Classification of Cassava (*Manihot sp.*) Leaf Variants Using Transfer Learning

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ABSTRACT

There are several types of cassava leaves with different characteristics, tastes, and nutritional content. Some people use cassava leaves as a vegetable ingredient for daily consumption as a source of fiber and minerals. However, people often have difficulty identifying the different types of cassava leaves, including cassava leaf variants that are locally referred to as gajah, karet, and mentega. This study aims to use transfer learning to identify the variant of cassava leaves. The Inception v3 architecture was selected to build the classification model. To demonstrate the superiority of transfer learning, the Inception v3 architecture was run with two different weights. The first weight was randomly initialized, while the second weight was taken from pre-trained weights from ImageNet. The experimental results show that the classification accuracy rate using the pre-trained weights reached 95.76%. This indicates that the classification model used in this study is promising and can be used for practical purposes in everyday life.

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1. INTRODUCTION

Cassava (*Manihot sp.*) leaves can be used as a vegetable in various culinary preparations. They are often boiled or sautéed and used as a side dish, or they can be added to soups, stews, or curries. Cassava leaves are rich in nutrients, including protein, fibre, vitamins, and minerals, and they are a good source of antioxidants. They also have some medicinal properties, as they contain compounds that may have anti-inflammatory, anti-microbial, and anti-cancer effects. In some regions, cassava leaves are a traditional food and an important part of the local cuisine. Overall, cassava leaves are versatile and nutritious vegetables that can be enjoyed in many different ways [1-4].

There are several variants of cassava leaves, including (called in local names): gajah (*Manihot esculenta var gajah*), karet (*Manihot glaziovii*), and mentega (*Manihot esculenta var mentege*). These variants differ in their characteristics, such as their texture, taste, and nutritional content [5-7]. Gajah cassava leaves are large and have a tough texture, and they are often used in dishes that require long cooking times, such as soups and stews. On the other hand, Karet cassava leaves are softer and have a smoother texture, often used in stir-fries or salads. Mentega cassava leaves are small and tender, and they have a buttery flavor that is prized in some culinary traditions. Each variant of cassava leaves has its own unique properties and culinary applications, and they can be used interchangeably in some recipes or combined to create new flavors and textures. Some examples of gajah, karet, and mentega variants of cassava leaves are presented in Figure 1.

As can be seen in Figure 1, the different variants of cassava leaves have a high degree of similarity, and this can make it difficult for people to distinguish between them. They may look very similar in terms of their shape, size, and color, and they may also have similar nutritional content and culinary applications. This can be particularly challenging for people who are not familiar with cassava leaves or who do not have much experience cooking with them. Without proper training or guidance, it can be hard to identify the different variants of cassava leaves, which can make it difficult to use them effectively in cooking or to take advantage of their nutritional benefits.

Figure 1. Some cassava variants leaves: gajah (top), karet (midle), and mentega (bottom)

Deep learning, especially transfer learning, can be used to easily classify different variants of cassava leaves. With the help of a pre-trained neural network and modern computer support, it is possible to accurately identify each variant based on its unique characteristics and features [8-13]. The transfer learning approach allows for the neural network to be adapted to the specific task of identifying cassava leaves, even with limited training data. By training a deep learning model, such as Inception v3, on a dataset of labeled cassava leaf images, the model can learn to differentiate between the different variants. It can learn to recognize the texture, shape, and other characteristics that distinguish each variant from the others. The resulting model can then be used to classify new cassava leaf images with a high degree of accuracy, making it easy to identify each variant [14-17].

Research related to the classification of cassava leaves has been carried out by researchers. Lilhore et al. used an enhanced convolutional neural network model to classify and identify diseases on cassava leaves [19]. Ravi et al. also build a classifier using deep learning to do similar work [20]. Surya et al. also detected cassava leaf disease using a convolutional neural network [21]. Similarly, Zhong et al. also classified cassava leaf disease in non-balanced datasets using transformer-embedded ResNet [22]. Again, the classification of cassava leaf disease was also carried out by Sangbamrung using deep learning [23]. Most research related to cassava leaves aims to detect and classify diseases in cassava leaves.

