoch training. The metrics used to assess the model's performance are validation accuracy and loss values. In the 29th epoch, the model showed a validation accuracy value of 0.97 (97%) with a validation loss value of 0.06. By paying attention to the visualization of the comparison between the training loss and validation level, there is no significant indication that leads to overfitting. Comparative data between training accuracy and validation also did not indicate the occurrence of overfitting. The visualization of the comparison of accuracy and loss during the training process can be observed in Figure 4 and Figure 5.

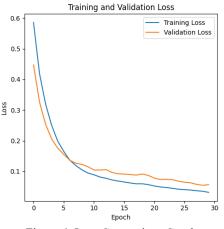


Figure 4. Loss Comparison Graph

Training and Validation Accuracy 1.00 0.95 0.90 Accuracy 0.85 0.80 Training Accuracy 0.75 Validation Accuracy 10 15 20 25 30 Epoch

Figure 5. Graph Comparison Accuracy

The model generated at the training model stage is then evaluated with several evaluation metrics to identify the model's performance by testing the model to conduct classification tests on the test data. The test data used came from data partitions of 40% of the total dataset. The test was carried out by paying attention to accuracy, precision, recall, and F-Score metrics. Based on the evaluation carried out. The model can classify test data with excellent performance with an accuracy level of 97%, accuracy of 98%, recall of 97%, and F-Score of 97%, as observed in Table 8.

The classification test conducted on the test data shows that 84 data have been properly classified as Input classes. Five data should have been included in the Input class but were incorrectly classified as class perception, 104 data were successfully classified as class perception, and no data class perception was incorrectly classified as an input class. The confusion matrix of the evaluation results can be observed in Figure 6.

Table 8. Classification Test Results Report

Aspect	Precision	Recall	F1- Score
Input Class	1.00	0.94	0.97
Perception Class	0.95	1.00	0.98
Accuracy	0.97		
Macro Average	0.98	0.97	0.97
Weighted Average	0.98	0.97	0.97

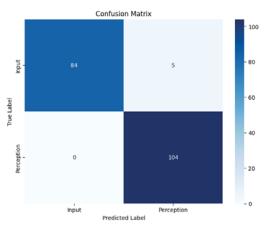


Figure 6. Confusion Matrix Model Evaluation Results

IV. CONCLUSION

Based on the research results, the Artificial Neural Network Algorithm can be used to classify a person's learning style based on the Felder and Silverman Learning Styles Model (FSLSM) domain. This is evidenced by the model's evaluation results, which showed an accuracy of 98%, *a recall* of 97%, and an F-Score of 97%. The resulting model shows good performance by paying attention to the balance of accuracy, recall, precision, and F-score metrics. High recall and precision values indicate the consistency of the model in making accurate predictions. The low number of classification errors also shows that the resulting model is reliable.

The application of the Isolation Forest method in this study succeeded in eliminating some outlier data that could affect the performance of the classifier model. The SMOTE method can solve the data imbalance problem for each class, which can influence the model training process. The dataset used in the study only consists of two labels, namely input and perception. This is due to the lack of quantity of datasets that can undoubtedly be added to future studies to cover other FSLSM domains. The dataset used to build the model also only consists of one study program and does not cover all courses. This has the potential to generate bias when the model is implemented in real-time, so in the future, it needs to be developed with a dataset that includes more data variants to get more accurate and reliable results. In addition, optimization can be performed on the model's hyperparameters to obtain the best performance.

ACKNOWLEDGMENT

The author expresses deepest gratitude to the Research and Community Service Institution of the University of Surabaya for funding this research through internal funding for a quality research publication scheme.

