Sriwijaya Electrical and Computer Engineering Journal (SELCO)
Vol. 1, No. 1, February 2024, pp. 30-36
DOI: 10.62420/selco.v1i1.4

Performance comparison of MobileNet, EfficientNet, and Inception for predicting crop disease

Salman Al Farizi Harahap[1] , Irmawan[1]
[1] Department of Electrical Engineering, Universitas Sriwijaya, Jl. Raya Palembang – Prabumulih Km. 32 Indralaya , OI, Sumatra Selatan, 30662, Indonesia

ARTICLE INFO

Article history:

Received December 22, 2023
Revised January 30, 2024
Published February 1, 2024

Keywords:

Convolutional Neural Networks
MobileNet ;
EfficientNet ;
Inception;
Agriculture ;
Disease Plant

ABSTRACT

Disease plant food can cause significant loss in production agriculture since difficult to detect early symptoms of disease. Apart from that, the selection of Convolutional Neural Network (CNN) architecture for the detection of disease plants often faces the challenge of trade-offs between accuracy and efficiency. In this research, we propose a solution with compares the performance of three current CNN architectures, ie MobileNet, EfficientNet, and Inception, in context predictions of disease plant food. We implement a transfer learning approach to increase efficiency and performance model predictions.The contribution of this study is located on the guide practical for researchers and practitioners in choosing appropriate CNN architecture with need-specific application detection disease plant food.In this experiment, we use 3 datasets to represent plant food in Indonesia, namely rice, corn, and potatoes. Metric evaluation performances like accuracy, precision, recall, and F1-score are used to compare the results of the experiment. Experimental results show a significant difference in performance third tested architecture. MobileNet stands out in speed inference and necessity source low power, temporary EfficientNet shows a good balance between accuracy and efficiency. Inception delivers superior results in detecting feature complex however needs to source more power. In conclusion, the selection of CNN architecture for predictions of disease plant food must consider the trade-off between accuracy, speed inference, and necessity source power. These experimental results can give a guide valuable for practitioners in making appropriate technology with need Specific application detection disease plant food.

Corresponding Author :

Irmawn, Department of Electrical Engineering, Universitas Sriwijaya, Jl. Raya Palembang Prabumulih KM 32, Indralaya 30662, Indonesua
Email: irwaman@unsri.ac.id

1. INTRODUCTION

The continuous growth of the world's population exerts significant pressure on the production of plant-based food to meet global nutritional needs. However, the production of plant-based food often faces various challenges, particularly in combating plant diseases [1], [2]. Plant diseases can lead to substantial agricultural losses, jeopardizing food security, and potentially destabilizing the agricultural sector's economy [3].

In an effort to address these challenges, technology intelligence, especially in image processing, has garnered considerable attention. The application of machine learning algorithms to analyze and predict plant diseases can assist farmers and researchers in early prevention, thereby reducing the adverse impact of plant diseases on agricultural yields [4]–[6].

One crucial aspect in developing an effective plant disease detection system is the selection of an efficient neural network architecture. In this research, we focus on three neural network architecture models that have received attention in the literature: MobileNet, EfficientNet, and Inception.

MobileNet is recognized for its superior real-time performance and energy-efficient utilization, making it suitable for application in resource-limited environments such as mobile devices or embedded systems [7], [8]. Meanwhile, EfficientNet was developed with a focus on optimizing the scale model to achieve a good balance between accuracy and computational efficiency. On the other hand, Inception, with a multi-scale convolution module design, offers the ability to capture features in a complex hierarchy.

Previous studies have addressed disease detection, primarily focusing on detecting diseases in paddy plants using only the VGG algorithm [9]. , or applying PSO as a detection algorithm [10]. Some studies have classified diseases in potatoes and corn; however, there is a lack of comparison with other algorithms.

In the context of this research, the goal is to compare the performance of MobileNet, EfficientNet, and Inception in predicting plant diseases. The comparative analysis covers aspects such as classification accuracy, inference time, and computational efficiency. The results of this study are expected to provide insights into the relative superiority of these three neural network architecture models in the context of plant disease detection. A deeper understanding is anticipated to contribute to the development of more effective and efficient plant disease detection systems.

2. METHODS

This study aims to compare the performance of three convolutional neural network architectures: MobileNet, EfficientNet, and Inception, in the context of predicting diseases in plant-based food. The study involves several stages, with the experiments described as follows.