Research on classifying cassava leave variants using deep learning techniques is still not very extensive. While there have been some studies on using deep learning for plant classification in general [24-30], the specific task of classifying different variants of cassava leaves is relatively new. One reason for this is that cassava leaves are not as widely used in cooking as other vegetables, so there may be less interest in studying them. Additionally, there may be challenges in obtaining a large dataset of labeled cassava leaf images, which is necessary for training deep learning models.

The proposed study aims to address a significant research gap by focusing on variant classification. While extensive research has been conducted on disease detection in cassava leaves, there has been a notable lack of investigation into the classification of the variants. This study aims to fill this crucial gap in knowledge.

2. RESEARCH METHOD

In this section, Inception v3 will be discussed as an architecture that will be used in the classification of cassava leaf variants. In addition, the preparation of data sets for experiments will also be presented. Furthermore, the use of image augmentation will also be discussed. Experiment details will also be provided. Finally, how to measure performance will be presented in the closing of this section.

2.1. Deep Learning and Transfer Learning

Deep learning is a subfield of machine learning that focuses on training artificial neural networks with multiple layers to learn and extract hierarchical representations of data. These networks, called deep neural networks, are capable of automatically learning features from raw input data, which makes them highly effective in tasks such as image and speech recognition, natural language processing, and more. A technique in deep learning where knowledge gained from training a model on one task is transferred and applied to a different but related task is called transfer learning. Instead of training a model from scratch, transfer learning leverages the learned representations from a pre-trained model and adapts them to the target task with a smaller dataset. This approach can significantly reduce the training time and resource requirements, especially when labeled data for the target task is limited. Transfer learning is widely used to achieve better performance in various domains and has become a common practice in deep learning applications. Some popular deep learning architectures are available such as VGG-16, VGG-19, and Resnet 50. In this study, Inception v3 is utilized to classify the variant of cassava leaves.

2.2. Inception v3

Inception v3 is a deep neural network architecture used for image classification tasks. It was introduced by Google in 2015 and is an extension of the original Inception architecture. The main idea behind Inception v3 is to create a deep neural network that is both accurate and efficient [31-34].

The Inception v3 architecture uses a combination of convolutional layers, pooling layers, and inception modules. Inception modules are a combination of convolutional layers of different sizes and pooling operations that are designed to extract features from the input image at different scales. This allows the network to capture features at different levels of granularity, which can improve the accuracy of the model.

One of the key features of Inception v3 is the use of batch normalization. Batch normalization is a technique that helps to address the problem of internal covariate shift, which can occur during the training of deep neural networks. By normalizing the input to each layer, batch normalization can help to stabilize the training process and improve the accuracy of the model.

Another important feature of Inception v3 is its use of auxiliary classifiers. These are small classifiers that are added to intermediate layers of the network and are trained to predict the class labels of the input images. The output of these classifiers is then used to provide additional feedback to the main classifier, which can help to improve the accuracy of the model.

2.3. Dataset and Image Augmentation

In this study, the dataset was obtained using a mobile phone camera. The image dataset obtained from cassava plantations for each class (variant) is 118 images. This number is relatively small for learning using deep learning. Fortunately, nowadays there are image augmentation methods [35-38].

Image augmentation is a technique used in machine learning to create variations in training data by transforming existing images. The goal is to increase the amount of training data and existing image variations, to improve model performance in classifying or detecting.

In the case of cassava leaf variant classification with a limited number of images, image augmentation can help increase the amount of data training by generating new images derived from transformations of existing images, such as image rotation, shift, zoom, and stop. This can help overcome the problem of overfitting the model, where the model learns too much from the existing patterns in the training data and cannot generalize well to the new test data.

In classifying cassava leaf variants, image augmentation can help increase the variety of cassava leaf images by performing image transformations such as horizontal or vertical flip, zoom in or zoom out, and image rotation. With more image variations, the model will be better at studying the characteristics of each cassava leaf variant and recognizing differences between one cassava leaf variant and another. Some of the results of image augmentation operations on an image of cassava leaves can be seen in Figure 2.

Figure 2. A number of image augmentations on a single image

2.4. Experiment settings

The following is a detailed description of the experiment step-by-step to classify cassava leaves variant using the Inception v3 model with image augmentation:

Firstly, the images are divided into ten folds and subsequently stratified cross-validation is applied [39-40]. In each sub-test, the images are divided into approximately 90% training and 10% validation, i.e., 9 and 1 folds, respectively. The training folds will be used to train the model, while the test fold will be used to evaluate the accuracy of the model. The splitting between the training and the testing folds in stratified cross-validation is described in Figure 3. Then, we perform data augmentation on the images in the training folder using techniques such as flipping, zooming, rotation, and more.

