JOIV : Int. J. Inform. Visualization, 8(3) - September 2024 1074-1081

INTERNATIONAL JOURNAL ON INFORMATICS VISUALIZATION

journal homepage : www.joiv.org/index.php/joiv

Modified Alexnet Architecture for Classification of Cassava Based on Leaf Images

Miftahus Sholihin [a,b,*], Mohd Farhan Md Fudzee [b], Mohd Norasri Ismail [b], Efi Neo Wati [c], Mohamad Syafwan Arshad [d] , Taufik Gusman [e]

[a] *Informatics Engineering, Universitas Islam Lamongan, Lamongan, Indonesia*
[b] *Faculty of Computer Sciences and Information Technology, University Tun Hussein Onn Malaysia, Johor, Malaysia.*
[c] *Department of Agriculture Universitas Islam Lamongan, Lamongan, Indonesia*
[d] *MZR Global Sdn Bhd, 40000 Shah Alam, Selangor, Malaysia*
[e] *Department of Information Technology, Politeknik Negeri Padang, Padang, Indonesia*
Corresponding author: [*]miftahus.sholihin@unisla.ac.id

***Abstract*—The objective of this study is to address the drawbacks of conventional classification approaches through the implementation of deep learning, specifically a modified AlexNet. The primary aim of this study is to precisely categorize the four distinct varieties of cassava, namely Manggu, Gajah, Beracun, and Kapok. The cassava dataset was obtained from farmers in Lamongan, Indonesia, and was used as a source of information. Data collection on cassava leaves was carried out with agricultural research specialists. A total of 1,400 images are included in the dataset, with 350 images corresponding to each variety of cassava produced. The central focus of this research lies in a comprehensive evaluation of the modified AlexNet architecture's performance compared to the original AlexNet architecture for cassava classification. Multiple scenarios were examined, involving diverse combinations of learning rates and epochs, to thoroughly assess the robustness and adaptability of the proposed approach. Among the evaluation criteria that were rigorously examined were accuracy, recall, F1 score, and precision. These metrics were used to determine the predictive capabilities of the model as well as its potential utilization in the actual world. The results show that the modified AlexNet design has better performance than the original AlexNet for recall, accuracy, precision, and F-1 score, all achieving a rate of 87%. In situations where a learning rate of 0.0001 and an epoch count of 150 are utilized, the performance of the approach stands out significantly, displaying an excellent level of competency. Nevertheless, it is crucial to recognize that distinct fluctuations in performance were noted within particular contexts and with diverse learning rates.**

***Keywords*—Alexnet; precision; recall; F1 score; accuracy.**

Manuscript received 15 Mar. 2024; revised 27 Jun. 2024; accepted 8 Aug. 2024. Date of publication 30 Sep. 2024.
International Journal on Informatics Visualization is licensed under a Creative Commons Attribution-Share Alike 4.0 International License.

I. INTRODUCTION

Plants have a significant role in human life [1], [2]. Plants can be the main source of food for humans and animals. Plants can also be used for medicine, clothing, fuel, materials for industry, and other areas of life. Plants are also important for protecting the environment because they keep the balance of oxygen and carbon dioxide in the Earth's atmosphere [3]. One type of plant that can be used as food is cassava. Cassava is a staple food for some people who live in tropical areas such as South America, Africa, Asia, and Indonesia. Based on research published by the Food and Agriculture Organization (FAO), cassava is positioned as the fourth most significant food crop in developing nations, following rice, corn, and wheat. According to the 2020 report published by the Food and Agriculture Organization (FAO), Nigeria holds the distinction of being the foremost global producer of cassava, with an annual production of 60 million tons. Congo is the second-largest producer of cassava, with a production of 41.01 million tons. Thailand and Ghana can produce 28.9 million cassava and 21.8 million tons, respectively. Indonesia ranks fifth in cassava production, which is 18.3 million tons. In the last three years, cassava production in Indonesia has increased, although the increase is not as significant as in 2016 and 2017.

The classification of plant types with the main object being leaves has been widely carried out in recent years. The use of leaves as the main object in classifying plant species is considered the most efficient because the leaves are available throughout the season and have many [4], [5]. Researchers generally use three types of features, namely shape [6]–[10], color, and texture [11], [12] extracted from leaves, to classify plant species. In addition, some researchers combine existing features [13]–[17] to increase accuracy. In general, botanists recognize plant species based on their knowledge and experience. It is common for botanists to take a long time to identify plant species [18]. For ordinary people, knowing the types of plants is a challenging job and takes a long time. Therefore, computer assistance will make introducing plant species easier and faster by utilizing digital image processing techniques [19], [20].

Deep learning has demonstrated promising results in recent years and has been implemented to a limited degree in the agricultural sector. Using Alexnet and GoogLeNet, Mohanty [21] achieved a 99.35% accuracy rate in classifying 14 crop species and 26 diseases. The authors utilized a range of input data, encompassing color images, grayscale images, and segmented images. Dudi [22] employs CNN to extract features. The process for classification uses Naive Bayes, Artificial Neural Networks (ANN), K-Nearest Neighbors (K-NN), and Support Vector Machines (SVM). The overall accuracy achieved is 98%. In the study conducted by Dyrmann [23], CNN model was employed to classify the plant leaf data. The results demonstrated an accuracy rate of 86.2%. Liu [24] reported that their CNN model, consisting of ten layers, attained a classification accuracy of 87.92% when applied to the categorization of plant leaves into 32 distinct categories. In her study, Zarrin [25] introduced a CNN model as a deep learning strategy to automatically categorize various tree species based on their leaf characteristics. The accuracy of the model in the test was extremely high, reaching 99.40%. A dual-path deep convolutional neural network (CNN) is proposed by Shah [26] as a method for detecting plant species based on images. Using the CNN model, Jeon [27] devised a novel method for classifying leaves. He then used GoogleNet to generate two models by varying the network depth. More than 94% of the leaves were identified, even though 30% of them were damaged.