2.1. Data collection

The dataset used in this study comprises images representing various types of diseases in plant-based food. These images have been sourced from reputable data providers and verified by agriculture experts. Each disease category is well-represented in the dataset to ensure sufficient diversity. The datasets used consist of different sets, with rice being the most complex dataset, totaling 10,407 data points, followed by corn with 4,118, and potato with 4,072 data points.

2.2. Data Preprocessing

The data extracted from the dataset underwent a series of preprocessing stages before being utilized as input for the model. Preprocessing included data augmentation in the form of a 45-degree rotation, a 50% reduction in brightness, and a 50% zoom. Data augmentation was selectively applied, with randomly chosen data undergoing transformation for an expanded data range. Subsequently, all data underwent image resizing to 224×224 pixels to ensure consistency and uniformity in the model input.

2.3. Dataset Sharing

The dataset is divided into three main parts: training data, validation data, and testing data. The distribution is set at a proportion of 75:20:5 to ensure the model undergoes sufficient training, effective validation, and unbiased testing.

2.4. Training

Three convolutional neural network architectures, namely MobileNet, EfficientNet, and Inception, are trained using frameworks suitable for deep learning work. During the training process, applying certain callbacks will affect parameters. The callbacks used include reducing learning rates on a plateau to decrease the learning rate if there is no significant change in evaluation accuracy, and early stopping to halt training and avoid overfitting. Each model is trained on the training data with optimized parameters to maximize performance.

2.5. Model Evaluation

The performance of each model is evaluated using several metrics, namely the confusion matrix, accuracy, precision, recall, and F1-score. These evaluation results allow for a possible comparison between the models in the context of detecting diseases in plant-based food.

3. RESULTS AND DISCUSSION

In the stages of model evaluation, we obtained interesting results from our experiments using three different convolutional neural network architectures, namely MobileNet, EfficientNet, and Inception, in the context of predicting diseases in plant-based food.

3.1. Model Performance

The model's performance will be presented through a classification report, including metrics such as accuracy, loss, precision, recall, and F1 score. Higher accuracy indicates better model performance, while lower losses are preferable. Additionally, precision, recall, and F1 score provide information about the model's predictions in terms of true positives, true negatives, and false negatives.

3.1.1. Potato

The performance of the three models is considered acceptable, as shown in Table 1, and can be deemed very good, almost perfect. The best result was achieved by EfficientNet with 97% accuracy and a loss of 0.128, followed by MobileNet with an accuracy of 91% and a loss of 0.360. The least favorable result was obtained by Inception, with an accuracy of 85% and a loss of 0.317.

Table 1. Evaluation of the Classification Model for Potatoes

Model	Metric Evaluation				
	Accuracy (%)	Losses	Precision	Recall	F1
MobileNet	91	0.360	0.92	0.92	0.91
EfficientNet	97	0.128	0.95	0.95	0.95
Inception	85	0.317	0.88	0.85	0.85

3.1.2. Corn

When compared with a model for potatoes, the model for corn, as shown in Table 2, performed better than the one for potatoes. However, EfficientNet secured the top ranking with near-perfect accuracy. Additionally, Inception, serving as the potato model, achieved an accuracy of only 85%, whereas the potato model reached an accuracy of 94%, albeit still ranking as the model with the worst outcome

Table 2. Evaluation of the Classification Model for Corn

Model	Metric Evaluation				
	Accuracy (%)	Losses	Precision	Recall	F1
MobileNet	96	0.101	0.96	0.92	0.91
EfficientNet	98	0.057	0.98	0.97	0.95
Inception	94	0.141	0.95	0.94	0.95

3.1.3. Paddy

From Table 3, EfficientNet continues to be the best-performing model, maintaining a close accuracy level with the previous models. Interestingly, despite having more extensive datasets and larger data sizes, paddy did not significantly influence metric evaluation, except for Inception, which experienced a decrease of up to 72%.