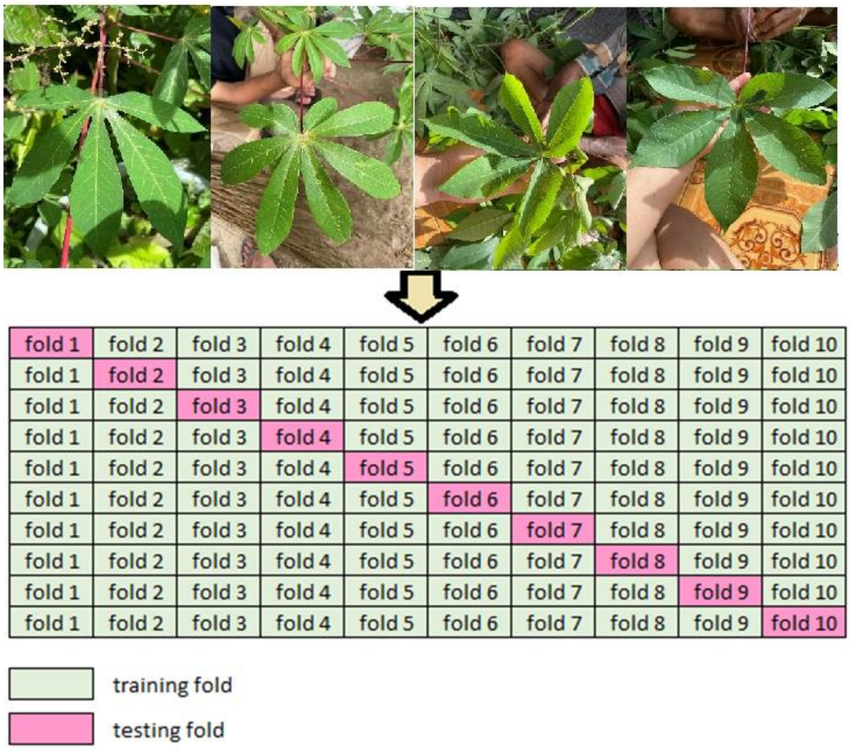

Figure 3. Stratified 10-Cross-Validation

Secondly, we employ Inception v3, a pre-trained deep learning model, as the base for the classification model. We add a few layers on top of it to create a custom model for cassava leaf classification. Then, we freeze the Inception v3 layers and compile the model using a categorical cross-entropy loss function.

Thirdly, the model is subsequently trained using the augmented training data set. We set the number of epochs and batch size based on the available hardware resources. By monitoring the model's accuracy and loss during training, we identify the point where it starts to overfit the training data.

Finally, test the model on new, unseen cassava leaves images to see how well it generalizes to new data. Use the model to classify the variant of the cassava leaves and compare the results to the actual labels to evaluate the model's accuracy.

2.5. Performance Evaluation

In supervised machine learning, a confusion matrix is a useful tool for evaluating the performance of a classification model, especially in the case of multi-class classification like cassava leaves variant classification, which has three classes: gajah, karet, and mentega.

A confusion matrix is a table that summarizes the performance of the classification model by comparing the actual class labels of the samples to the predicted class labels. In the case of cassava leaves variant classification, the confusion matrix will have three rows and three columns, corresponding to the three classes: gajah, karet, and mentega. The diagonal elements of the matrix represent the correctly classified samples, while the off-diagonal elements represent the misclassified samples.

The accuracy of the classification model can be calculated using the values in the confusion matrix. The accuracy is the ratio of the correctly classified samples to the total number of samples. It is calculated as follows:

$$a = \frac{t}{n} \times 100\% \quad \text{(Eq. 1)}$$

where

a : accuracy,
t : number of correct predictions,
n : number of predictions

Moreover, precision, recall, and F1 score are also commonly used in classification tasks to evaluate the effectiveness of a model in predicting the correct class labels.

