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AlexNet-Based Feature Extraction for Cassava Classification: A Machine Learning Approach

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Abstract

Cassava, a significant crop in Africa, Asia, and South America, is a staple food for millions. However, classifying cassava species using conventional color, texture, and shape features is inefficient, as cassava leaves exhibit similarities across different types, including toxic and non-toxic varieties. This research aims to overcome the limitations of traditional classification methods by employing deep learning techniques with pre-trained AlexNet as the feature extractor to accurately classify four types of cassava: Gajah, Manggu, Kapok, and Beracun. The dataset was collected from local farms in Lamongan Indonesia. To collect images with agricultural research experts, the dataset consists of 1,400 images, and each type of cassava has 350 images. Three fully connected (FC) layers were utilized for feature extraction, namely fc6, fc7, and fc8. The classifiers employed were support vector machine (SVM), k-nearest neighbors (KNN), and Naive Bayes. The study demonstrated that the most effective feature extraction layer was fc6, achieving an accuracy of 90.7% with SVM. SVM outperformed KNN and Naive Bayes, exhibiting an accuracy of 90.7%, sensitivity of 83.5%, specificity of 93.7%, and F1-score of 83.5%. This research successfully addressed the challenges in classifying cassava species by leveraging deep learning and machine learning methods, specifically with SVM and the fc6 layer of AlexNet. The proposed approach holds promise for enhancing plant classification techniques, benefiting researchers, farmers, and environmentalists in plant species identification, ecosystem monitoring, and agricultural management.

Keywords: Color, Feature extraction, KNN, Naïve Bayes, Shape, SVM, Texture.

Introduction

Cassava is a staple food crop for millions in Africa, Asia, and South America. It is a significant crop for small-scale farmers since it provides a supply of carbohydrates, vitamins, and minerals and because it can grow in a variety of soil types[1,2]. There are a lot of different kinds of cassava, and each has its traits and uses. Traditionally, cassava classification has relied on morphological traits such as leaf shape, stem color, and root characteristics. One of the challenges in cassava production is identifying and classifying different types of cassava, which can be time-consuming and challenging to do manually. Accurate classification of cassava is important for crop management, disease prevention, and food security. Using digital image processing methods, the classification of plant species will be easier, faster, and more accurate[3–6].

Plants can be identified by looking at their flowers, fruits, and leaves. Flowers and fruits only appear for a limited period. Thus they can't be relied on to permanently resolve concerns with identifying

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plants. Since it can be obtained in large quantities throughout the year, the leaf is regarded as the most credible source of information[7–9]. Shape, color, and texture derived from leaves are the three main traits used by researchers in categorizing plant species.

Classification of plants within the same species but under different categories poses unique challenges. Prasetyo[10] researched detecting mango species using shape and texture features and showed an accuracy of 78% using k-nearest neighbors (KNN) for classification. Prasetyo[11] classified mango species using the centroid contour distance (CCD) shape feature in another study. This study provides the highest accuracy of 67.3% with support vector machine (SVM). The accuracy of the sweet potato classification system developed by Unajan[12,] which takes into account color features, morphological features, and textural features, is 71.43%.

Deep learning has shown remarkable results in image recognition and classification tasks in recent years[13,14.] Many studies use deep learning for the classification of plant species[13,15–18]. The convolution neural network (CNN) is a famous deep learning architecture for image classification[19]. CNN has been used for feature extraction and classification in several studies[20]. Using the CNN model for feature extraction gives better results than handcrafted feature extraction[21–23]. This is because CNN can learn features from images automatically during training[24,25]. Lee[26] employs Multilayer Perceptron for classification, whereas CNN is used for feature extraction. Villaruz[27] classified Berry Trees in this study, where the feature extraction process uses the Alexnet architecture. The SVM algorithm is used for the classification process. Using artificial neural networks (ANN), K-NN, SVM, and Naive Bayes, Dudi[28] can classify images and extract their features using CNN. Koklu[29] classifies grapevine leaves. The pre-trained Logits layer of MobileNetv2 was mined for features, and the application of a variety of SVM kernels accomplished classification.