Several researchers made modifications to the Alexnet architecture [28]–[31]. Sameer [32] uses modified Alexnet for the classification of pests and diseases in plants. The results of this research showed that the modified Alexnet gave better results. Yeh [33] modified Alexnet to detect crop disease with an accuracy of 98.16%. This accuracy is higher when compared to the basic Alexnet. Huang [34] categorizes the leaves of Chinese herbal medicine. This research uses the improved Alexnet model. The results of this study show that the results of the improved Alexnet model provide better results when compared to the original Alexnet model. Wei Tan [35] performed Plant Species Classification with feature extraction using Alexnet, fine-tuned Alexnet, and D-Leaf. Classification in this study uses SVM, ANN, k-NN, and Naive Bayes. The D-Leaf model is 94.88% accurate, the Alexnet model is 93.26% accurate, and the fine-tuned AlexNet model is 95.54% accurate. Dong [36] improvised the Alexnet architecture, which is used to classify diseases and pests in strawberry plants. The results of this study show that the Alexnet architecture is 94.25% accurate, and the Improved Alexnet architecture is 94.70% accurate. Chen [37] classified the types of diseases in tomato plants using the Alexnet architecture. This study yielded the best results 98%, with epochs 75, batch size 128 and rate 0.0005.

Using color, texture, and shape features is considered less efficient in classifying cassava species. This is because cassava leaves have the same color morphology between one type and another. In addition, cassava leaves have a relatively similar shape to one type of cassava, likewise, with the texture of cassava leaves. Our research aims to solve these important problems. Alexnet is used for plant species classification because of its: 1) simple structure that is clear and easy to use; 2) lack of need to calculate many parameters when changing the structure; and 3) ability to run on computers with low specifications. Besides some of the advantages of Alexnet, the Alexnet algorithm also has several drawbacks, including 1) it requires a long computational time in the recognition process [38]; and 2) it has the lowest accuracy. Our study will modify Alexnet architecture to obtain better results than the basic architecture of Alexnet.

The contribution of this research is expected to cover the following: to create a comprehensive dataset of cassava images; to propose a classification system based on modified Alexnet architecture. The structure of the subsequent sections of the paper is as follows: The materials and data sets are outlined in Section 2. Results and discussion are reported in Section 3, while ideas for further research are provided in Section 4 to conclude the paper.

II. MATERIALS AND METHOD

Fig. 1 illustrates the research carried out in this study. The first step is to acquire images. The main goal of obtaining pictures is to visually depict cassava leaves and categorize the image according to its unique features. The next step includes augmentation. Image segmentation is the following stage. Image segmentation aims to eliminate noise from images and identify distinct objects within an image, making them available for subsequent processing tasks. Classification is performed in the final stage with the adapted Alexnet architecture.

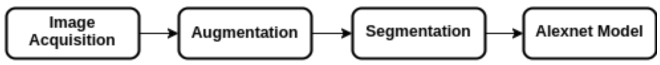

Fig. 1 Research process

A. Image Acquisition

The image of cassava leaves was the dataset that was used for this investigation. These images were taken by cassava growers in Lamongan, Indonesia, directly from them.

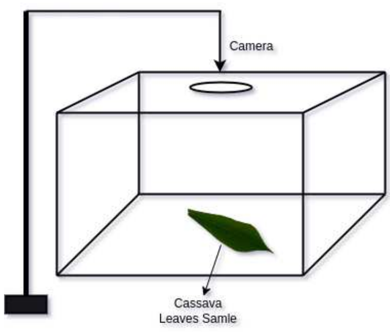

Fig. 2 The acquisition of images

The process of taking a cassava image is done by placing the cassava image in the box that has been made. Then, the image is taken with a smartphone camera. The camera is placed at the top of the box shown in Fig. 2. The study utilized a dataset consisting of 1400 images, which were categorized into four classes: Beracun, Gajah, Kapok, and Manggu. Each class contained 350 images.

B. Data augmentation

When classifying images, especially with deep learning, they often encounter the problem of insufficient samples [39]. Typically, image classification accuracy tends to diminish when the training dataset exhibits an imbalance. For this reason, increasing the size of the dataset using data augmentation techniques is a common practice for better training results [40], [41]. Table I displays the parameters of the augmentation data.

TABLE I
DATA AUGMENTATION

No	Parameter	Value
1	Rescale	1/255
2	Rotation_range	20
3	width_shift_range	0.1
4	height_shift_range	0.1
5	zoom_range	0.2
6	Horizontal_flip	true

C. Segmentation

The purpose of image segmentation is to separate objects from the background and transform them into something simpler, more understandable, and less time-consuming. This research used the segmentation method to take image objects of cassava leaves using the k-means method. K-mean clustering works by partitioning image pixels into K clusters, each representing a different segment. K-means can be applied to group similar pixels based on color or intensity information in image segmentation. K-means clustering is shown in Algorithm 1 [42]:

Algorithm 1. Segmentation using k-means clustering.
Input: image, number of clusters k
Output: image segmented

1. Randomly select K data points as initial centroids.
2. Determine x's cluster I centroid and assign it to x.
3. The new centroid is determined by calculating the mean of all points inside cluster I.
4. Repeat steps 2 and 3 until there are no significant changes in the placement of data points or a certain iteration limit is reached.

This study's segmentation process begins with entering cassava images into the system. After the image is entered, the system will perform segmentation using the k-mean algorithm. The segmentation process results in an image free from noise and other unwanted objects. After obtaining the cassava image object, the process is continued by cutting unnecessary backgrounds. This process is carried out because the background size of the image is too wide. The image segmentation results are shown in Fig. 3. The image is used as input for the classification process with modified Alexnet architecture.

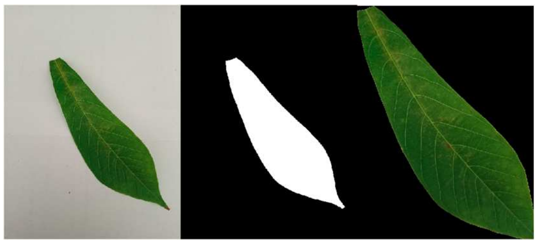

Fig. 3 Image segmentation

D. Modified Alexnet Model

Alexnet is one of the architectures often used for image classification problems because it is computationally efficient. The Alexnet architecture generally consists of five convolution layers and three fully connected layers. The features of the first layer are simple lines and dots. The most powerful capabilities for feature extraction are found in the third and fourth layers of the original AlexNet model [34].