Precision is a measure of the accuracy of positive predictions made by a model. It calculates the proportion of true positive predictions (correctly predicted positive instances) out of the total instances predicted as positive (the sum of true positives and false positives). In other words, precision focuses on the model's ability to avoid false positives. A high precision value indicates that the model has a low rate of falsely predicting positive instances.

Recall, also known as sensitivity or true positive rate, measures the model's ability to correctly identify positive instances out of all the actual positive instances in the dataset. It calculates the proportion of true positive predictions to the sum of true positives and false negatives (positive instances incorrectly classified as negative). Recall focuses on the model's ability to capture all positive instances without missing any. A high recall value indicates that the model has a low rate of falsely predicting negative instances.

The F1 score is a single metric that combines both precision and recall into a balanced evaluation of a model's performance. It is the harmonic mean of precision and recall and provides an overall measure of a model's accuracy. The F1 score is calculated using the formula:

$$F1_{score} = \frac{= 2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}} \quad \text{(Eq. 2)}$$

The F1 score ranges from 0 to 1, where a value of 1 represents perfect precision and recall, while 0 indicates the worst performance.

3. RESULTS AND DISCUSSION

3.1. Results

The cassava leaf variant classification experiment was carried out in two schemes with the difference being the weight settings in the inception v3 architecture. The first scheme uses randomly initialized weights. The results of the first scheme experiment are presented in Table 1 column randomly initialization while the second scheme which employs weights taken from pre-trained models from ImageNet are listed in the column pre-trained from ImageNet.

Table 1. Classification Accuracy for randomly and pre-trained weights

Fold test	Randomly Initialization	Pre-trained from ImageNet
1	33.33	91.67
2	61.11	94.44
3	33.33	97.22
4	36.11	100.00
5	34.29	100.00
6	34.29	97.14
7	34.29	94.29
8	34.29	91.43
9	31.43	100.00
10	42.86	91.43
Average	37.53	95.76

We also record the detailed results of the cumulative classification for further analysis in the form of a confusion matrix. The confusion matrices for the first and second schemes are presented in Figures 4 and 5, respectively. In addition, the computation time for each fold is shown in Table 2.

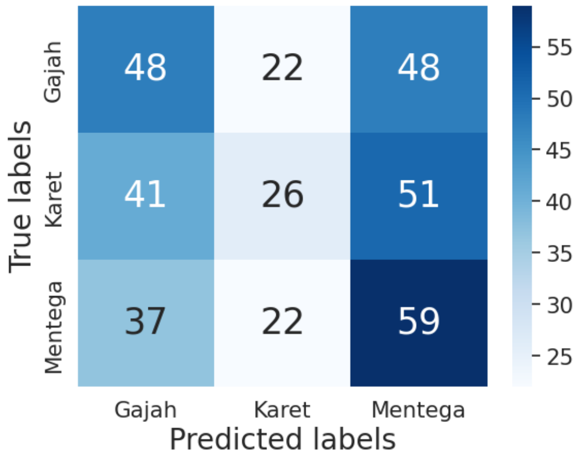

Figure 4. Confusion Matrix for Random-Initialization Weights

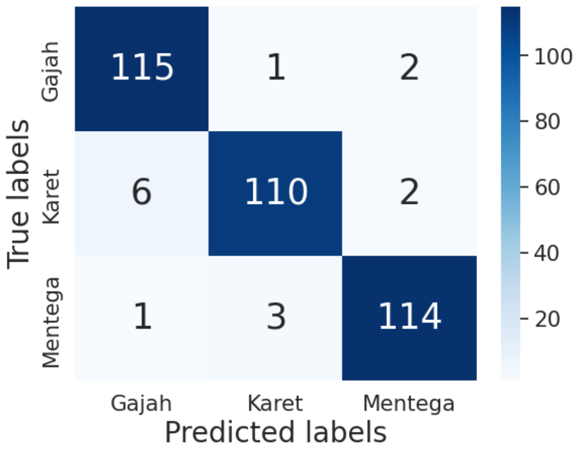

Figure 5. Confusion Matrix for Pre-trained Weights

Table 2. The Computation Time forEach Fold

Fold	Training	Testing
1	25.02	2.08
2	15.58	1.62
3	16.05	1.53
4	15.96	1.54
5	16.23	1.99
6	15.52	1.51
7	15.87	1.46
8	15.79	1.50
9	15.60	1.54
10	16.09	1.56
Total	167.72	16.33