REFERENCES

- T. Sheeba and R. Krishnan, "Prediction of student learning style using modified decision tree algorithm in e-learning system," in *Proceedings of the 2018 International Conference on Data Science and Information Technology*, 2018, pp. 85–90.
- [2] J. Cuauhtemoc et al., "AI-Based Prediction of Capital Structure: Performance Comparison of ANN SVM and LR Models," Wiley Online LibraryJC Tellez Gaytan, K Ateeq, A Rafiuddin, HM Alzoubi, TM Ghazal, TA Ahanger, S ChaudharyComputational intelligence and neuroscience, 2022•Wiley Online Library, vol. 2022, 2022, doi: 10.1155/2022/8334927.
- [3] K. Alhumaid, M. Habes, and S. A. Salloum, "Examining the Factors Influencing the Mobile Learning Usage during COVID-19 Pandemic: An Integrated SEM-ANN Method," *IEEE Access*, vol. 9, pp. 102567–102578, 2021, doi: 10.1109/ACCESS.2021.3097753.
- [4] S. Tiodora, S. | Umi, L. Yuhana, * Umi, and P. Address, "Student behaviour analysis to detect learning styles using decision tree, Naïve Bayes, And K-Nearest Neighbor method in moodle learning management system," *iptek.its.ac.idST Sianturi, UL YuhanaIPTEK The Journal for Technology and Science,* 2022•*iptek.its.ac.id*, vol. 33, no. 2, pp. 853–4098, doi: 10.12962/j20882033.v33i2.13665.
- [5] K. Dobashi, C. P. Ho, C. P. Fulford, M. F. Grace Lin, and C. Higa, "Learning pattern classification using moodle logs and the visualization of browsing processes by time-series cross-section," *Computers and Education: Artificial Intelligence*, vol. 3, Jan. 2022, doi: 10.1016/J.CAEAI.2022.100105.
- [6] Y. Ikawati, M. U. H. Al Rasyid, and I. Winarno, "Student Behavior Analysis to Detect Learning Styles in Moodle Learning Management System," *IES 2020 -International Electronics Symposium: The Role of Autonomous and Intelligent Systems for Human Life and Comfort*, pp. 501–506, Sep. 2020, doi: 10.1109/IES50839.2020.9231567.
- M. Liyanage, ... K. G.-... I. J. on, and undefined 2014, "Using learning styles to enhance learning management systems," *journal.icter.orgMPP Liyanage, KSL Gunawardena, M HirakawaThe International Journal on Advances in ICT for Emerging Regions,* 2014•*journal.icter.org*, Accessed: Sep. 18, 2024. [Online]. Available: https://journal.icter.org/index.php/ICTer/article/view/1 79
- [8] A. S. Sprock, "Inclusion of the FuzzyILS method in MOODLE for creating effective courses," *International Journal of Learning, Teaching and Educational Research*, vol. 19, no. 10, pp. 32–59, Oct. 2020, doi: 10.26803/IJLTER.19.10.3.
- [9] I. Azzi, A. Jeghal, A. Radouane, A. Yahyaouy, and H. Tairi, "A robust classification to predict learning styles in adaptive E-learning systems," *Educ Inf Technol*

(Dordr), vol. 25, no. 1, pp. 437–448, Jan. 2020, doi: 10.1007/S10639-019-09956-6.

- [10] G. G. Murillo, P. Novoa-Hernández, H. Hernández, and R. Serrano Rodríguez, "Technology Acceptance Model and Moodle: A systematic mapping study," *journals.sagepub.comGG Murillo, P Novoa-Hernández, RS RodriguezInformation Development,* 2021•*journals.sagepub.com*, vol. 37, no. 4, pp. 617– 632, Nov. 2021, doi: 10.1177/02666666920959367.
- [11] M. Zabolotniaia, Z. Cheng, E. Dorozhkin, and A. Lyzhin, "Use of the LMS Moodle for an effective implementation of an innovative policy in higher educational institutions.," pdfs.semanticscholar.orgM E Dorozhkin, Zabolotniaia, Z Cheng, Α LyzhinInternational Journal of Emerging Technologies in Learning, 2020 pdfs.semanticscholar.org, vol. 15, no. 13. pp. 172–189, Jan. 2020, doi: 10.3991/ijet.v15i13.14945.
- [12] D. Keržič, A. Aristovnik, N. Tomaževič, and L. Umek, "An assessment of the effectiveness of Moodle elearning system for undergraduate public administration education," *International Journal of Innovation and Learning*, vol. 21, no. 2, p. 165, 2017, doi: 10.1504/IJIL.2017.10002132.
- [13] B. Bervell, I. U.-E. J. of Mathematics, S. and, and undefined 2017, "A decade of LMS acceptance and adoption research in Sub-Sahara African higher education: A systematic review of models, methodologies, milestones and main," *ejmste.comB Bervell, IN UmarEurasia Journal of Mathematics, Science and Technology Education, 2017. ejmste.com,* vol. 13, no. 11, pp. 7269–7286, 2017, doi: 10.12973/ejmste/79444.
- [14] N. Kadoic and D. Oreski, "Analysis of student behavior and success based on logs in Moodle," 2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics, MIPRO 2018 - Proceedings, pp. 654– 659, Jun. 2018, doi: 10.23919/MIPRO.2018.8400123.
- [15] F. Amankwah, F. K. Sarfo, M. O. Aboagye, D. Konin, and R. K. Dzakpasu, "Concerns of university teachers about the adoption of the Moodle learning management system in a Ghanaian University campus," *Taylor & FrancisF Amankwah, FK Sarfo, MO Aboagye, D Konin, RK DzakpasuEducation inquiry, 2024*•*Taylor & Francis*, vol. 15, no. 3, pp. 312–332, 2022, doi: 10.1080/20004508.2022.2109849.
- [16] R. Felder, L. S.-E. education, and undefined 1988, "Learning and teaching styles in engineering education," academia.eduRM Felder, LK SilvermanEngineering education, 1988•academia.edu, Accessed: Sep. 18, 2024. [Online]. Available: https://www.academia.edu/download/31039406/LS-1988.pdf
- [17] M. Dominic, B. Anthony Xavier, and S. Francis, "A Framework to Formulate Adaptivity for Adaptive e-Learning System Using User Response Theory," *International Journal of Modern Education and*