This study uses a modified Alexnet architecture. This study uses three convolution layers and two pooling layers.The use of three convolution layers is based on the fact that the third layer produces strong and complex features so that it can be used to differentiate types of cassava plants. The convolution in the first layer has a size of 227x227x3. A pooling process with a kernel size of 3x3 follows this process. The image size resulting from this first convolution process is 113x113 pixels with 96 filters. This first convolution also uses a 2x2 stride using the RuLE activation function. The second and third convolutions use kernels with a size of 3x3. Stridge size 2x2 using the RuLE activation function. After the third convolution, a pooling operation is applied using a 3x3 size and a 384 filter. The proposed architecture can be seen in Table II and Fig. 4.

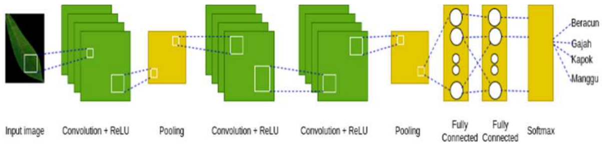

Fig. 4 Proposed method

TABLE II
PROPOSED METHOD MODIFIED ALEXNET

	Layer	Size	Kernel	Stridge	Activation
Input	**Image**	**227x227x3**	**-**	**-**	**-**
1	Convolution	113x113x96	3x3	2	Rule
	Max pooling	56x56x96	3x3	2	Rule
2	Convolution	27x27x384	3x3	2	Rule
3	Convolution	13x13x384	3x3	2	Rule
	Max pooling	6x6x384	3x3	2	Rule
4	Fully connected	1024	-	-	-
5	Fully connected	1024	-	-	-
Output	Fully connected	4	-	-	softmax

E. Evaluation Performance

The evaluation of the deep learning model in this study employs a confusion matrix. The confusion matrix is a widely used evaluation technique in the field of system classification, wherein it facilitates the comparison between the classification outcome and the true value. A classification system is said to be good if it can produce a relatively small error rate. Classification performance is assessed using F1 score, recall, accuracy, and precision [43]. The equation is shown in Equations (1)–(4).

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

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

$$f1\ score = \frac{2*recall*precision}{recall+precision} \quad (3)$$

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (4)$$

TP stands for "true positive," TN for "true negative," FP for "false positive," and FN for "false negative."

F. Experiment Setting

The hardware configuration for the experiment training and testing model consists of an Intel® CoreTM i7-4790 processor running at 3.60 GHz Ram 16GB. The models were constructed utilizing TensorFlow API version 2.5 and Keras version 2.5. The algorithm implementation was carried out using Python 3.8.10. In this study, to mitigate the overfitting issue, the dataset is divided into three separate sets, namely the training set including 70% of the data, the validation set consisting of 10%, and the testing set encompassing 20% [43]. The training parameters utilized for the proposed approach are presented in Table III.

TABLE III
TRAINING PARAMETERS

Parameter	Value
Batch size	16
Epoch	100 and 150
Learning rate	0.001, 0.0001, and 0.00001
Optimizer	Adam

III. Result and Discussion

This part is where we offer the findings of the evaluation that was performed on the proposed approach. Testing is carried out after the training process is complete. The test procedure commences by conducting image segmentation through the utilization of the k-means clustering technique. After obtaining the second image object, the next process is to change the image size to 227x227. The test was carried out with three scenarios.

A. Scenario I

This scenario uses several parameters for the training process. For the optimizer using Adam, the epochs of this research were made 100 and 150, batch size 16, and learning rate 0.001. Fig. 5 displays the performance outcomes of the training and validation process for the modified Alexnet architecture, while the Alexnet architecture is shown in Fig. 6 for accuracy and validation of the training. Fig. 7(a) and (b) confusion matrices of the suggested approach, and Fig. 7(c) and (d), which depict the Alexnet architecture.

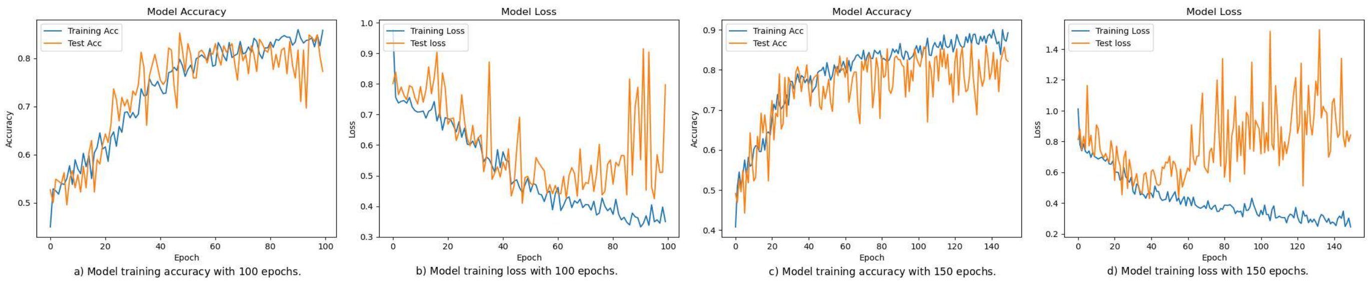

Fig. 5 Results of the training and validation process of the proposed model.