This study aims to address the challenges in accurately classifying different types of cassava using images of cassava leaves. Traditional methods relying solely on color, texture, and shape features have shown limitations due to the similarities in these characteristics among various cassava species. Furthermore, accurately distinguishing between poisonous and non-poisonous cassava varieties based on these traits is critical to prevent severe consequences if misidentified. Previous research[10–12] has highlighted the limitations of using leaf color, shape, and texture features for precise classification of plant species with diverse categories. As a result, this research aims to overcome these limitations by proposing novel and robust approaches for classifying cassava species.

This research leverages deep learning and machine learning to overcome these challenges to propose novel approaches for classifying cassava. Features are extracted using the AlexNet model and then classified using the k-nearest neighbor, support vector machine, and naive Bayes algorithms. This research aims to develop a reliable and accurate method for classifying various types of cassava, which in turn can help farmers and researchers in the field. Another study objective was to demonstrate the effectiveness of using a pre-trained AlexNet model for feature extraction for the cassava classification task and highlight its potential for use in other similar agricultural applications.

In this study, the main contributions are as follows:

1. Development of a cassava image dataset. This dataset consists of four types of cassava.
2. Overcoming challenges in traditional classification methods: This study addresses the limitations of conventional color, texture, and shape-based classification approaches, which often struggle to distinguish between different cassava varieties due to leaf similarities.
3. Exploration of pre-trained CNN models for feature extraction: This study investigates the effectiveness of utilizing pre-trained CNN models, such as AlexNet, for feature extraction in cassava classification, aiming to improve feature representation and enhance classification accuracy.

The rest of the Research Paper is organized as follows. In Section 2, the proposed method is thoroughly introduced. Experiment findings and discussion are presented in Section 3. Section 4 finally concludes the paper.

Related works:

In recent years, deep learning models have been used to a small extent in agriculture. Lee[26] uses deep convolution neural networks (CNN) for the character extraction process, while the classification uses multilayer perceptron (MLP), where the accuracy obtained is 99.4%. Beikmohammadi[30] uses the CNN mobile net architecture for character extraction, while classification uses a logistic regression classifier. This study provides an accuracy of 99.6% with Flavia datasets and 90.54% with LeafSnap datasets. Huynh[31] uses the CNN method, where the input image used for the red color channel is replaced with vein shape data. The accuracy obtained is 98.22% with the Flavia leaf data set and the Swedish leaf data set.

Dudi[28] uses CNN for feature extraction and machine learning for the classification process. Machine learning methods used for classification include ANN, K-NN, SVM, and Naive Bayes. Using the Flavia datasets, this study achieved a 98% accuracy. According to Liu[32], their ten-layer CNN model achieved an accuracy of 87.92% by classifying plant leaves into 32 types. In their research on classifying plant leaves, Barré[33] used the LeafSnap, Foliage, and Flavia datasets to classify various classes using their suggested model, LeafNet. With an accuracy of 86.3%, 184 classes of LeafSnap and 60 classes from the Foliage dataset with an accuracy of 95.8%. Their performance accuracy for the Flavia dataset with 32 classes was 97.9%. Jeon[34] proposed a new method to classify leaves using the CNN model and created two models by adjusting the network depth using GoogleNet. The recognition rate achieved was greater than 94%, even when 30% of the leaf was damaged.

From the study and analysis of the literature, the following problems were found:

1. There is no deep-learning study to distinguish cassava leaves species.
2. Very little work has been done to classify plants within the same species.

Materials and Methods

Fig.1 is the overall work in this study. The first step is image acquisition. The purpose of image acquisition is to obtain an image of cassava leaves, which is used to identify the image's class. The second step is pre-processing. The goal of the preprocessing step is to improve the image quality before moving on to the next step. Image segmentation aims to remove noise from images or extract objects from an image so that they can be used as input for further processing. The next step is segmentation. The final step is feature-extracting and classification. Feature extraction based on Alexnet architecture and classification using SVM, KNN, and Naive Bayes.