Computer Science, vol. 7, no. 1, pp. 23–30, Jan. 2015, doi: 10.5815/IJMECS.2015.01.04.

- [18] T. Sheeba and R. Krishnan, "Prediction of student learning style using modified decision tree algorithm in e-learning system," in *Proceedings of the 2018 International Conference on Data Science and Information Technology*, 2018, pp. 85–90.
- [19] F. Baharuddin, "Dataset Log Data Moodle for SLSA," Sep. 2024, Zenodo. doi: 10.5281/zenodo.13819870.
- [20] T. Nyitrai and M. Virág, "The effects of handling outliers on the performance of bankruptcy prediction models," *Socioecon Plann Sci*, vol. 67, pp. 34–42, Sep. 2019, doi: 10.1016/J.SEPS.2018.08.004.
- [21] F. T. Liu, K. M. Ting, and Z.-H. Zhou, "Isolation Forest," in 2008 Eighth IEEE International Conference on Data Mining, 2008, pp. 413–422. doi: 10.1109/ICDM.2008.17.
- [22] W. R. Chen, Y. H. Yun, M. Wen, H. M. Lu, Z. M. Zhang, and Y. Z. Liang, "Representative subset selection and outlier detection: Via isolation forest," *Analytical Methods*, vol. 8, no. 39, pp. 7225–7231, Oct. 2016, doi: 10.1039/C6AY01574C.
- [23] Z. Cheng, C. Zou, and J. Dong, "Outlier detection using isolation forest and local outlier factor," in *Proceedings* of the Conference on Research in Adaptive and Convergent Systems, in RACS '19. New York, NY, USA: Association for Computing Machinery, 2019, pp. 161–168. doi: 10.1145/3338840.3355641.
- [24] R. C. Ripan *et al.*, "An Isolation Forest Learning Based Outlier Detection Approach for Effectively Classifying Cyber Anomalies," in *Hybrid Intelligent Systems*, A. Abraham, T. Hanne, O. Castillo, N. Gandhi, T. Nogueira Rios, and T.-P. Hong, Eds., Cham: Springer International Publishing, 2021, pp. 270–279.
- [25] S. Bujang, A. Selamat, O. Krejcar, ... F. M.-I., and undefined 2022, "Imbalanced classification methods for student grade prediction: a systematic literature review," *ieeexplore.ieee.org*, Accessed: Sep. 18, 2024. [Online]. Available:

https://ieeexplore.ieee.org/abstract/document/9965398/

- [26] A. Yaqin, M. Rahardi, F. A.-I. J. of, and undefined 2022, "Accuracy Enhancement of Prediction Method using SMOTE for Early Prediction Student's Graduation in XYZ University," *researchgate.net*, vol. 13, no. 6, p. 2022, 2022, doi: 10.14569/IJACSA.2022.0130652.
- [27] M. Shrinidhi, ... T. K. J.-A. in S., and undefined 2023, "Classification of Imbalanced Datasets Using Various Techniques along with Variants of SMOTE Oversampling and ANN," *Trans Tech Publ*, Accessed: Sep. 18, 2024. [Online]. Available: https://www.scientific.net/AST.124.504
- [28] T. Riston, S. Suherman, ... Y. Y.-... S. and I., and undefined 2023, "Oversampling Methods for Handling Imbalance Data in Binary Classification," *Springer*, Accessed: Sep. 18, 2024. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-031-37108-0_1