3.2. Discussions

The experiments aimed to classify three different types of cassava leaves, namely gajah, karet, and mentega, using an image classification algorithm. The experiment used two different approaches to build the model: using a pre-trained model with weights from ImageNet (Inception v3), and random initialization. The results of the experiment showed that the pre-trained model with Inception v3 achieved a much higher accuracy rate of 95.76% compared to random initialization, which only achieved an accuracy rate of 37.53%. This indicates that using a pre-trained model with weights from ImageNet can significantly improve the performance of the image classification algorithm for cassava leaf classification. The reason why the pre-trained model performed better is because it had already been trained on a large dataset of images, including many different types of plants and leaves, including cassava leaves. This means that the model already had a good understanding of the features that distinguish cassava leaves from other types of leaves. By using the pre-trained weights from ImageNet, the model could leverage this prior knowledge and adapt it to the specific task of cassava leaf classification. On the other hand, random initialization involves starting with a blank slate and training the model from scratch. This approach can work well for some tasks, but it requires a much larger dataset and more training time to achieve the same level of performance as a pre-trained model.

The experimental results of Tables 1 and 2 are clarified by Figures 4 and 5. In Figure 4, the confusion matrix has an irregular heatmap pattern where the classification results look random. In contrast, the confusion matrix in Figure 5 is very regular where the main diagonal has large values and strong colors indicating that a lot of correct predictions occur. According to the matrix, there are three labels for cassava leaves: gajah, karet, and mentega. The first row indicates that out of 118 cassava leaves labeled as gajah, 115 were correctly identified as gajah, 1 was misclassified as karet, and 2 were misclassified as mentega. The second row indicates that out of 118 cassava leaves labeled as karet, 110 were correctly identified as karet, 6 were misclassified as gajah, and 2 were misclassified as mentega. Finally, the third row indicates that out of 118 cassava leaves labeled as mentega, 114 were correctly identified as mentega, 1 was misclassified as gajah, and 3 were misclassified as karet.

From the above values, the classification performance, besides accuracy, can be evaluated using the F1 score, which can be calculated using equation (2). For the gajah class, the F1 score is approximately 0.958. This indicates that the model achieved a balanced performance in correctly identifying gajah leaf variants, considering both precision and recall. A higher F1 score implies that the model had a good balance between identifying true positive gajah samples and minimizing false positives and false negatives. For the karet class, the F1 score is approximately 0.949. This suggests that the model achieved a relatively good overall performance in correctly classifying karet leaf variants, with a balanced consideration of precision and recall. The F1 score demonstrates the model's ability to effectively identify true positive karet samples while minimizing false positives and false negatives. For the mentega class, the F1 score is approximately 0.965. This indicates that the model exhibited a strong performance in correctly identifying "butter" leaf variants, considering both precision and recall. The high F1 score suggests that the model was effective in accurately recognizing true positive mentega samples while minimizing false positives and false negatives.

According to the information provided in Table 2, the computational time for each image during the training and testing phases was recorded as 0.053s and 0.046s, respectively. The computational time was obtained based on the fact that the dataset used in this study consisted of 354 images, and the testing process was performed using a 10-fold cross-validation approach. These values indicate that the computational time for processing each image is relatively low, suggesting that the proposed method is efficient in terms of computational speed. Considering the context of real-time applications, the obtained computational time is still considered reliable. Real-time applications typically require fast processing and response times to provide instantaneous results. In this case, the reported computational times of 0.053s and 0.046s for training and testing, respectively, demonstrate that the proposed method is capable of handling the analysis of cassava leaf images in near real-time scenarios. By achieving such low computational times, it is likely that the proposed method can be effectively deployed in various real-time applications related to cassava leaf classification.

To conclude this discussion session, we would like to compare the classification results of cassava leaf variants with similar classifications, although the classification goals may not be exactly the same. Several studies related to cassava leaf classification can be found in the literature, and some of them will be discussed here.

Lilhore et al. achieved 99.3% accuracy by applying an enhanced convolutional neural network model to classify and identify diseases on cassava leaves. Ravi et al. also used deep learning to do similar work and achieved an accuracy rate of 87.08%. Surya et al. obtained an accuracy rate of 74.96% when detecting cassava leaf disease using a convolutional neural network. Zhong et al. achieved an accuracy rate of 91.12% for cassava leaf disease classification in non-balanced datasets using transformer-embedded ResNet. Finally, Sangbamrung used deep learning to do a similar task and obtained an accuracy of 96.0%. A summary of other research results and our research is presented in Table 2.

