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Convolutional neural network for estimation of harvest time of forage sorghum (sorghum bicolor) cultivar samurai-1

Kahfi Heryandi Suradiradja[1], Imas Sukaesih Sitanggang[1], Luki Abdullah[2], Irman Hermadi[1]
[1]Department of Computer Science, Faculty of Mathematics and Natural Science, IPB University, Bogor, Indonesia
[2]Department of Nutrition and Feed Technology, Faculty of Animal Science, IPB University, Bogor, Indonesia

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ABSTRACT

One of the economic alternatives to improve the quality of ruminant feed is combining grass as the main feed with high-protein forages such as sorghum. To get a quality sorghum harvest during the period, it must be right when it has good biomass content, nutrients, and digestibility. The problem is that measuring quality in the laboratory has additional costs and time, which is not short, causing delays. An approach with machine learning using a convolutional neural network can be a better solution. This research uses a convolutional neural network algorithm with the right architecture to estimate sorghum harvest time from imaging results of unmanned aerial vehicles. The stages of this research include data collection, pre-processing, modeling, and finally, the evaluation stage. This research compares the results of several convolutional neural network (CNN) algorithm architectural models: simple CNN, ResNet50 V2, visual geometry group-16 (VGG-16), MobileNet V2, and Inception V3. The result is determining the CNN algorithm architectural model that can estimate sorghum harvest time with maximum accuracy. The best result is the simple CNN architectural model with an accuracy of 0.95. This research shows that the classification model obtained from the CNN algorithm with a simple CNN architecture is the choice model for estimating sorghum harvest time.

Corresponding Author:

Kahfi Heryandi Suradiradja
Department of Computer Science, Faculty of Mathematics and Natural Sciences, IPB University
Jl. Agatis, IPB Campus Darmaga Bogor 16680, Indonesia
Email: kahfi.heryandi@apps.ipb.ac.id

1. INTRODUCTION

Animals, feed, and land are the main concerns in the livestock industry. Grass is the core feed in the cattle breeding industry, but it has a high crude fiber content and low protein, causing low livestock digestibility. Increasing nutrition's value must be combined with additional feed or concentrated feed such as corn, dregs, and other similar feeds, but of course, this will increase production costs. According to [1], there is a solution to improve livestock performance and reduce ration production costs by lowering concentrate ingredients by providing quality forage by combining main feed and Gramineae, one of which is sorghum. In Indonesia, sorghum plants can be planted in marginal and dry areas [2]. The best solution to provide forage for ruminants is by choosing sorghum as the main feed [3]. According to [4], sorghum has a greater biomass than corn. Forage sorghum can be harvested from the flowering stage [5]. One of the uses of information technology support in agriculture and animal farming is applying one of the algorithm models from machine learning, namely computer programming using historical data [6]. According to [7], machine learning methodology generally involves learning from training data. Machine learning can assist with quick plant phenotyping, agricultural monitoring, and yield prediction [8]. Previous studies using machine learning solutions on sorghum plant objects were by [9] and [10]. Several other studies related to predictions in agriculture and animal husbandry are predictions of wheat yields [11], crop disease prediction [12], and [13]. One widely used algorithm for forecasting or predicting the target value is the convolutional neural network (CNN). Inspired by that, this research primarily estimates the harvest time of forage sorghum using CNN. Contributing to this field has developed our profound interest.

The harvesting must be done appropriately to obtain suitable fiber for livestock digestibility and high-quality biomass. The decision to determine the right time to harvest is based on the laboratory analysis results and will take several days. It is an obstacle because the decision-making time for harvesting must be noticed.

Some studies related to sorghum used machine learning, such as sorghum yield prediction and machine learning [14], sorghum biomass prediction research [10], [15], and sorghum head detection and counting [9], [16], [17]. Using machine learning models, we developed a CNN model that can be used to predict or estimate the classification of harvest time based on the image of sorghum crop fields from drones. This research compares the best type of architecture from the five CNN architectures for estimating the harvest time of sorghum plants.