Table 3. Evaluation of the Classification Model for Rice

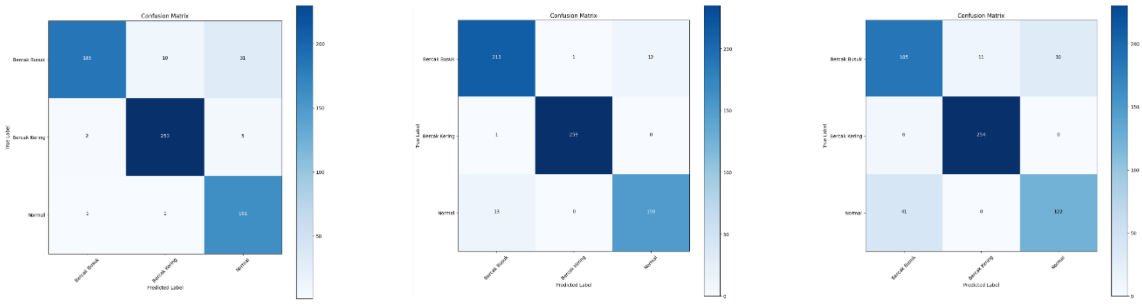
Model	Metric Evaluation				
	Accuracy (%)	Losses	Precision	Recall	F1
MobileNet	94	0.244	0.94	0.94	0.94
EfficientNet	97	0.166	0.96	0.96	0.96
Inception	72	2,845	0.68	0.63	0.64

3.2. Confusion Matrix

The confusion matrix helps identify patterns of frequent classification errors with the method and compares them with actual labels. If the model is good, the confusion matrix will display a diagonal pattern.

3.2.1. Potato

In Fig. 1, the confusion matrix for the potato model is presented. The matrix is quite clear as it involves only three classes. As discussed earlier regarding the model's performance, EfficientNet achieved the best confusion matrix. However, MobileNet still outperforms in predicting plants with the normal class. Since the evaluation data involves spotting dry distribution classes, the predictions tend to be concentrated in the middle, making the central region visibly thicker than the other boxes.

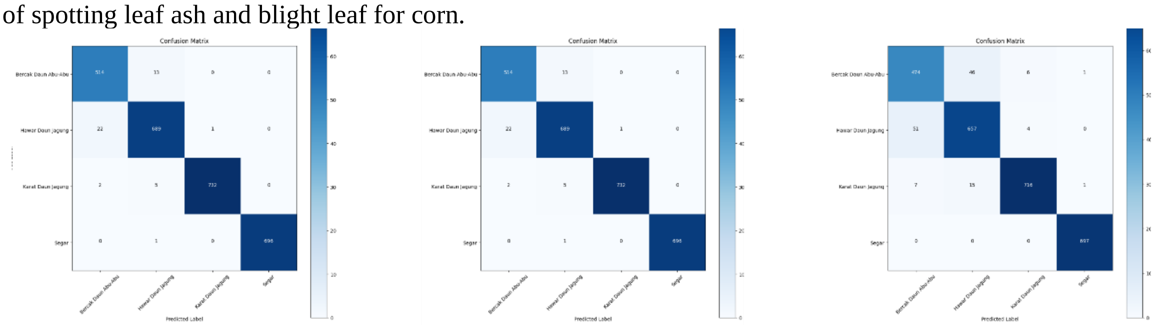


(a) **(b)** **(c)**

Fig. 1. Confusion matrix (a) MobileNet , (b) EfficientNet , (c) Inception potato model

3.2.2. Corn

The confusion matrix for corn, as shown in Fig. 2, tends to have a better shape compared to that of the potato. The distribution of predictions tends to form a diagonal, with only a few mistakes in predicting the classes of spotting leaf ash and blight leaf for corn.

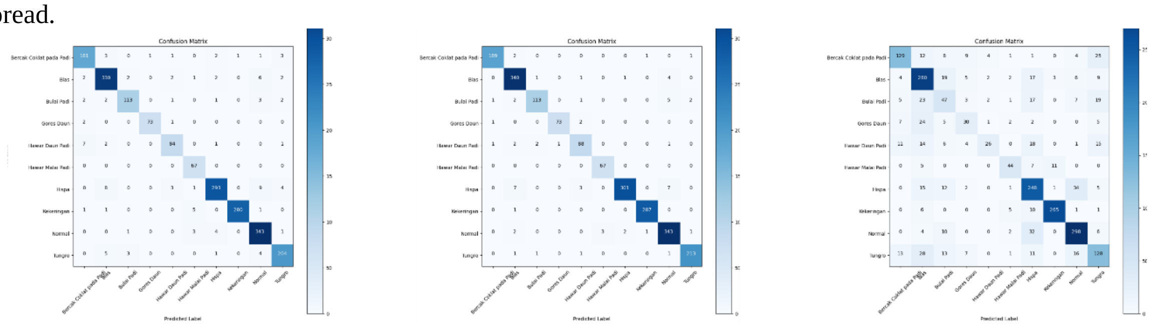


(a) **(b)** **(c)**

Fig. 2. Confusion matrix (a) MobileNet , (b) EfficientNet , (c) Inception corn model