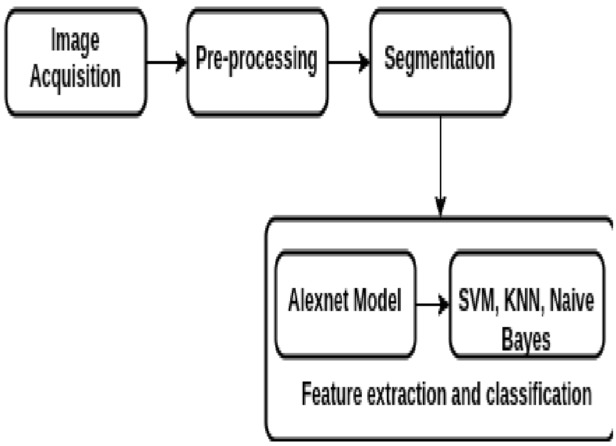

Figure 1. Overall work in this study

Image Acquisition:

This study's dataset is the image of cassava leaves containing four different types: Gajah, Manggu, Kapok, and Beracun. The dataset was collected from local farms in Lamongan Indonesia. To collect images with agricultural research experts, the dataset consists of 1,400 images, and each type of cassava has 350 images. Images are captured using smartphones. The camera was positioned 35 centimeters above the samples at the top of the box. To prevent the formation of shadows and reduce noise in the images to be taken from the camera, the system is equipped with adequate interior lighting so that it does not receive outside light. For the sake of efficiency in working with cassava leaves, white background has been used. Fig.2 Tool for image acquisition.

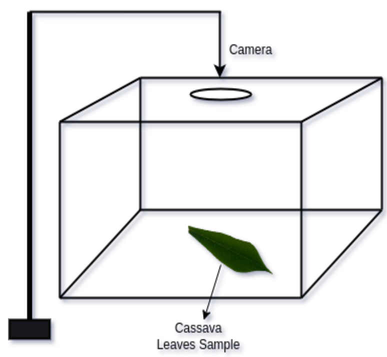

Figure 2. Tool for image acquisition.

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Preprocessing:
The preprocessing aims to improve the input image quality before entering the following process. The preprocessing carried out in this study was to change all image sizes to 227x227. This process is done so that the computation used to process the image is short.

Image Segmentation:
Image segmentation is a process that aims to separate an area in an image from other areas. Segmentation refers to separating an image into parts or dividing an image into expected parts, including the object being analyzed in that image. The segmentation carried out in this study aims to take cassava leaves. The segmentation method used is k-means clustering, because the k-means algorithm provides the significant advantage of being simple and quick to apply[35]. The main principle of the K-means algorithm is to divide data into k classes based on distance. K-means algorithm classifies pixels in an image into k number of clusters according to similarity features like grey level intensity of pixels and distance of pixel intensities from centroid pixel intensity. The algorithm flow is as follows[36].

1. Randomly select K initial cluster centers from the data set;
2. Calculate the distance of each remaining point to each cluster center according to some distance function, and classify each point into the category of the nearest cluster center;
3. Recalculate the arithmetic mean of each cluster as a new cluster center;
4. Judging convergence or not, comparing the last and second last cluster center. If there is no change, the clustering is over. Otherwise, continue to repeat steps 2 and 3.

Segmentation using k-means clustering begins with determining the number of K clusters and then assuming the cluster center point. Next, calculate the object distance to the cluster center and group objects based on the minimum distance. If there are objects that move, then return to the step to calculate the object distance to the cluster center. If there are no objects that move, then the process is complete. Fig.3 is the result of the segmentation process using the k-means method.

Figure 3. K-means image segmentation

Alexnet for feature extraction:
In this research, feature extraction using Alexnet architecture. The Alexnet architecture consists of 5 convolution layers, 3 pooling layers, 2 dropout layers, and 3 fully connected layers. The first convolution has 11×11×3 filter sizes. If it is assumed the filter's size is the beam's volume, then x = 11, y = 11, z = 3. The volume is the result of representing the size of the image 227 × 227 × 3. The first layer has 96 filters of 55 × 55 × 96. This size is obtained from convolution and max pooling results in the previous process. The second layer has a size of 55 × 55 × 96 and will be eliminated (max pooling) using a kernel size of 3 × 3 × 27. This step forms a new layer with a filter number of 96. The second layer has a new size, namely 27 × 27 × 256, with max pooling using matrix 3 × 3 × 26 and filters as many as 384. The third layer has a size of 13 × 13 × 384 with a number of filters 384, as well as the fourth layer. Meanwhile, the fifth layer has a size of 6 × 6 × 256 to extract to start merging various features. The feature extraction results on the fully connected layer are classified using Machine learning (SVM, KNN, and Naive Bayes) into the 4 classes shown in Fig.4.