Table 3. Research Comparison

Researchers	Goal	Acc.
Lihore et al. [19]	Cassava leaf disease classification	99.3
Ravi et al. [20]	Cassava leaf disease classification	87.08
Surya et al. [21]	Cassava leaf disease classification	74.97
Zhong et al. [22]	Cassava leaf disease classification	91.12
Sangbamrung et al. [23]	Cassava leaf disease classification	96.0
Our works	Cassava leaf variant classification	95.76

As seen in Table 2, the classification results of cassava leaf variants are generally good and comparable to the cassava leaf classification done by other researchers. The accuracy of cassava leaf disease classification results can vary due to the differences in datasets and methods employed. The accuracy of disease identification heavily relies on the quality and diversity of the dataset used for training and evaluation. A well-curated dataset that includes a wide range of cassava leaf diseases and their corresponding labels is crucial for developing accurate disease identification models. Furthermore, the methods utilized for feature extraction, model selection, and training procedures can significantly impact the accuracy of disease identification. Various techniques, such as deep learning models like CNNs or machine learning algorithms like random forests or support vector machines, may yield different results depending on the specific dataset and methodology chosen. Therefore, careful consideration of dataset quality and appropriate method selection are essential for achieving reliable and accurate cassava leaf disease identification results.

The classification results of cassava leaf variant identification typically fall within an accuracy range that lies between the accuracy achieved in cassava leaf disease classification. The accuracy results of our experiment are lower than those of Lihore et al. and higher than other researchers' experiments. This difference is still acceptable since the two problems fundamentally belong to different problem domains. Cassava leaf variant classification involves distinguishing and categorizing different variations of cassava leaves based on visual characteristics such as shape, color, or texture. While it can be challenging, it is relatively more straightforward compared to cassava leaf disease classification. The latter task involves identifying specific diseases or abnormalities present in cassava plants, which requires recognizing subtle symptoms and patterns associated with various diseases. Due to the inherent differences in these problem domains, it is reasonable to observe variations in accuracy between cassava leaf variant and disease classifications. Despite the variances, both tasks contribute valuable insights to the field of cassava research and management, aiding in crop improvement and disease control efforts.

To the best of our knowledge, there have been no prior studies on the classification of cassava leaf variants similar to ours. The achievement of 95.76% accuracy can serve as a baseline for other researchers in the same problem domain. Furthermore, this level of accuracy is deemed sufficient for practical applications in everyday scenarios. The ability to accurately classify cassava leaf variants opens up possibilities for various applications in the agricultural sector. The findings of this research contribute to the existing knowledge in the field and offer a valuable tool for researchers and practitioners alike.

4. CONCLUSION

The classification study of cassava leaf variants has been conducted using VGG-16 and Inception v3 architectures, employing both random weight initialization and pre-trained weights from ImageNet. The highest accuracy achieved in this study was 95.76%, which was obtained using Inception v3 with weights from ImageNet. This indicates the superior performance of Inception v3 in accurately classifying cassava leaf variants compared to VGG-16. The utilization of pre-trained weights from ImageNet played a crucial role in enhancing the model's accuracy and efficiency. These findings suggest that Inception v3 with ImageNet weights is a promising approach for the classification of cassava leaf variants, paving the way for potential applications in crop management and agricultural research.

For future works, there are several suggestions that can be explored. Firstly, increasing the dataset size could potentially improve the accuracy of the classification. Secondly, experimenting with different deep learning architectures or applying different pre-processing techniques can potentially yield better results. Additionally, the inclusion of more classes or extending the classification to include other cassava plant parts could also be an interesting avenue to explore. Finally, exploring the transfer learning approach using models trained on other similar plant datasets could also be a promising area for future research.