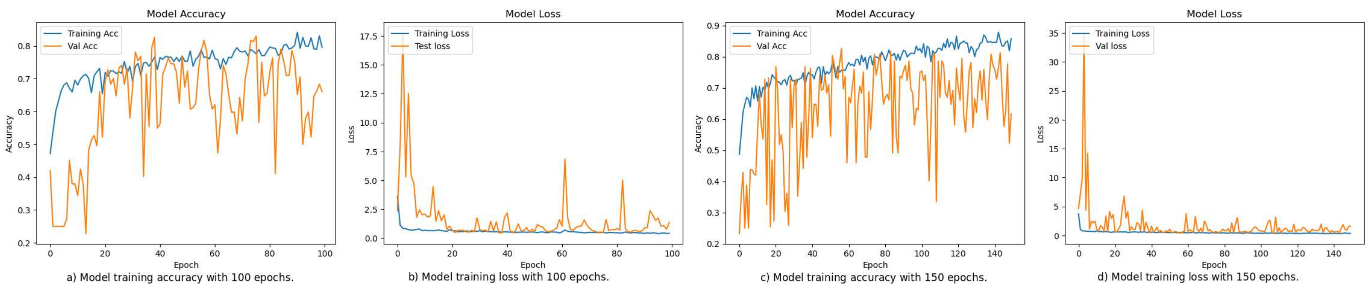

Fig. 6 Results of the training and validation process of the Alexnet model.

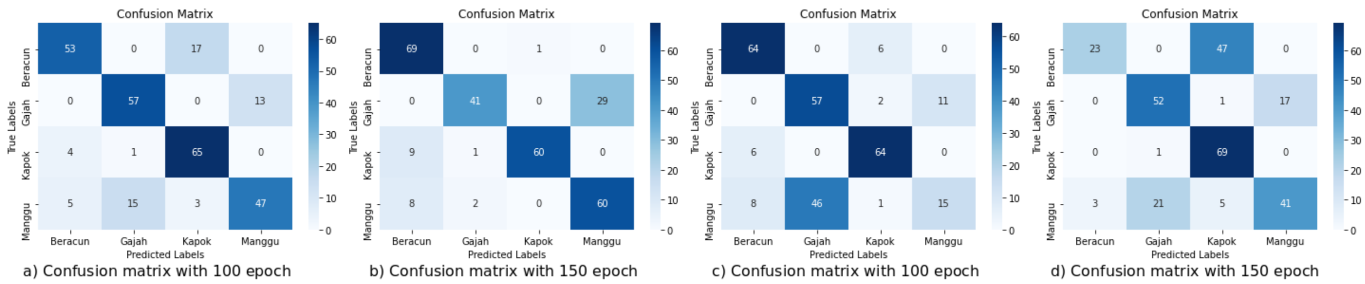

Fig. 7 The proposed model and Alexnet results are in the form of a confusion matrix.

According to the findings presented in Table IV, it is clear that the modified Alexnet architecture produces better results when compared to the Alexnet architecture. The proposed method achieves precision, recall, F1 score, and 79% accuracy, outperforming the original Alexnet 71% accuracy, 70% precision, 71% recall, and 68% F1 score at 100 epochs. The suggested technique still delivers advantages in comparison to the Alexnet method even when the epoch value is increased to 150. The proposed method has 84% precision, 82% recall, 81% F1 score, and 82% accuracy, whereas the Alexnet method only has 71% precision, 66% recall, 64% F1 score, and 66% accuracy.

TABLE IV
LEARNING RATE 0.001

Epoch	**Proposed methods**				**Alexnet**			
	Precision	Recall	F1 score	accuracy	Precision	Recall	F1 score	accuracy
100	79%	79%	79%	79%	70%	71%	68%	71%
150	84%	82%	81%	82%	71%	66%	64%	66%

B. Scenario II

The test results in this scenario, Adam Optimizer, are used for training with a learning rate of 0.0001 and a batch size of 16, and the maximum epochs allowed are 100 and 150. The performance results of the training and validation process of the modified Alexnet architecture are shown in Fig. 8, while the Alexnet architecture is shown in Fig. 9 for accuracy and validation of the training. Fig. 10 (a) and (b) are a confusion matrix from the modified Alexnet architecture, and Fig. 10 (c) and (d), which depict the Alexnet architecture.

The outcomes of comparing the suggested approaches with the AlexNet architecture at a learning rate of 0.0001 are shown in Table V. The metrics evaluated include precision, recall, F1 score, and accuracy at two epochs (100 and 150). Based on Table V, the proposed method gives better results. The proposed method provides 81% recall, 85 accuracy, 82% presision, and 81% F1 score, while the Alexnet basic architecture provides 80% precision, 71% recall, 65% F1 score, and 71% accuracy with 100 epochs. The performance of the proposed methods improved further with epoch 150. They achieved precision, recall, f score, and accuracy 87% each. However, AlexNet also improved but remained behind, with 76% accuracy, 72% recall, 71% F1 score, and 71% accuracy. In this scenario, the proposed method provides better results overall than the Alexnet architecture.

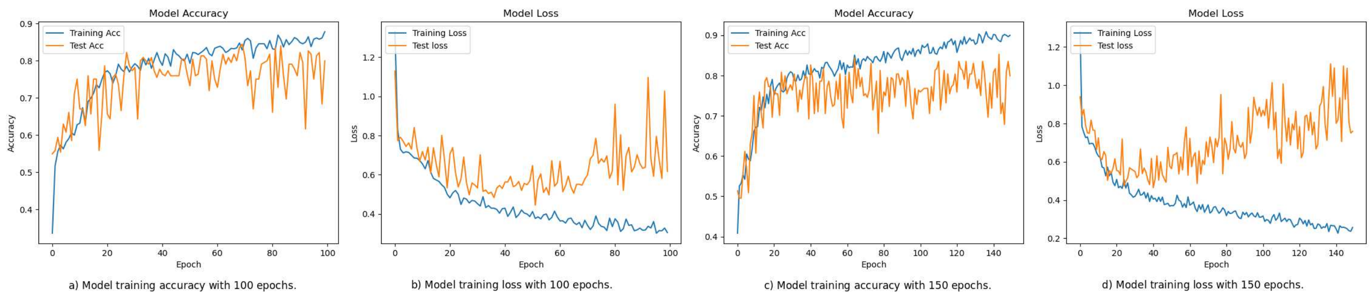

Fig. 8 Results of the training and validation process of the proposed model.