- [29] A. Bokhare, A. Bhagat, R. B.-S. C. Science, and undefined 2023, "Multi-layer perceptron for heart failure detection using SMOTE technique," *Springer*, Accessed: Sep. 18, 2024. [Online]. Available: https://link.springer.com/article/10.1007/s42979-022-01596-x
- [30] C. Kaope, Y. P.-M. Jurnal, and undefined 2023, "The Effect of Class Imbalance Handling on Datasets Toward Classification Algorithm Performance," *journal.universitasbumigora.ac.id*, vol. 22, no. 2, pp. 227–238, 2023, doi: 10.30812/matrik.v22i2.2515.
- [31] A. Jalal and M. Mahmood, "Students' behavior mining in e-learning environment using cognitive processes with information technologies," *Educ Inf Technol* (*Dordr*), vol. 24, no. 5, pp. 2797–2821, Sep. 2019, doi: 10.1007/S10639-019-09892-5.
- [32] J. L. Rastrollo-Guerrero, J. A. Gómez-Pulido, and A. Durán-Domínguez, "Analyzing and predicting students' performance by means of machine learning: A review," *Applied Sciences (Switzerland)*, vol. 10, no. 3, Feb. 2020, doi: 10.3390/APP10031042.
- [33] C. Yu, J. Wu, A. L.-E. sciences, and undefined 2019, "Predicting learning outcomes with MOOC clickstreams," *mdpi.comCH Yu, J Wu, AC LiuEducation sciences, 2019-mdpi.com*, vol. 9, no. 2, Jun. 2019, doi: 10.3390/educsci9020104.
- [34] K. Nahar, B. I. Shova, T. Ria, H. B. Rashid, and A. H. M. S. Islam, "Mining educational data to predict students performance: A comparative study of data mining techniques," *Educ Inf Technol (Dordr)*, vol. 26, no. 5, pp. 6051–6067, Sep. 2021, doi: 10.1007/S10639-021-10575-3.

ISSN 2549-8037 EISSN 2549-8045



0770070 0000700

0077700 70070701 00007770

110001110 111010101

0010

TEKNIKA Jurnal Teknologi Informasi dan Komunikasi

> Terakreditasi SINTA-3 (SK Kemdikbudristek No. 105/E/KPT/2022)

	6 0				
Pusat Penelitian dan Pengabdian Kepada Masyarakat Institut Informatika Indonesia Surabaya, Indonesia					
TEKNIKA	Vol. 13	No. 3	Hlm. 324-492	Surabaya, November 2024	ISSN 2549-8037 EISSN 2549-8045



Visitor Statistics

Home / Editorial Team

Editorial Team

EDITOR IN CHIEF



Ir. Raymond Sutjiadi, S.T., M.Kom. Institut Informatika Indonesia Surabaya Email: raymond@ikado.ac.id [SINTA ID: 169088] [SCOPUS ID: 56958612100] [GOOGLE SCHOLAR ID: bN9grIAAAAA]]

EDITORS



Alexander Wirapraja, S.Kom., M.Kom., M.M. Institut Informatika Indonesia Surabaya Email: alex@ikado.ac.id [SINTA ID: 5997715] [SCOPUS ID: 57213520423] [GOOGLE SCHOLAR ID: uUZW-kIAAAA]]



David Sundoro, S.T., M.M.T. Universitas Ciputra Surabaya Email: david.sundoro@ciputra.ac.id [SINTA ID: 6796599] [GOOGLE SCHOLAR ID: 1|GQ2vYAAAAJ]



Eddy Triswanto Setyoadi, S.T., M.Kom. Institut Informatika Indonesia Surabaya Email: eddy@ikado.ac.id [SINTA ID: 5990918] [SCOPUS ID: 57202506394] [GOOGLE SCHOLAR ID: XcW2BV8AAAAJ]



Edwin Meinardi Trianto, S.Kom., M.Kom. Institut Informatika Indonesia Surabaya Email: edwin@ikado.ac.id [SINTA ID: 6191237] [SCOPUS ID: 57202504215] [GOOGLE SCHOLAR ID: uCXOsvYAAAAJ]



Prof. Dr. Ir. Gunawan, M.Kom. Institut Sains dan Teknologi Terpadu Surabaya Email: gunawan@istts.ac.id



ISSN 2549-8037



EISSN 2549-8045





Teknika has been accredited SINTA-3 (S3) by the decree of Ministry of Education, Culture, Research, and Technology, Republic of Indonesia No. 105/E/KPT/2022, 7 April 2022.