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REFERENCES

[1] A. Laya and B. B. Koubala, "Polyphenols in cassava leaves (manihot esculenta crantz) and their stability in antioxidant potential after in vitro gastrointestinal digestion," Heliyon, vol. 6, no. 3, p. e03567, 2020.
[2] S. Chaiareekitwat, S. Latif, B. Mahayothee, P. Khuwijitjaru, M. Nagle, S. Amawan, and J. M ̈uller, "Protein composition, chlorophyll, carotenoids, and cyanide content of cassava leaves (manihot esculenta crantz) as influenced by cultivar, plant age, and leaf position," Food Chemistry, vol. 372, p. 131173, 2022.
[3] A. Chahyadi et al., "The influence of extraction methods on rutin yield of cassava leaves (manihot esculenta crantz)," Saudi pharmaceutical journal, vol. 28, no. 11, pp. 1466–1473, 2020.
[4] L. Chang, L. Wang, C. Peng, Z. Tong, D. Wang, G. Ding, J. Xiao, A. Guo, and X. Wang, "The chloroplast proteome response to drought stress in cassava leaves," Plant Physiology and Biochemistry, vol. 142, pp. 351–362, 2019.
[5] C. Y. Liu, R. Amani, S. Sulaiman, K. Mahmood, F. Ariffin, and A. Mohammadi Nafchi, "Formulation and characterization of physicochemical, functional, morphological, and antioxidant properties of cassava-based rice analogue," Food Science & Nutrition, vol. 10, no. 5, pp. 1626–1637, 2022.
[6] M. H. Saggaf, J. Ndunguru, F. Tairo, P. Sseruwagi, J. T. AscencioIb ́a ̃nez, D. Kilalo, and D. W. Miano, "Immunohistochemical localization of cassava brown streak virus and its morphological effect on cassava leaves," Physiological and molecular plant pathology, vol. 105, pp. 6776, 2019.
[7] L. F. M. Pereira, H. L. Santos, S. Zanetti, I. A. de Oliveira Brito, L. R. dos Santos Tozin, T. M. Rodrigues, and M. de Almeida Silva, "Morphology, biochemistry, and yield of cassava as functions of growth stage and water regime," South African Journal of Botany, vol. 149, pp. 222–239, 2022.
[8] A. Pratondo, S. H. Ong, and C. K. Chui, "Region growing for medical image segmentation using a modified multiple-seed approach on a multicore cpu computer," in The 15th International Conference on Biomedical Engineering. Springer, 2014, pp. 112–115, in Press.
[9] A. Pratondo, R. Roedavan, A. P. Sujana, and M. I. Rizqyawan, "Medical image segmentation using a robust edge-stop function with 2× 2 window patch," in 2020 IEEE 10th International Conference on System Engineering and Technology (ICSET). IEEE, 2020, pp. 224–227.
[10] S. D. Budiwati, T. Fatyanosa, M. Data, D. R. Wijaya, P. A. Telnoni, A. A. Suryani, A. Pratondo, and M. Aritsugi, "To optimize, or not to optimize, that is the question: Telu-ku models for wmt21 large-scale multilingual machine translation," in Proceedings of the Sixth Conference on Machine Translation, 2021, pp. 387–397.
[11] A. Pratondo, "Fuzzy rule base for analytical demand forecasting enhancement," in 2010 Second International Conference on Advances in Computing, Control, and Telecommunication Technologies. IEEE, 2010, pp. 188–190.
[12] M. F. D. Jong and A. Pratondo, "Voice record on rise (radio broadcasting integrated system) on air application," in International Conference on Advances in Communication, Network, and Computing. Springer, 2011, pp. 368–372.
[13] G. Mutiara, G. Hapsari, and A. Pratondo, "Estimote-based location awareness on mobile devices for visually impaired," J. Theor. Appl. Inf. Technol, vol. 96, no. 1, pp. 215–226, 2019.
[14] A. Pratondo and A. Bramantoro, "Classification of zophobas morio and tenebrio molitor using transfer learning," PeerJ Computer Science, vol. 8, p. e884, 2022.
[15] A. Pratondo and A. Novianty, "Classification of longan edibility using machine learning," in 2022 1st International Conference on Smart Technology, Applied Informatics, and Engineering (APICS). IEEE, 2022, pp. 108–112.
[16] A. Pratondo and A. Novianty, "Pear classification using machine learning," in 2022 10th IEEE Conference on Systems, Process & Control (ICSPC). IEEE, 2022, in press.
[17] A. Pratondo and D. M. Harahap, "Classification of apples using machine learning," in 2022 IEEE 13th Control and System Graduate Research Colloquium (ICSGRC). IEEE, 2022, pp. 182–186.
[18] A. Pratondo, E. Elfahmi, and A. Novianty, "Classification of Curcuma longa and Curcuma zanthorrhiza using transfer learning," PeerJ Computer Science, 2022, in press.
[19] U. K. Lilhore, A. L. Imoize, C.-C. Lee, S. Simaiya, S. K. Pani, N. Goyal, A. Kumar, and C.-T. Li, "Enhanced convolutional neural network model for cassava leaf disease identification and classification," Mathematics, vol. 10, no. 4, p. 580, 2022.
[20] V. Ravi, V. Acharya, and T. D. Pham, "Attention deep learning-based large-scale learning classifier for cassava leaf disease classification," Expert Systems, vol. 39, no. 2, p. e12862, 2022.
[21] R. Surya and E. Gautama, "Cassava leaf disease detection using convolutional neural networks," in 2020 6th international conference on science in information technology (ICSITech). IEEE, 2020, pp. 97–102.
[22] Y. Zhong, B. Huang, and C. Tang, "Classification of cassava leaf disease based on a non-balanced dataset using transformer-embedded resnet," Agriculture, vol. 12, no. 9, p. 1360, 2022.
[23] I. Sangbamrung, P. Praneetpholkrang, and S. Kanjanawattana, "A novel automatic method for cassava disease classification using deep learning," Journal of Advances in Information Technology Vol, vol. 11, no. 4, pp. 241–248, 2020.
[24] R. Szeliski, Computer vision: algorithms and applications. Springer Science & Business Media, 2010.
[25] T. M. Mitchell and T. M. Mitchell, Machine learning. McGraw-hill New York, 1997, vol. 1, no. 9.
[26] C. M. Bishop and N. M. Nasrabadi, Pattern recognition and machine learning. Springer, 2006, vol. 4, no. 4.
[27] R. O. Duda, P. E. Hart et al., Pattern classification. John Wiley & Sons, 2006.