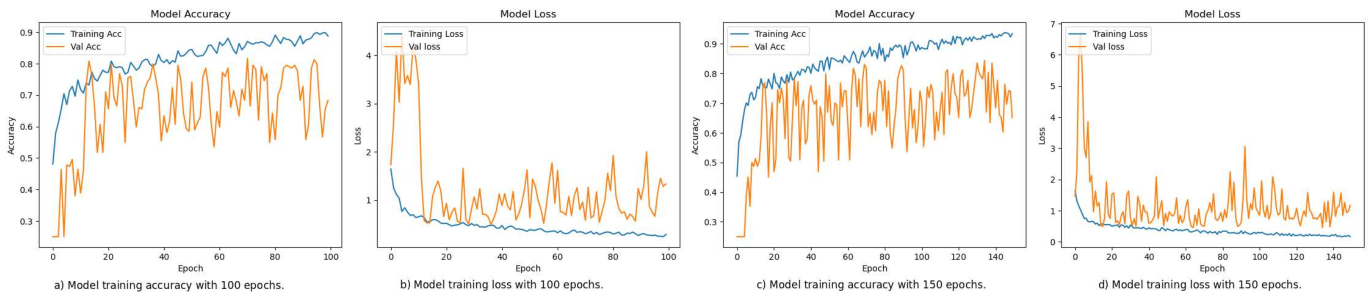

Fig. 9 Results of the training and validation process of the Alexnet model.

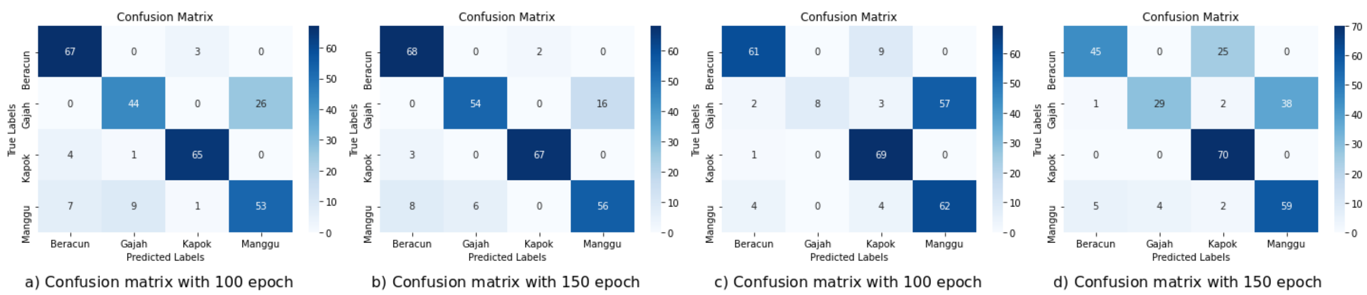

Fig. 10 The proposed model and Alexnet results are in the form of a confusion matrix.

TABLE V
LEARNING RATE 0.0001

Epoch	Proposed methods				Alexnet			
	Precision	Recall	F1 score	accuracy	Precision	Recall	F1 score	accuracy
100	82%	81%	81%	81%	80%	71%	65%	71%
150	87%	87%	87%	87%	76%	72%	71%	72%

C. Scenario III

This section presents the proposed methods' performance results compared to the AlexNet architecture using a learning rate of 0.00001. Adam optimizers are used for training with a batch size of 16, and the maximum epochs allowed are 100 and 150. Fig. 11 displays the outcomes of the training and validation processes using the modified Alexnet architecture, while the Alexnet architecture is shown in Fig. 12 for accuracy and validation of the training. Fig. 13 shows the confusion matrix for the modified Alexnet architecture in a) and b), and for the Alexnet design in c) and d).

Based on Table VI with epoch 100, the proposed methods achieve a precision of 73%, slightly trailing behind AlexNet's precision of 80%. However, the recall of the proposed methods is 72%, and the recall for Alexnet with 77% values. The F1 scores for the proposed methods are slightly lower than those of AlexNet, with the proposed methods achieving 71% compared to AlexNet's 76%. When the epoch value is increased to 150, the proposed method obtains 73% precision, 73% recall, 73% F1 score, and 73% accuracy, lower than the Alexnet architecture with 80% precision, 77% recall, 76% F1 score, and 77% accuracy.

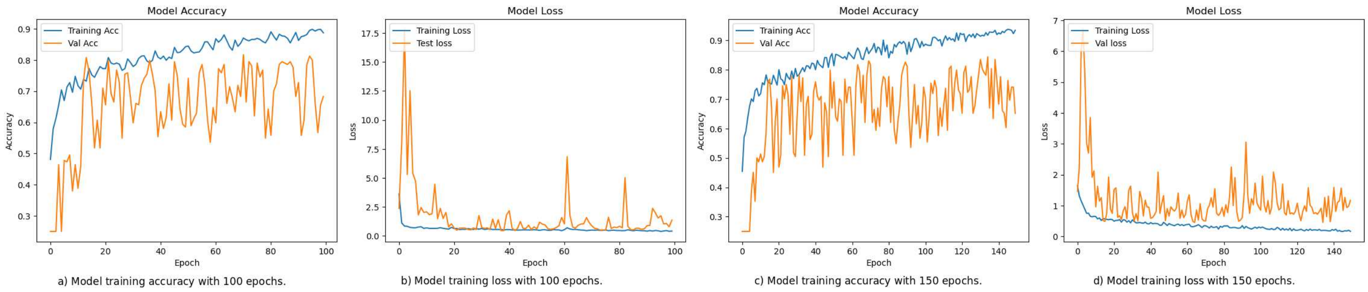

Fig. 11 Results of the training and validation process of the proposed model.

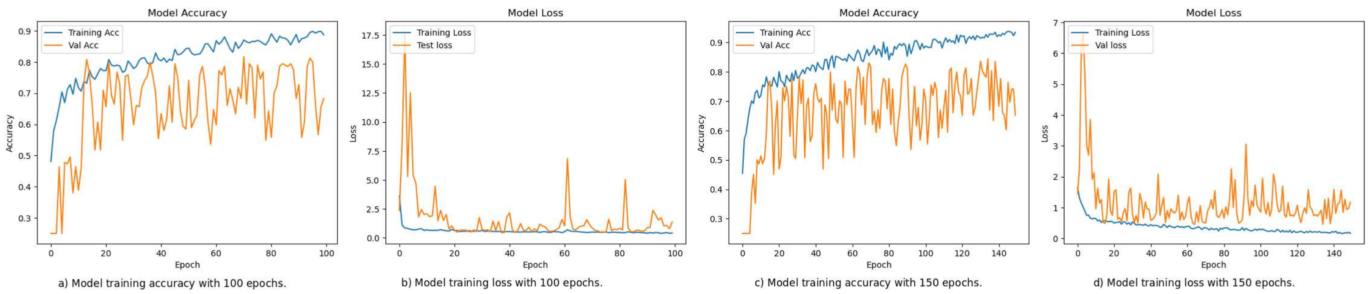

Fig. 12 Results of the training and validation process of the Alexnet model.