3.2.3. Paddy

In Fig. 3, comparing the distribution of predicted labels with the actual labels reveals disparities, resulting in an insufficient number of predictions along the middle of the diagonal. Nevertheless, the diagonal is still clearly visible in all three confusion matrices, even though the predictions for the inception label tend to be more spread.



(a) **(b)** **(c)**

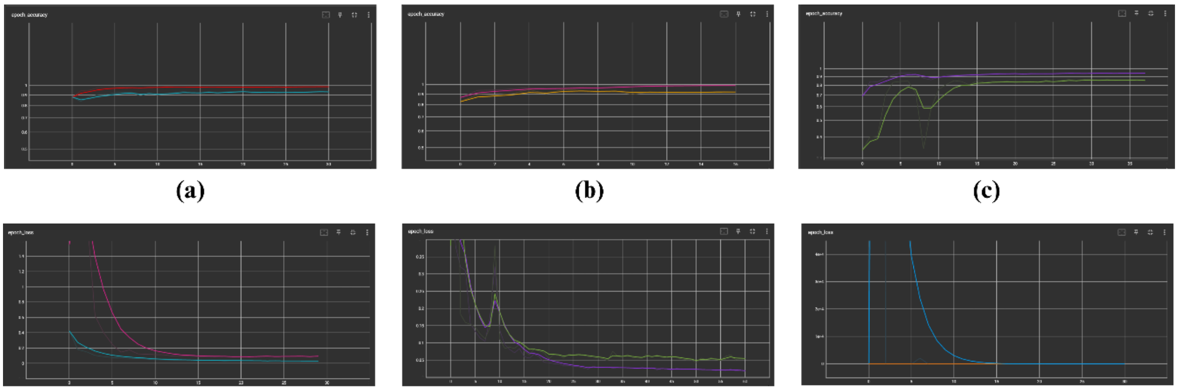
Fig. 3. Confusion matrix (a) MobileNet, (b) EfficientNet, (c) Inception rice model

3.3. Graphic Training Analysis

Training analysis charts are essential to observe how quickly the model learns from the given data. Additionally, the graph illustrates the usage of performance parameters and callbacks.

3.3.1. Potato

On the training graph, it is evident that MobileNet and EfficientNet achieved good results in the first epoch, rendering the reduction in the learning rate by callbacks less influential. In contrast to MobileNet and EfficientNet, the Inception model's performance improved when callbacks were reduced in the middle of the training process, although ultimately, none matched the performance of these models. If the learning rate continues to decrease and the epoch count increases, there is a possibility that Inception may equal or even outperform both models. However, this might also lead to the risk of overfitting. Model accuracy can be seen in Fig. 4.



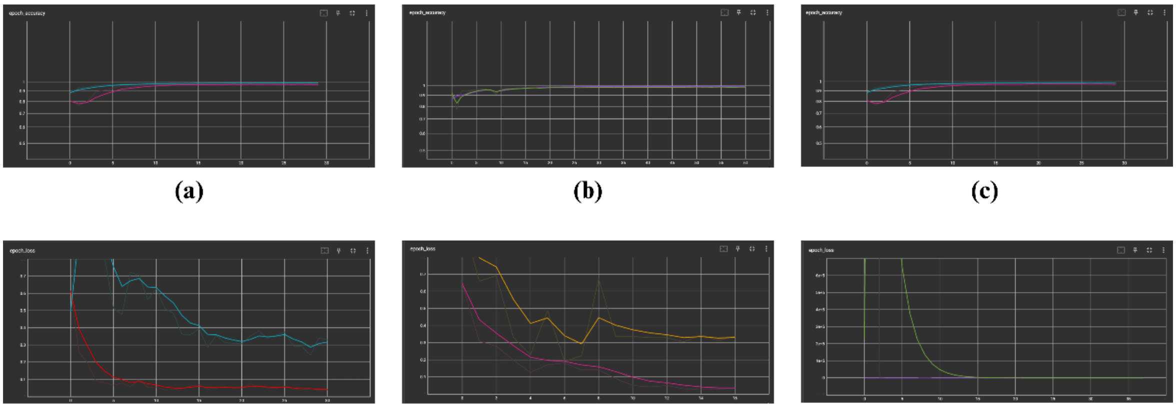
(a) (b) (c)