2. METHOD

There are four stages in the research methodology: a data collection stage, a pre-processing stage, a modeling stage, and an evaluation stage, which is shown in Figure 1. Briefly, from the flow stages of Figure 1 starting from the data that has been collected, pre-processing is carried out first. Then, at the modeling stage, the focus is on conducting research with several CNN algorithm architectural models. Several architectural models were compared to find the maximum accuracy value at the evaluation stage.

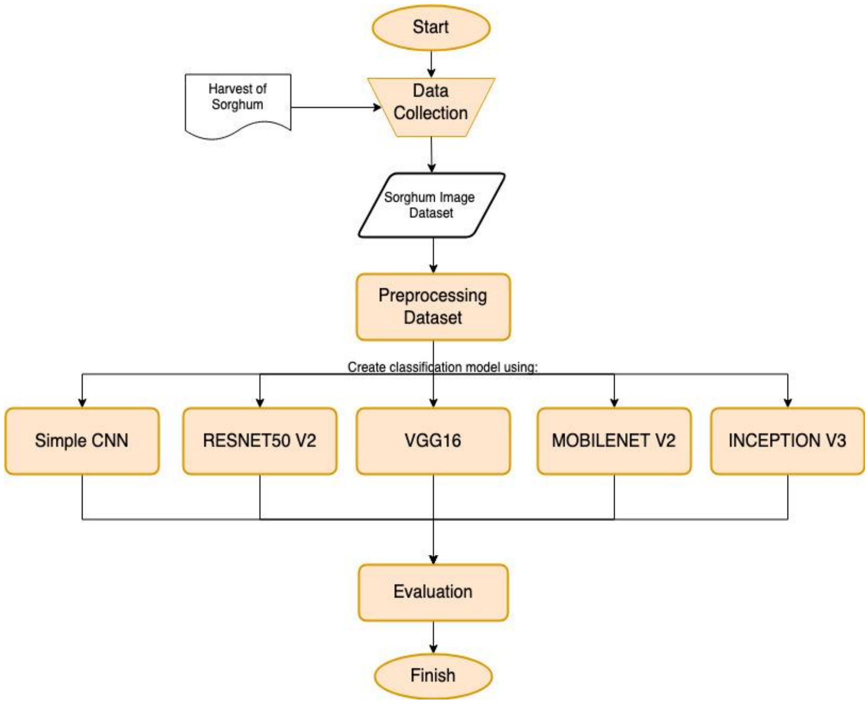


Figure 1. Research steps

3.1. Data collection

The dataset used in this research is obtained from direct observation of samurai-1 sorghum fields, shown in Figure 2. The research location is in Jonggol, Bogor, Indonesia. The drone captures the image data at 80 meters from the ground and has dimensions of 5464×3640 pixels. Data collection starts from January 2021 to February 2021, with collection times around 10.00 to 12.00 when the sorghum crops are not yet harvested (January 28, 2021), shown in Figure 2(a), at harvest time (February 10, 2021) shown in Figure 2(b), and past harvest time (February 21, 2021) shown in Figure 2(c).

(a) (b) (c)

Figure 2. Example of data collection when the sorghum field is in the period of (a) not enough harvest time, (b) harvest time, and (c) harvest late

3.2. Pre-process

At this stage, the catches are sorted from several photos for classification based on shooting. It takes time before, during, and after the harvest has passed, but the harvest has yet to take place. From the sliced photos with 224×224 pixels, 231 images as pre-processing datasets are produced. These images are separated into 208 training and 23 test data images, as shown in Figure 3.