[28] C. Cortes and V. Vapnik, “Support-vector networks,” Machine learning, vol. 20, no. 3, pp. 273–297, 1995.
[29] L. Breiman, “Random forests,” Machine learning, vol. 45, no. 1, pp. 5–32, 2001.
[30] T. K. Ho, “Random decision forests,” in Proceedings of 3rd international conference on document analysis and recognition, vol. 1. IEEE, 1995, pp. 278–282.
[31] X. Xia, C. Xu, and B. Nan, “Inception-v3 for flower classification,” in 2017 2nd international conference on image, vision and computing (ICIVC). IEEE, 2017, pp. 783–787.
[32] F. Chollet, “Xception: Deep learning with depthwise separable convolutions,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 1251–1258.
[33] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, “Inception-v4, inception-resnet and the impact of residual connections on learning,” in hirty-first AAAI conference on artificial intelligence, 2017.
[34] K. P. Murphy, Probabilistic machine learning: an introduction. MIT press, 2022.
[35] M. D. Bloice, P. M. Roth, and A. Holzinger, “Biomedical image augmentation using augmentor,” Bioinformatics, vol. 35, no. 21, pp. 4522–4524, 2019.
[36] A. Buslaev, V. I. Iglovikov, E. Khvedchenya, A. Parinov, M. Druzhinin, and A. A. Kalinin, “Albumentations: fast and flexible image augmentations,” Information, vol. 11, no. 2, p. 125, 2020.
[37] C. Shorten and T. M. Khoshgoftaar, “A survey on image data augmentation for deep learning,” Journal of big data, vol. 6, no. 1, pp. 1–48, 2019.
[38] I. Kostrikov, D. Yarats, and R. Fergus, “Image augmentation is all you need: Regularizing deep reinforcement learning from pixels,” arXiv preprint arXiv:2004.13649, 2020.
[39] X. Zeng and T. R. Martinez, “Distribution-balanced stratified cross-validation for accuracy estimation,” Journal of Experimental & Theoretical Artificial Intelligence, vol. 12, no. 1, pp. 1–12, 2000.
[40] N. Diamantidis, D. Karlis, and E. A. Giakoumakis, “Unsupervised stratification of cross-validation for accuracy estimation,” Artificial Intelligence, vol. 116, no. 1-2, pp. 1–16, 2000.

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