Teknika has been covered by the following services:



[SINTA ID: 5986811] [SCOPUS ID: 36983740800] [GOOGLE SCHOLAR ID: elY--F4AAAAI]



Ir. Resmana Lim, M.Eng. Universitas Kristen Petra Surabaya Email: resmana@petra.ac.id [SINTA ID: 27072] [SCOPUS ID: 57141791400] [GOOGLE SCHOLAR ID: uKixL-4AAAA]]



Timothy John Pattiasina, S.T., M.Kom. Institut Informatika Indonesia Surabaya Email: temmy@ikado.ac.id [SINTA ID: 5974935] [SCOPUS ID: 57202505132] [GOOGLE SCHOLAR ID: -YTKIdUAAAAJ]



Titasari Rahmawati, S.Pd., M.Kom. Institut Informatika Indonesia Surabaya Email: tita@ikado.ac.id [SINTA ID: 6114398] [GOOGLE SCHOLAR: DM0ZJ_0AAAAJ]





Source WorldCat*

INDEX COPERNICUS



Google



BASE Bielefeld Academic Search Engine









<mark>%nelitj</mark>



Tools:





Teknika has been sponsored by the following institutions:



Visitor Statistics

Home / Archives / Vol. 13 No. 3 (2024): November 2024

Vol. 13 No. 3 (2024): November 2024



Teknika (ISSN 2549-8037, EISSN 2549-8045) is a peerreviewed scientific journal, published three times a year in March, July, and November by the Center for Research and Community Service, Institut Informatika Indonesia (IKADO) Surabaya. It presents articles on Information and Communication Technology (ICT) area that come from the results of empirical research or conceptual works.

Teknika has been accredited <u>SINTA-3 (S3)</u> by the decree of the Ministry of Education, Culture, Research, and Technology, Republic of Indonesia No. 105/E/KPT/2022, 7 April 2022.

DOI: https://doi.org/10.34148/teknika.v13i3

Published: 2024-11-01

Articles

⁶¹ Inst. 4: A Bandmin structure and the integration of the integr



The Analysis and Improvement of User Interface Design on Climate Information Service Mobile Application Using the Lean UX Method

Muhammad Fauzi, Ni Kadek Ayu Wirdiani, Ni Kadek Dwi 324-338 Rusjayanthi

M Abstract views: 248, 💪 PDF downloads: 234



Descending Stairs Detection Using Digital Image Processing to Guide Visually Impaired

Ahmad Wali Satria Bahari Johan, Rizky Fenaldo Maulana 339-345

🎢 Abstract views: 72, 😼 PDF downloads: 74



Precision in Obstetric Care: A Machine Learning Approach

with CatBoost and Grid Search Optimization



ISSN 2549-8037



EISSN 2549-8045





Teknika has been accredited SINTA-3 (S3) by the decree of Ministry of Education, Culture, Research, and Technology, Republic of Indonesia No. 105/E/KPT/2022, 7 April 2022.



Teknika has been covered by the following services:



Marselina Endah Hiswati, Mohammad Diqi, Izattul Azijah, 346-352 Yeyen Subandi, Azzah Fathinah, Rahayu Cahya Ariani

📶 Abstract views: 238, 💪 PDF downloads: 82



Optimalisasi Proses Data Warehouse Melalui Business Process Optimization (BPO) Untuk Meningkatkan Efisiensi Pengambilan Keputusan

Fajar Ciputra Daeng Bani, Agus Wahyudin, Bayu 353-360 Prabowo Sutjiatmo, Intan Maria Lewiayu Vierke, Avia Enggar Tyasti

📶 Abstract views: 170, 💪 PDF downloads: 186



-	International Art. In al. Programming at March 2 in	Wat foreigned from Thinks
-		of other shared using
Pengent	hangan Mudat Klasifikasi Kendaruan Parkir Bengan Algoritma YO	Kelsar Marak Area LOv8
	Any he installed fight free factors".	and the local data
-	 Total (Monethe Protocols (Meanwhild Science) Total (Meanwhile Colored) and (Meanwhile & Colored) 	a Teac Tanadali, Astronom
	Part and (1977), \$1.0 (1977) and	10.00
		and the state of the state
harber i	igned (14.) the Dalifur Inside Teaching State	or the second second lines
Bertige	ment of a Folicle Classification Model the Participation Fring THEPAR	for Earry and Eals in
		St
	plant who included the street is being the	a the second second second
5000 T.L.	the distance of the state of th	to make the later later
	Lana (t), housin 201 g 20-25	NO 811000000010100

Zuhdi M Abstract views: 176, 💪 PDF downloads: 220

Klasterisasi Data Obat Farmasi Berdasarkan Jumlah Persediaan Dengan Menggunakan Metode K-Means Heri Supriyanto, Mohammad Al Hafidz, Ari Cahaya

Puspitaningrum, Rayhan Abdillah Putra Firmansyah, Rafi



Pengembangan Model Klasifikasi Kendaraan Keluar Masuk Area Parkir Dengan Algoritma YOLOv8