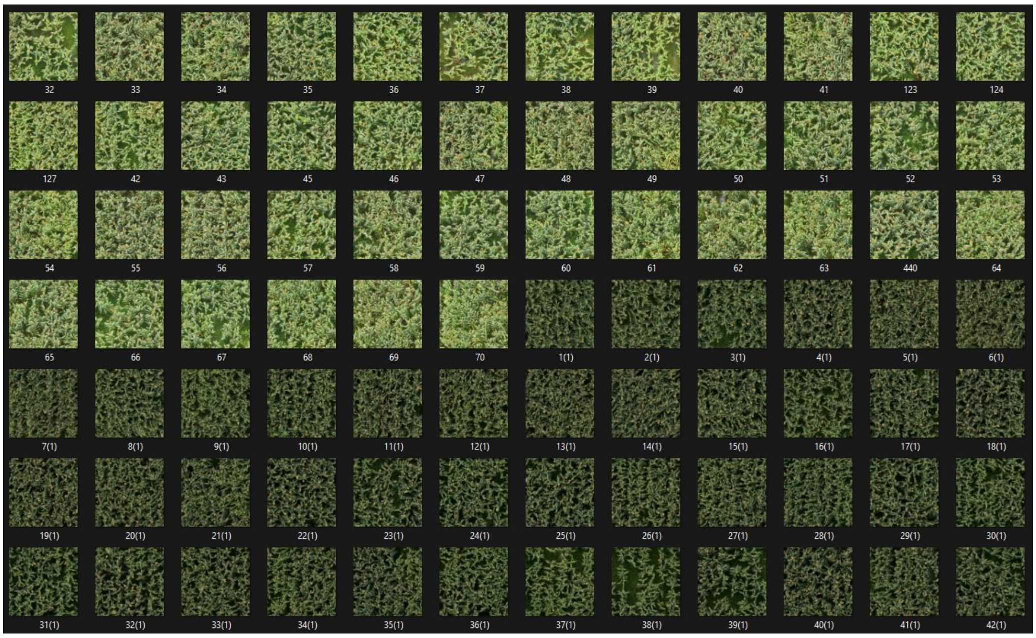
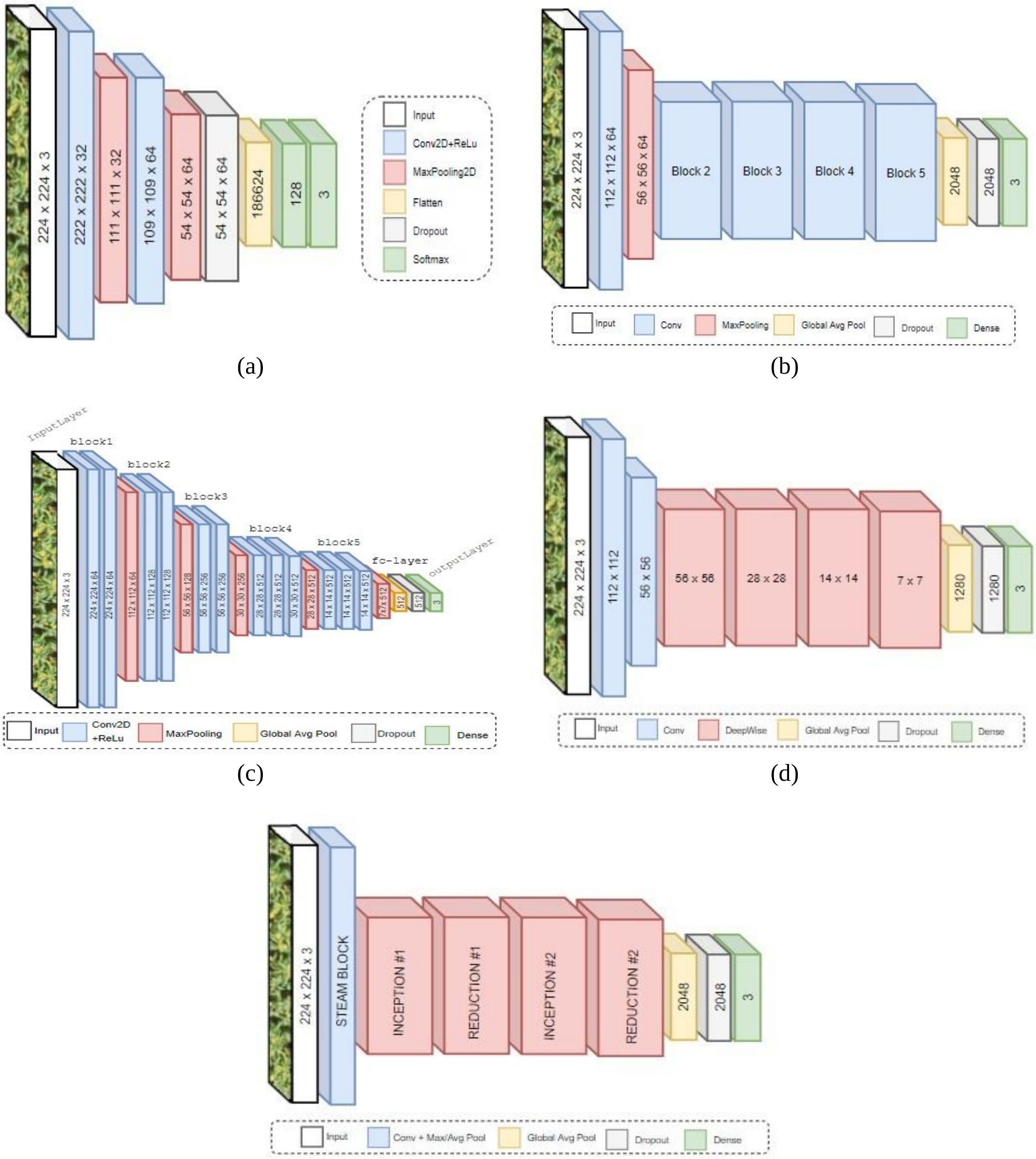