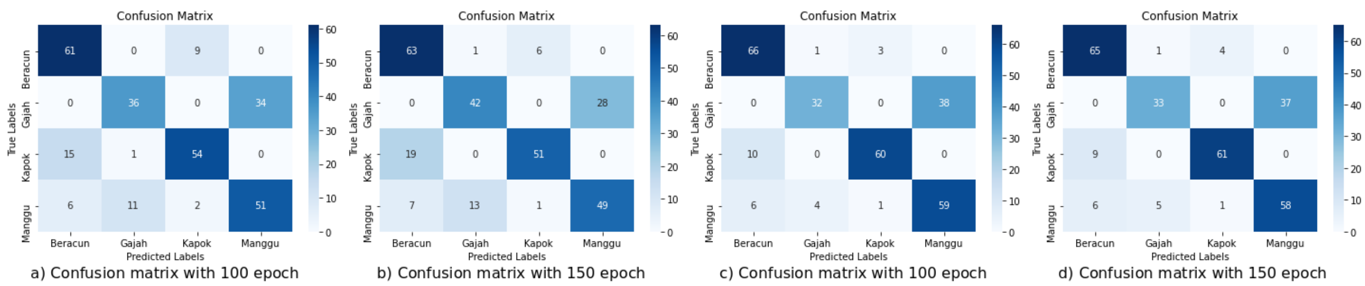

Fig. 13 The proposed model and Alexnet results are in the form of a confusion matrix.

TABLE VI
LEARNING RATE 0.00001

Epoch	Proposed methods				Alexnet			
	Precision	Recall	F1 score	accuracy	Precision	Recall	F1 score	accuracy
100	73%	72%	71%	72%	80%	77%	76%	76%
150	74%	73%	73%	73%	79%	77%	76%	77%

TABLE VII
OVERALL RESULT OF PROPOSED METHODS AND ALEXNET

Epoch	Learning rate	Proposed methods				Alexnet			
		Precision	Recall	F1 score	Accuracy	Precision	Recall	F1 score	Accuracy
100	0.001	79%	79%	79%	79%	70%	71%	68%	71%
100	0.0001	82%	81%	81%	81%	80%	71%	65%	71%
100	0.00001	73%	72%	71%	72%	80%	77%	76%	76
150	0.001	84%	82%	81%	82%	71%	66%	64%	66%
150	0.0001	87%	87%	87%	87%	76%	72%	71%	72%
150	0.00001	74%	73%	73%	73%	79%	77%	76%	77%

Table VII is the overall result of the proposed method and Alexnet architecture. Based on Table VII, we analyze and interpret the results obtained from the experimental evaluations of the proposed methods and the Alexnet architecture. The evaluation results indicate that modified Alexnet architecture consistently performs better or comparably to the Alexnet architecture across different scenarios and learning rates. The proposed method this research presents achieves an excellent performance of recall of 87%, F1 score of 87%, precision of 87%, and accuracy of 87%. The approach shows potential for improving item identification and classification tasks, according to these results. However, the comparative advantage of the proposed method becomes more evident at higher learning rates (0.001 and 0.0001) compared to the lower learning rate (0.00001). Generally, a learning rate of 0.0001 and 0.001 seems to perform better than 1E-05 across both the proposed methods and Alexnet.

D. Limitations of This Work

This study presents promising advancements in cassava plant classification through a modified Alexnet architecture. Limitations in this study should be acknowledged and addressed in future research:

1) *Limited Dataset*: In our study, the data set may be limited in representing cassava plant variations. This research only focused on local varieties and did not use diseased cassava leaves.

2) *Hyperparameter:* Although our work investigates a variety of learning rates and epochs, additional hyperparameters such as batch size, weight initialization, and dropout rates may substantially impact model performance.

3) *Architectural Variations:* Our proposed Alexnet architecture modification shows promising results. Other architectural modifications or completely different CNN architecture can yield better performance.

IV. CONCLUSION

This study evaluated the proposed method's performance compared to the Alexnet architecture for the classification of cassava. The architecture has three convolution layers and two pooling layers. The research utilizes the following parameters: batch size of 16, learning rates of 0.00001, 0.0001, and 0.001, epochs of 100 and 150, and the Adam optimizer. Our findings consistently demonstrate the proposed method's performance advantage over Alexnet across various evaluation metrics and scenarios. The testing carried out in this research consisted of three scenarios. Scenario 1 of the proposed method provides the highest accuracy value of 82% with a learning rate value of 0.001 and epoch 150, while Alexnet's highest accuracy is 71%. Scenario 2 with a learning rate of 0.0001, the proposed method provides the highest accuracy of 87%, while Alexnet has the highest accuracy of 72%. In the final scenario with a learning rate of 0.00001, the proposed method provides an accuracy of 73%, slightly lower when compared to the Alexnet architecture, namely 76%. In general, the proposed method provides better results when compared with the Alexnet architecture. Where the proposed method consistently achieves higher recall, accuracy, precision, and f1 score of 87%, with a learning rate of 0.0001 and epoch 150. Meanwhile, the Alexnet method with the same parameters gives recall, accuracy, precision, and f1 scores of 72%, 72%, 76%, and 71% respectively.

Although the method proposed exhibits impressive outcomes, it is important to realize that variations in performance were observed in particular settings and with different learning rates. The observations mentioned above indicate potential avenues for future investigation, including optimizing hyperparameters and the execution of comparative assessments with alternative advanced architectures. These endeavors aim to enhance and optimize the capabilities of the proposed method.