Argi Nur Faturrohman, Sayekti Harits Suryawan, Abdul 370-379 Rahim

📶 Abstract views: 154, 💪 PDF downloads: 138



	Contrast, Section, and and a section of the section
and the same of the second second	In cash disk is the line burner of the second secon
and the product of the second state of the sec	reserve barring the Allowy and adds where
Property of the Party of the Array of the Party of the Pa	Annual provide states in the limit of the second states and the second states and the second states are set of the second states and the second states are set of the second states are second states are second states are set of the second states are set of the second states are second st

Optimizing Tourism Promotion for Situ Bagendit Through Innovation in a Web-Based Virtual Tour Application Sri Rahayu, Syahrul Yanuar, Yosep Bustomi 380-387

M Abstract views: 72, 😼 PDF downloads: 56



Analisis Sentimen Ulasan Game Stumble Guys Pada Playstore Menggunakan Algoritma Naïve Bayes Awang Herjunie Nurdy, Abdul Rahim, Arbansyah

m Abstract views: 431, 💪 PDF downloads: 264



Crossref





INDEX 🛞 COPERNICUS TIONAI





361-369



BASE Bielefeld Academic Search Engine













Tools:





Teknika has been sponsored by the following institutions:

388-395

-	coloris, R., et al. Names or lance that has to the coloris of the fraction in the format of the coloris.
Prestages	Monode ROC date MATRCA Datase Possibless Wolt Hunting VPS Claud
	on Adams", Star Schlins, Pargert, Find Sciping Parglement"
122	aged had feed blackses for this lances, because, her leads
	and party 1 all little down if the PAL of the PAL down of the PAL
	The second se
Spece Area (The set of the set

Penerapan Metode ROC dan MAIRCA Dalam Pemilihan Web **Hosting VPS Cloud**

Brian Ardianto, Mey Tri Widya Pangesti, Prind Triajeng 396-402 Pungkasanti

Analysis of LoRaWAN Network Signal Coverage and Quality Parameters in Real-Time: Case Study of Cikumpa River

📶 Abstract views: 82, 💪 PDF downloads: 106

Water Quality Monitoring, Depok City

m Abstract views: 71, 💪 PDF downloads: 82

Wulan Sri Lestari, Yuni Marlina Saragih, Caroline

📶 Abstract views: 89, 😼 PDF downloads: 70

Hasri Ariansa, Legenda Prameswono Pratama, Safira

Faizah, Arisa Olivia Putri, Ariep Jaenul, Brainvendra Widi Dionova, Safaa Najah Sahud Al-Humairi, M. N.



Mohammed

🕒 PDF

PDF





Information

- For Readers
- For Authors
- For Librarians

Latest publications



Visit	ors		
ID	136,470	IE	61
SG	6,240	PE	54
us 📃	3,944	AE	51
IN IN	664	FI	44
	510	۲. IR	38
MY DI	472	SE	32
GB GB	293	a MX	32
рн 🚬	276	👛 кн	31
RU RU	238	PL	31
AU	182	IT	30
DE	168	ES	28
× VN	158	SA 🗧	28
TW	145	RO	28
e Jb	134	BD BD	27
🛪 нк	133	== IQ	24
🔶 CA	126	• EG	23
KR KR	126	🛄 LK	22
NG	124	e dz	22
NL	116	🛎 EC	21
FR FR	101	UA	20
C· TR	99	cz	20
📀 BR	92	РТ	19
ТН	82	BE	19
TL	70	NP	18
Срк	67	c 0	18
Pageview	ws: 245,06	4	
2	JAK F	LAG	counter

Comparison of Deep Neural Networks and Random Forest Algorithms for Multiclass Stunting Prediction in Toddlers 412-417

403-411

418-427





Coloring Pekalongan Batik Using a Madura Dataset: A Comparative Study of GAN and Caffe-Based CNN Models

Muhamad Machrus Ali Wahyudi, Arik Kurniawati, Fitri



Damayanti, I Ketut Adi Purnawan M Abstract views: 106, 💪 PDF downloads: 131



428-434





The Role of Information and Communication Technology in Advancing Sustainable Energy Transition in Developing **Countries: Progress, Opportunities and Challenges**

Dalam Pemilihan Supplier Terbaik Pada Industri Manufaktur

Penerapan Metode Simple Additive Weighting (SAW)

Zaenul Muttaqin, Dini Handayani, Gandung Triyono

📶 Abstract views: 323, 🝌 PDF downloads: 207

PDF

Yusak Tanoto

📶 Abstract views: 82, 💪 PDF downloads: 77

	Annual could say i hitsen out
	perform per l'in citte half all contract and
	provide the set of the state of the
mant transform and sound to make all	Realling and the second second second
	taken blong i Property and approximite
	-hearing and believe a store hear