(d) (e) (f)

Fig. 4. Model accuracy (a) MobileNet, (b) EfficientNet, (c) Inception and loss model (d) MobileNet, (e) EfficientNet, (f) Inception on potato data

3.3.2. Corn

The training graph, as seen in Fig. 5, reveals a pattern similar to the one observed in the potato model graph. However, all three models performed exceptionally well in the first epoch, including the Inception model, despite a slight overlap in the loss graph.



(a) (b) (c)

(d) (e) (f)

Fig. 5 . Model accuracy (a) MobileNet, (b) EfficientNet, (c) Inception and loss model (d) MobileNet, (e) EfficientNet, (f) Inception on corn data

3.3.3. Paddy

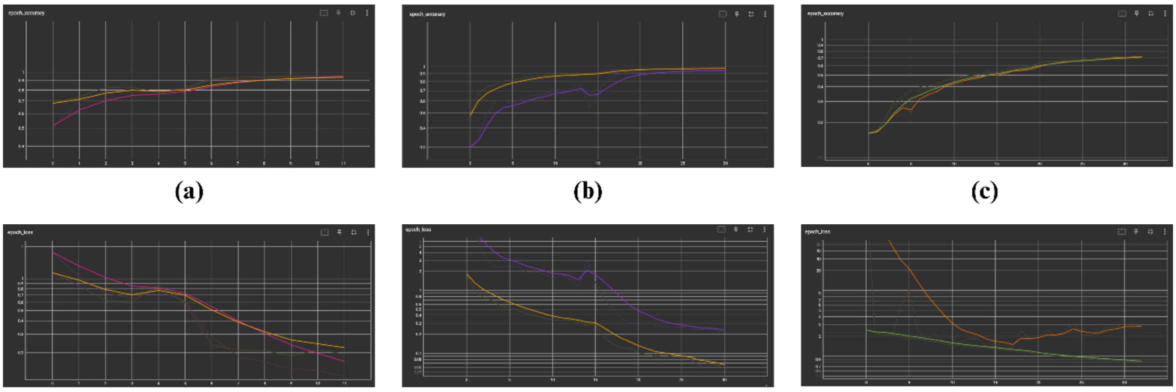
The training graph for rice (Fig. 6) exhibit a notable difference compared to the previous charts, as all models tend to yield fewer results at the beginning of the epoch. However, with the increase in epochs and a decrease in the learning rate during the training process, the models seem to reach a peak, although the peak of the Inception model is lower than that of the other two models.

3.1. Discussion

In discussing the performance of all three models, we observe that the superiority of EfficientNet can be attributed to its fusion efficiency and high computational power with complex datasets. The renowned MobileNet, while effective and lightweight, is less capable of handling variations in dataset complexity, while Inception shows the poorest performance.

Further analysis reveals that an adequate dataset size and hyperparameter optimization play a key role in increasing model performance. However, the success of EfficientNet also underscores the need for continued exploration in designing architectures that can overcome specific challenges in detecting diseases in plant-based food. While the results are promising, this research has its limitations, such as a limited dataset size and constraints in computing power. These factors need to be considered when evaluating the generalization of study results.

Based on our findings, we recommend that further studies be conducted to explore more sophisticated network architectures and utilize larger datasets. A deeper understanding of the factors influencing model performance can pave the way for the development of more effective systems for detecting diseases in plants.



(a) (b) (c)

(d) (e) (f)

Fig. 6. Chart Model accuracy (a) MobileNet, (b) EfficientNet, (c) Inception and loss model (d) MobileNet, (e) EfficientNet, (f) Inception on rice data

4. CONCLUSION

In this research, we succeeded in comparing three architecture network nerve convolutional, that is MobileNet, EfficientNet, and Inception, to predict disease in plant food. Based on the evaluation of the results, the conclusion main thing that can be done is :

Superior performance EfficientNet in a way significantly surpasses MobileNet and Deep Inception matter accuracy, precision, recall, and F1-score. This superiority shows the potency big EfficientNet in increasing the detection of disease plant food.