ACKNOWLEDGMENT

This research was funded by the Malaysian Ministry of Education (Vote No. H939) and the University Tun Hussein Onn Malaysia (UTHM). The authors are grateful to both organizations. Universitas Islam Lamongan also provided financial support for this study.

REFERENCES

[1] Z.-Y. Gao, “Spatial-Structure Siamese Network for Plant Identification.” Accessed: Jan. 18, 2023. [Online]. Available: https://en.x-mol.com/paper/article/1307844345494474752.

[2] J. Huixian, “The Analysis of Plants Image Recognition Based on Deep Learning and Artificial Neural Network,” IEEE Access, vol. 8, pp. 68828–68841, 2020, doi: 10.1109/access.2020.2986946.

[3] M. Akbar et al., “An effective deep learning approach for the classification of Bacteriosis in peach leave,” Frontiers in Plant Science, vol. 13, Nov. 2022, doi: 10.3389/fpls.2022.1064854.

[4] X. Yang, H. Ni, J. Li, J. Lv, H. Mu, and D. Qi, “Leaf recognition using BP-RBF hybrid neural network,” Journal of Forestry Research, vol. 33, no. 2, pp. 579–589, Jun. 2021, doi: 10.1007/s11676-021-01362-4.

[5] R. N. A. Hamdan, R. Zakaria, and S. Daliman, “Identification of Zingiberaceae Species Based on Leaf Recognition Using Multiclass Support Vector Machine,” IOP Conference Series: Earth and Environmental Science, vol. 1102, no. 1, p. 012008, Nov. 2022, doi: 10.1088/1755-1315/1102/1/012008.

[6] E. Yousefi, Y. Baleghi, and S. M. Sakhaei, “Rotation invariant wavelet descriptors, a new set of features to enhance plant leaves classification,” Computers and Electronics in Agriculture, vol. 140, pp. 70–76, Aug. 2017, doi: 10.1016/j.compag.2017.05.031.

[7] M. Murat, S.-W. Chang, A. Abu, H. J. Yap, and K.-T. Yong, “Automated classification of tropical shrub species: a hybrid of leaf shape and machine learning approach,” PeerJ, vol. 5, p. e3792, Sep. 2017, doi: 10.7717/peerj.3792.

[8] F. Haque and S. Haque, "Plant Recognition System Using Leaf Shape Features And Minimum Euclidean Distance," ICTACT Journal on Image and Video Processing, vol. 9, no. 2, pp. 1919–1925, Nov. 2018, doi: 10.21917/ijivp.2018.0272.

[9] M. I. Rusydi, A. Anandika, B. Rahmadya, K. Fahmy, and A. Rusydi, "Implementation of Grading Method for Gambier Leaves Based on Combination of Area, Perimeter, and Image Intensity Using Backpropagation Artificial Neural Network," Electronics, vol. 8, no. 11, p. 1308, Nov. 2019, doi: 10.3390/electronics8111308.

[10] R. A. Asmara, M. Mentari, N. S. Herawati Putri, and A. Nur Handayani, "Identification of Toga Plants Based on Leaf Image Using the Invariant Moment and Edge Detection Features," 2020 4th International Conference on Vocational Education and Training (ICOVET), Sep. 2020, doi: 10.1109/icovet50258.2020.9230343.

[11] A. Kumar, V. Patidar, D. Khazanchi, and P. Saini, "Optimizing Feature Selection Using Particle Swarm Optimization and Utilizing Ventral Sides of Leaves for Plant Leaf Classification," Procedia Computer Science, vol. 89, pp. 324–332, 2016, doi:10.1016/j.procs.2016.06.079.

[12] M. Turkoglu and D. Hanbay, "Leaf-based plant species recognition based on improved local binary pattern and extreme learning machine," Physica A: Statistical Mechanics and its Applications, vol. 527, p. 121297, Aug. 2019, doi: 10.1016/j.physa.2019.121297.

[13] S. Kaur and P. Kaur, "Plant Species Identification based on Plant Leaf Using Computer Vision and Machine Learning Techniques," Journal of Multimedia Information System, vol. 6, no. 2, pp. 49–60, Jun. 2019, doi: 10.33851/jmis.2019.6.2.49.

[14] T. V. Janahiraman, L. K. Yee, C. S. Der, and H. Aris, "Leaf Classification using Local Binary Pattern and Histogram of Oriented Gradients," 2019 7th International Conference on Smart Computing & Co.

[15] G. Kayhan and E. Ergün, "Medicinal and Aromatic Plants Identification Using Machine Learning Methods," Balkan Journal of Electrical and Computer Engineering, vol. 8, no. 1, pp. 81–87, Jan. 2020, doi: 10.17694/bajece.651286.

[16] J. P. G. Lakshika and T. S. Talagala, "Computer-aided Interpretable Features for Leaf Image Classification," *CoRR*, vol. abs/2106.08077, 2021, Accessed: Nov. 16, 2022. [Online]. Available: https://arxiv.org/abs/2106.08077.

[17] J. Vishalini, T. N. Kirubalini, and D. R. Subhashini, "Plant Classification Using Leaf Images Processing," *Annals of the Romanian Society for Cell Biology*, pp. 76–81, Apr. 2021, Accessed: Nov. 16, 2022. [Online]. Available: https://www.annalsofrscb.ro/index.php/journal/article/view/2440.

[18] P. Barré, B. C. Stöver, K. F. Müller, and V. Steinhage, "LeafNet: A computer vision system for automatic plant species identification," Ecological Informatics, vol. 40, pp. 50–56, Jul. 2017, doi: 10.1016/j.ecoinf.2017.05.005.

[19] V. Bodhwani, D. P. Acharjya, and U. Bodhwani, "Deep Residual Networks for Plant Identification," Procedia Computer Science, vol. 152, pp. 186–194, 2019, doi: 10.1016/j.procs.2019.05.042.

[20] G. Wang, Y. Sun, and J. Wang, "Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning," *Comput Intell Neurosci*, vol. 2017, pp. 1–8, 2017, doi: 10.1155/2017/2917536.