Figure 3. Sliced drone image pre-process

3.3. Modeling

The pre-processed dataset will be a source for input into each CNN algorithm with various architectures, shown in Figure 4. There is the CNN algorithm with simple architectures [18], the CNN algorithm with a residual network-50 (ResNet50) architecture [19], [20], the CNN algorithm with a visual geometry group (VGG) 16 architecture [21], the CNN algorithm with convolutional neural networks for mobile vision applications (MobileNet) architecture [22] and CNN algorithm with an inception architecture [23]. Comparison graphically, the visualization CNN model architectures are simple architectures shown in Figure 4(a), ResNet50 architecture that shown in Figure 4(b), VGG16 architecture that shown in Figure 4(c), MobileNet architecture that shown in Figure 4(d), and Inception architecture that shown in Figure 4(e).



(e)

Figure 4 Comparing CNN architecture model in (a) simple architecture, (b) ResNet50 architecture, (c) VGG16 architecture, (d) MobileNet architecture, and (e) Inception architecture

The dataset was analyzed with CNN and developed with Python programming language version 3.7 using the scikit-learn library. It contains some main class packages for training and testing separate data sets as training data and tests data with each data according to its classification. Process with simple architecture with input_shape parameters, image size 224×224 pixels, activation type = ReLU, dropout to avoid overfitting = 0.9, and target output three classifications with SoftMax and epoch activation types of 100. In the observation model, the early stop parameter is used with a value of 15, so during the model process, the process will be stopped if the loss value for each epoch has a fixed value. Meanwhile, the modeling process with ResNet50 V2, VGG16, MobileNet, and inception architecture using parameters such as weights = ImageNet, image size 224×224 pixels, and target output three classifications with SoftMax, and uses optimizer = Adam, and epoch activation types of 100. Use the early stop parameter if it is stable at a loss during 15 epochs have a fixed value.

3.1. Evaluation

The classification model was evaluated using a confusion matrix. The confusion matrix is an $n \times n$ matrix that is used to measure the performance of the classification model by calculating the values: i) true positive (TF) is a positive actual and predicted value; ii) true negative (TN) means negative actual and predicted values; iii) false positive (FP) means that the actual value is negative, but the predicted value is positive; and iv) false negative (FN) indicates the actual value is positive, but the predicted value is negative.

Furthermore, based on the performance value between the prediction and the actual performance value can be calculated for precision, recall and F1-Score. The precision measures formula, as shown in (1), is the percentage of the main sorghum image successfully validated out of an overall optimistic prediction [24]. The higher precision indicates the lower FP [25].

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

The recall measures formula as in (2) represents how many positive records are predicted correctly, the higher recall indicates the higher probability for the accurate image classification in the model [25].