Optimization of parameters and dataset size plays a role important in increasing model performance. The results show the necessity for attention specifically on aspects in the development of detection models of disease plants.

Impact positive for agriculture which can help farmers identify in a way early potency disease in plants, minimize loss results harvest, and improve the efficiency of agriculture.

Limitations and opportunities in research furthermore cover exploration architecture more network sophisticated and the use more bigger datasets to increase generalization results.

REFERENCES

[1] B. Nuryanto, “Pengendalian Penyakit Tanaman Padi Berwawasan Lingkungan Melalui Pengelolaan Komponen Epidemik,” *J. Penelit. dan Pengemb. Pertan.*, vol. 37, no. 1, p. 1, 2018, doi: 10.21082/jp3.v37n1.2018.p1-8.

[2] V. K. Singh, R. Singh, A. Kumar, and R. Bhadouria, “Chapter 2 - Current status of plant diseases and food security,” A. Kumar and S. B. T.-F. S. and P. D. M. Droby, Eds. Woodhead Publishing, 2021, pp. 19–35. doi: https://doi.org/10.1016/B978-0-12-821843-3.00019-2.

[3] D. He, J. Zhan, and L. Xie, “Problems, challenges and future of plant disease management: from an ecological point of view,” *J. Integr. Agric.*, vol. 15, no. 4, pp. 705–715, 2016, doi: https://doi.org/10.1016/S2095-3119(15)61300-4.

[4] E. Omrani, B. Khoshnevisan, S. Shamshirband, H. Saboohi, N. B. Anuar, and M. H. N. M. Nasir, “Potential of radial basis function-based support vector regression for apple disease detection,” *Measurement*, vol. 55, pp. 512–519, 2014, doi: https://doi.org/10.1016/j.measurement.2014.05.033.

[5] A. Johannes *et al.*, “Automatic plant disease diagnosis using mobile capture devices, applied on a wheat use case,” *Comput. Electron. Agric.*, vol. 138, pp. 200–209, 2017, doi: https://doi.org/10.1016/j.compag.2017.04.013.

[6] P. Siricharoen, B. Scotney, P. Morrow, and G. Parr, “A Lightweight Mobile System for Crop Disease Diagnosis BT - Image Analysis and Recognition,” 2016, pp. 783–791.

[7] J. Chen, D. Zhang, M. Suzauddola, and A. Zeb, “Identifying crop diseases using attention embedded MobileNet-V2 model,” *Appl. Soft Comput.*, vol. 113, p. 107901, 2021, doi: 10.1016/j.asoc.2021.107901.

Vol. 1, No. 1, February 2024, pp. 30-36
DOI: 10.62420/selco.v1i1.4

[8] E. Elfatimi, R. Eryigit, and L. Elfatimi, "Beans Leaf Diseases Classification Using MobileNet Models," *IEEE Access*, vol. 10, pp. 9471–9482, 2022, doi: 10.1109/ACCESS.2022.3142817.
[9] J. Cai *et al.*, "Improved EfficientNet for corn disease identification," *Front. Plant Sci.*, vol. 14, no. September, pp. 1–17, 2023, doi: 10.3389/fpls.2023.1224385.
[10] Y. Lu, J. Du, P. Liu, Y. Zhang, and Z. Hao, "Image Classification and Recognition of Rice Diseases: A Hybrid DBN and Particle Swarm Optimization Algorithm," *Front. Bioeng. Biotechnol.*, vol. 10, no. April, pp. 1–12, 2022, doi: 10.3389/fbioe.2022.855667.

BIOGRAPHY OF AUTHORS

Salman Al Farizi Harahap was born in Padangsidimpuan on October 22, 2002. Currently, he is a final-year student in the Department of Electrical Engineering at Universitas Sriwijaya. His research interest lies in artificial intelligence. He can be contacted at 03041282025085@student.unsri.ac.id.

Irmawan was born in 1973. He received a B.S. degree in Physics from Universitas Gadjah Mada, and his master's degree is in Electrical Engineering. Currently, he serves as a lecturer in the Department of Electrical Engineering at Universitas Sriwijaya. His research interests include electronics and signal processing. For contact, he can be reached at irmawan@unsri.ac.id.