[21] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," Frontiers in Plant Science, vol. 7, Sep. 2016, doi: 10.3389/fpls.2016.01419.

[22] B. Dudi, "Medicinal Plant Recognition based on CNN and Machine Learning," International Journal of Advanced Trends in Computer Science and Engineering, vol. 8, no. 4, pp. 999–1003, Aug. 2019, doi: 10.30534/ijatcse/2019/03842019.

[23] M. Dyrmann, H. Karstoft, and H. S. Midtiby, "Plant species classification using deep convolutional neural network," Biosystems Engineering, vol. 151, pp. 72–80, Nov. 2016, doi:10.1016/j.biosystemseng.2016.08.024.

[24] J. Liu, S. Yang, Y. Cheng, and Z. Song, "Plant Leaf Classification Based on Deep Learning," 2018 Chinese Automation Congress (CAC), Nov. 2018, doi: 10.1109/cac.2018.8623427.

[25] I. Zarrin and saiful Islam, "Leaf Based Trees Identification Using Convolutional Neural Network," 2019 IEEE 5th International Conference for Convergence in Technology (I2CT), Mar. 2019, doi:10.1109/i2ct45611.2019.9033914.

[26] M. P. Shah, S. Singha, and S. P. Awate, "Leaf classification using marginalized shape context and shape+texture dual-path deep convolutional neural network," 2017 IEEE International Conference on Image Processing (ICIP), Sep. 2017, doi:10.1109/icip.2017.8296403.

[27] W.-S. Jeon and S.-Y. Rhee, "Plant Leaf Recognition Using a Convolution Neural Network," The International Journal of Fuzzy Logic and Intelligent Systems, vol. 17, no. 1, pp. 26–34, Mar. 2017, doi: 10.5391/ijfis.2017.17.1.26.

[28] A. Shakarami, H. Tarrah, and A. Mahdavi-Hormat, "A CAD system for diagnosing Alzheimer's disease using 2D slices and an improved AlexNet-SVM method," Optik, vol. 212, p. 164237, Jun. 2020, doi:10.1016/j.ijleo.2020.164237.

[29] Z. Ju and Y. Xue, "Fish species recognition using an improved AlexNet model," Optik, vol. 223, p. 165499, Dec. 2020, doi:10.1016/j.ijleo.2020.165499.

[30] G. Hu, X. Yang, Y. Zhang, and M. Wan, "Identification of tea leaf diseases by using an improved deep convolutional neural network," Sustainable Computing: Informatics and Systems, vol. 24, p. 100353, Dec. 2019, doi: 10.1016/j.suscom.2019.100353.

[31] T. Shanthi and R. S. Sabeenian, "Modified Alexnet architecture for classification of diabetic retinopathy images," *Computers & Electrical Engineering*, vol. 76, pp. 56–64, Jun. 2019, doi:10.1016/j.compeleceng.2019.03.004.

[32] S. Sameer, B. D. Niharika, S. Vasavi, M. Rohith, and V. Abhishek, "Pest and Disease Detection from Plant Leaves using Enhanced AlexNet Model," 2021 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), Jul. 2021, doi: 10.1109/conecct52877.2021.9622569.

[33] J.-F. Yeh, S.-Y. Wang, and Y.-P. Chen, "Crop Disease Detection by Image Processing Using Modified Alexnet," 2021 IEEE 3rd Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability (ECBIOS), May 2021, doi: 10.1109/ecbios51820.2021.9510426.

[34] F. Huang, L. Yu, T. Shen, and L. Jin, "Chinese Herbal Medicine Leaves Classification Based on Improved AlexNet Convolutional Neural Network," 2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Dec. 2019, doi: 10.1109/iaeac47372.2019.8997578.

[35] J. wei Tan, S.-W. Chang, S. Abdul-Kareem, H. J. Yap, and K.-T. Yong, "Deep Learning for Plant Species Classification Using Leaf Vein Morphometric," IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 17, no. 1, pp. 82–90, Jan. 2020, doi:10.1109/tcbb.2018.2848653.

[36] C. Dong, Z. Zhang, J. Yue, and L. Zhou, "Classification of strawberry diseases and pests by improved AlexNet deep learning networks," 2021 13th International Conference on Advanced Computational Intelligence (ICACI), May 2021, doi:10.1109/icaci52617.2021.9435893.

[37] H.-C. Chen et al., "AlexNet Convolutional Neural Network for Disease Detection and Classification of Tomato Leaf," Electronics, vol. 11, no. 6, p. 951, Mar. 2022, doi: 10.3390/electronics11060951.

[38] S. Arya and R. Singh, "A Comparative Study of CNN and AlexNet for Detection of Disease in Potato and Mango leaf," 2019 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), Sep. 2019, doi:10.1109/icict46931.2019.8977648.

[39] A. Setiawan, R. Sigit, and R. Rokhana, "Face Recognition Using Convolution Neural Network Method with Discrete Cosine Transform Image for Login System," JOIV : International Journal on Informatics Visualization, vol. 7, no. 2, p. 502, May 2023, doi:10.30630/joiv.7.2.1546.

[40] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," Journal of Big Data, vol. 6, no. 1, Jul. 2019, doi: 10.1186/s40537-019-0197-0.

[41] H. Xu et al., "An Enhanced Framework of Generative Adversarial Networks (EF-GANs) for Environmental Microorganism Image Augmentation With Limited Rotation-Invariant Training Data," IEEE Access, vol. 8, pp. 187455–187469, 2020, doi:10.1109/access.2020.3031059.

[42] K. Tian, J. Li, J. Zeng, A. Evans, and L. Zhang, "Segmentation of tomato leaf images based on adaptive clustering number of K-means algorithm," Computers and Electronics in Agriculture, vol. 165, p. 104962, Oct. 2019, doi: 10.1016/j.compag.2019.104962.

[43] M. Castelli, L. Vanneschi, and Á. R. Largo, "Supervised Learning: Classification," Encyclopedia of Bioinformatics and Computational Biology, pp. 342–349, 2019, doi: 10.1016/b978-0-12-809633-8.20332-4.