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

F1-score formula in (3) is the weighted average of precision and recall [26].

$$F1\_score = \frac{2x(Precision\ x\ Recall)}{Precision+Recall} \quad (3)$$

They use the measurement evaluation method to obtain an accuracy of dataset classification with the confusion matrix as a tool in the form of a matrix measuring 3(×)3. The confusion matrix evaluates the classification model by determining which test objects are predicted to be true and false [27]. Using the confusion matrix as a measuring tool determines the precision, accuracy, and F-measures value. According to [28], an accuracy value between 0.90 and 1.00 indicates an excellent; 0.80 and 0.90 for good classification; 0.70 and 0.80 for proper; 0.60 and 0.70 for bad; and 0.50 and 0.60 for failure.

3. RESULTS AND DISCUSSION

The simple CNN modeling process stops when epoch=88. The accuracy of each epoch visualization and confusion matrix result is shown in Figure 5. The following modeling process with ResNet50 model algorithm. The modeling process stops when epoch=40. Graphically, the accuracy of each epoch visualization and confusion matrix result is shown in Figure 6.

The third modeling process is the VGG16 model algorithm. The modeling process stops when epoch=24. Graphically, the accuracy and loss of each epoch visualization and confusion matrix result of this observation with VGG16 architecture is shown in Figure 7.

The fourth modeling process is the MobileNet V2 model algorithm. The modeling process stops when epoch=45. Graphically, the accuracy and loss of each epoch visualization and confusion matrix result of this observation with MobileNet V2 architecture is shown in Figure 8.

The fifth modeling process is the inception V3 model algorithm. The modeling process stops when epoch=28. Graphically, the accuracy and loss of each epoch visualization and confusion matrix result of this observation with inception V3 architecture is shown in Figure 9.