🖾 PDF

Method, MAUT, and Talepton	of a Web-Based Freed Asset Combination of Scraight Line in But Jaiogration: Case Study of District Haspital
	Enter wit Hospital
The last start whet he	Andread They Frances Magda Tread
Children Labora Institute 1	where there been he been
	In the same starting
ment Property and	Contraction and the state

Design and Construction of a Web-Based Fixed Asset Management System with a Combination of Straight Line Method, MAUT, and Telegram Bot Integration: Case Study of North Lombok District Hospital

I Made Teguh Arthana, Ni Kadek Ayu Wirdiani, Desy 443-451 Purnami Singgih Putri

📶 Abstract views: 88, 😼 PDF downloads: 84



el anno 1	 Construint of National Assesses Wester 1 (top 1980) National Transition of Markanel (Top.
Classification of Stadent Learnin Networks on In	ng Siyles Ling Artificial Neural abalanced Buta
No Security Court	the last in here
	Consult of Section Sections for the Second
Annual Inter-Tris and	interest and the state
-	
	ner principal principal de devenir d'a realité d'arte de la construction de la realité de la construction de la construction de realité de realité de la construction de realité de realité de la construction de realité
- Augusta 1 contrar & along prove charge and contrar of a second second prove contrar of a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second second in a contrar beam including bits on a second second second in a contrar beam including bits on a second second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second in a contrar beam including bits on a second second second in a contrar beam including bits on a second second second in a contrar beam including bits on a second second second in a contrar beam including bits on a second second second in a contrar beam including bits on a second second second in a contrar beam including bits on a second	And the second stands of the last of the second stands of the second stand stands of the seco
Spirit Spirit of Spirit and Allerian Spirit Property and Spirit Property of Spirit Property and Spirit Pro	All reaches having digitality day is advected in- distributed proved by Bendrick and Collinson and an or- stand of provide the best of the second second

Classification of Student Learning Styles Using Artificial Neural Networks on Imbalanced Data

Fikri Baharuddin, Ahmad Miftah Fajrin, Felix Handani 452-459



÷	Henrik & Artin The Kein (2017) of 12 or 12 abroading Technology (Adapted A field of the Booline's Graphic Technol. Survey (Method Inc.).
The Bale A Number	of UTAVT2 in Understanding Tucknology Adoption: of the Mouleka Mougajar Platform Among Information Tumbers
	the insurant' while harpy? These beauty bases?
	Advantation (Marcelle) Taggia (Marcelle) & A support of Astronomy Control of A Stationers Control and Astronomy Control (Control of Astronomy Control of Ast
Tapani da	bioastor lovat, bailde loga interactio d'Unique lattares titles, bailes
	Red "manual (do. a. b. 'strength and 'strength and
	States (16, 25, and 210 (16 and 100 (16)
1 7 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4	
	an said a report standy reported in some fragment with the standard line standard

The Role of UTAUT2 in Understanding Technology Adoption: A Study of the Merdeka Mengajar Platform Among Indonesian Teachers

Siti Aminah, Addin Aditya, Yekti Asmoro Kanthi 🎢 Abstract views: 180, 💪 PDF downloads: 111

🖾 PDF

 Total Status Status Strategy
 Total Status Strategy

 Status Strategy
 Total Status Strategy

 Strategy
 Total Strategy

 Strategy

Analisis Faktor Yang Mempengaruhi Kepuasan Pengguna Media Sosial X Menggunakan Metode End User Computing Satisfaction (EUCS)

Flourensia Sapty Rahayu, Generosa Lukhayu Pritalia, 471-480 Felix Kurniawan

M Abstract views: 395, 💪 PDF downloads: 246



And an experimental and a second seco



Classification of Foods Based on Nutritional Content Using K-Means and DBSCAN Clustering Methods

Fitria Nurulhikmah, Deden Nur Eka Abdi

📶 Abstract views: 172, 😼 PDF downloads: 109

🖄 PDF

435-442

460-470

481-486

the last \$1. and there is a last to be in the basis of th
Peratuangan Aplikasi Malole Menggunakan Machine Learning Lutuh Monotukan Klasifikasi Kategori Berita
Text Inclusions", Incar Security Streets Wingson"
The second secon
a presidente de la companya de la c
for the last factor, the last inter last last house
Application of Machine Learning Using the Legistic Repression Algorithm in News Category Changlustion
And the second dealer since any second data and the second data and the
Repared York, "Sections, 1993, ApJ and, Arrive Scoreg, Spin-Reprint.
and the second s
$\label{eq:state} (1000 \pm 0.01).$ There are a state a
102/01.1 Sector 201 (01) (02/01.1 Sector 201 (01) (02/01.1 Sector 201 (02/01)))