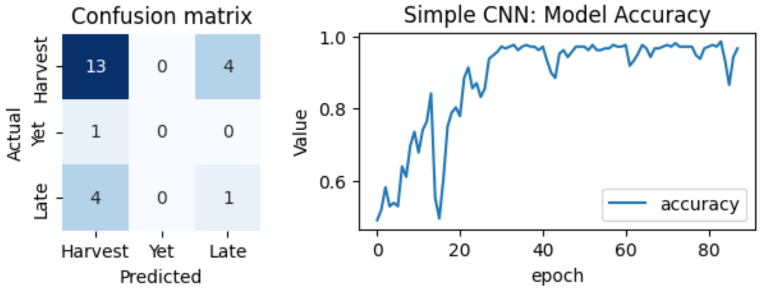


Figure 5. CNN with simple architecture modeling result

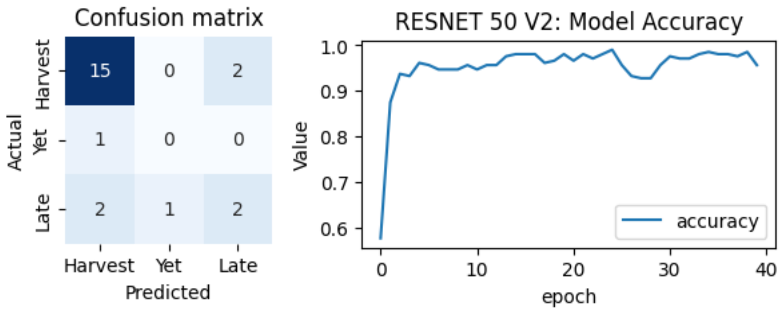


Figure 6. CNN with ResNet50 architecture modeling result

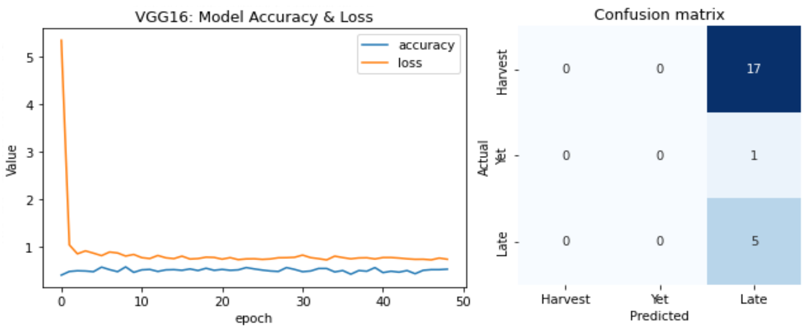


Figure 7. CNN with VGG16 architecture modeling result

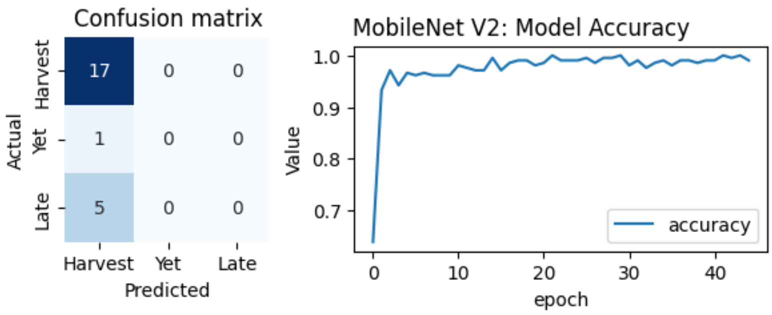


Figure 8. CNN with MobileNet V3 architecture modeling result

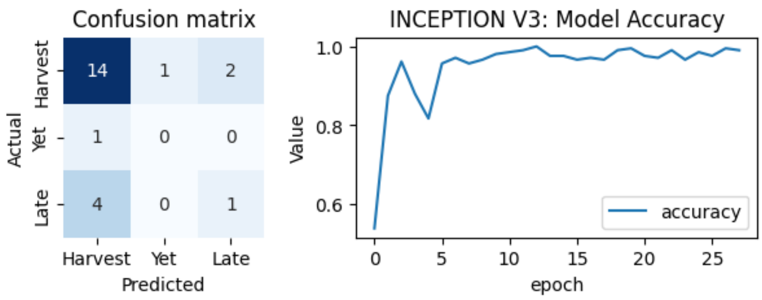


Figure 9. CNN with Inception architecture modeling result

The evaluation of the modeling results from each architecture is calculated into accuracy and lost measurement values. It is shown in Table 1. A comparison of the simple CNN architecture, ResNet50 V2 architecture, VGG16 architecture, MobileNet architecture and Inception architecture, which has the highest accuracy value, is the simple CNN architecture. So based on this research, the simple CNN architecture is the best architectural model for use in estimating the harvest time classification of sorghum (sorghum bicolor) cultivar samurai-1.

Table 1. Metric comparison result

Metric Score	Simple CNN	ResNet50 V2	VGG16	MobileNet V2	Inception V3
Precision					
Harvest	0.72	0.83	0.74	0.74	0.74
Late	1.00	0.00	1.00	1.00	0.00
Yet	0.20	0.50	1.00	1.00	0.33
Weighted Avg	0.62	0.72	0.81	0.80	0.62
Recall					
Harvest	0.76	0.88	1.00	1.00	0.82
Late	0.00	0.00	0.00	0.00	0.00
Yet	0.20	0.40	0.00	0.00	0.20
Weighted Avg	0.61	0.73	0.74	0.74	0.65
F1-Score					
Harvest	0.74	0.85	0.85	0.85	0.78
Late	0.00	0.00	0.00	0.00	0.00
Yet	0.20	0.44	0.00	0.00	0.25
Weighted Avg	0.59	0.73	0.63	0.63	0.63
Accuracy	**0.95**	0.78	0.74	0.74	0.91

4. CONCLUSION

This study evaluated various combinations of CNN model architectures to obtain a model for predicting sorghum harvest time: simple CNN, ResNet50 V2, VGG16, MobileNet V2, and Inception V3. All architectural models use the same parameters: image size, pre-termination state, maximum epoch, and optimizer. The experimental results show that the simple CNN architecture has the best accuracy. That model can be recommended as a choice of algorithm models to estimate sorghum harvest time. We plan to experiment with other models and find the best accuracy for future work, such as DenseNet and XceptionNet.

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BIOGRAPHIES OF AUTHORS

Kahfi Heryandi Suradiradja completed an associate degree in information technology from the Polytechnic of Institute Technology Bandung, 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. He 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.

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 is 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 via email: irman.hermadi@apps.ipb.ac.id.