Perancangan Aplikasi Mobile Menggunakan Machine Learning Untuk Menentukan Klasifikasi Kategori Berita

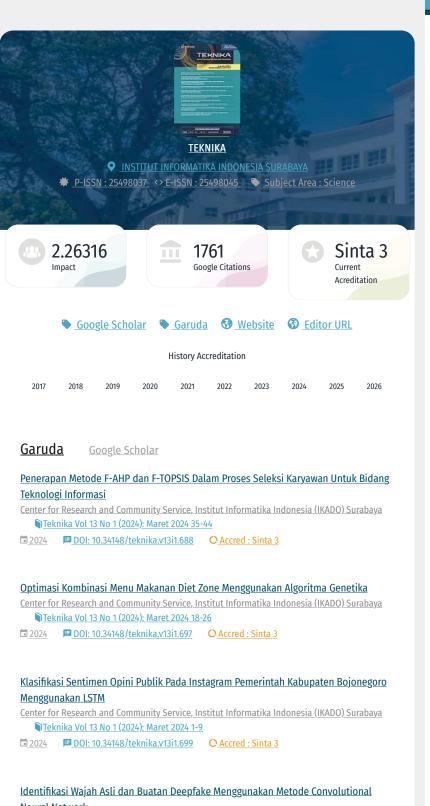
487-492

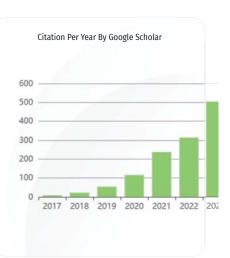
Novi Tri Hariyanti, Titasari Rahmawati, Alexander Wirapraja

📶 Abstract views: 144, 💫 PDF downloads: 129



Platform & workflow by OJS / PKP





Jouri	nal By Google Sch	nolar
	All	Since 2020
Citation	1761	1715
h-index	19	19
i10-index	40	40

Neural Network

Center for Research and Community Service, Institut Informatika Indonesia (IKADO) Surabaya Teknika Vol 13 No 1 (2024): Maret 2024 45-50

□ 2024 □ DOI: 10.34148/teknika.v13i1.705 ○ Accred : Sinta 3

Pengenalan Aktivitas Manusia Dalam Ruangan Dengan Convolutional Neural Networks Center for Research and Community Service, Institut Informatika Indonesia (IKADO) Surabaya Teknika Vol 13 No 1 (2024): Maret 2024 58-64

DOI: 10.34148/teknika.v13i1.707 OAccred : Sinta 3

Electronics Spare Part Goods Demand Forecasting Using Markov Model

Center for Research and Community Service, Institut Informatika Indonesia (IKADO) Surabaya

□ 2024 □ DOI: 10.34148/teknika.v13i1.709 O Accred : Sinta 3

Data Mining Untuk Prediksi Penjualan Menggunakan Metode Simple Linear Regression

Center for Research and Community Service, Institut Informatika Indonesia (IKADO) Surabaya

■ <u>2024</u> ■ <u>DOI: 10.34148/teknika.v13i1.712</u> <u>O Accred : Sinta 3</u>

Perancangan Low-Cost Testbed Untuk Validasi Lokasi dan Orientasi Mobile Robot

Center for Research and Community Service, Institut Informatika Indonesia (IKADO) Surabaya

■ 2024 ■ DOI: 10.34148/teknika.v13i1.714 OAccred : Sinta 3

Towards Development of a Multilingual Mobile Chat Application for Enhanced Global Communication

Center for Research and Community Service, Institut Informatika Indonesia (IKADO) Surabaya

DOI: 10.34148/teknika.v13i1.717 OAccred : Sinta 3

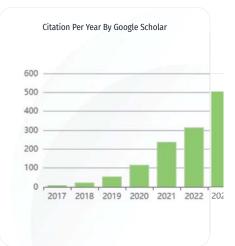
Identifikasi Kerusakan Badan Kontainer Pada Waktu Pengiriman Berdasarkan Citra CCTV Memanfaatkan YOLO dan Deep Transfer Learning

Center for Research and Community Service, Institut Informatika Indonesia (IKADO) Surabaya

□ <u>2024</u> □ <u>DOI: 10.34148/teknika.v13i1.718</u> <u>O Accred : Sinta 3</u>







Jour	nal By Google Scl	holar
	All	Since 2020
Citation	1761	1715
h-index	19	19
i10-index	40	40