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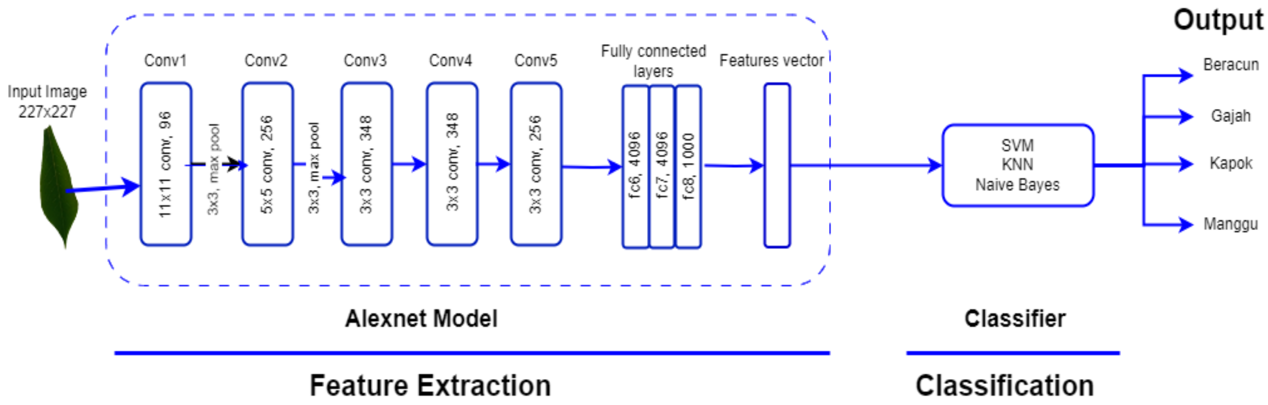

Figure 4. Feature Extraction using Alexnet

Data Augmentation:
This study uses data augmentation to expand and vary the training dataset to improve performance and prevent overfitting. Data augmentation is a popular technique in deep learning, in which the original image randomly manipulate to create new variations of that image. The purpose of data augmentation is to provide a training model with a wider variety of training data so that the model can better generalize and deal with images that have never been seen before. This method includes image rotation, reflection, and shear parameters. This transformation operation effectively increases the variety of the training data set and helps the model to be more adaptive to different situations. By using data augmentation like this, the CNN model has a better chance of more accurately identifying and classifying objects in test data that have never been seen before. Table 1 is the augmentation data parameters in this study.

Table 1. Parameter data augmentation

Properties	Value
'RandRotation'	-15, 15
'RandXTranslation'	-30, 30
'RandYTranslation'	-30, 30
'RandXScale'	0.8, 1.2
'RandYScale'	0.8, 1.2
'RandXReflection'	True
'RandYReflection'	True

Evaluation Setup:
The training parameters used in this study are as follows: Adam optimizer is used for optimization, the learning rate is 0.0001, MiniBatchSize 32, and epoch 20 to give the model more learning opportunities from the training data. 'ValidationPatience', 5 stops the training process if validation performance does not improve in 5 consecutive epochs. This helps prevent overfitting and avoid overtraining the model on the validation dataset. The dataset is split into 80% training and 20% validation sets.

All experiments were conducted on a computer with an Intel Core i7 processor and 16GB RAM. The MATLAB version used in this study was 2018b. The pre-trained AlexNet model and the classifiers were implemented in MATLAB using the Deep Learning Toolbox and the Statistics and Machine Learning Toolbox

Results

Model performance is evaluated using sensitivity, specificity, accuracy, and F1-score, which measures the percentage of correctly classified samples. The confusion matrices present the results of the several experiments that were performed on the dataset consisting of four cassava leaves and illustrate how well the models performed on the test set. The accuracy is calculated using Eq.1, specificity is represented in Eq.2, sensitivity is represented in Eq. 3, and F1-score is calculated using Eq.4.

$$Accuracy = \frac{TP+TN}{TN+FP+FN+TP} \quad (1)$$

$$Specificity = \frac{TN}{TN+FP} \quad (2)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (3)$$

$$F1-Score = \frac{2TP}{2TP+FP+FN} \quad (4)$$

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where TN = true negative, TP = true positive, FP = false positive, and FN = false negative.

Scenario 1: Alexnet (fc6, fc7, fc8) with SVM
In this scenario, features extracted from each layer in a fully-connected (FC) layer 'fc6', 'fc7', and 'fc8', and compared the performance with different features. Then, SVM is used to perform the classification task. In this study, SVM uses a linear kernel function without any optimization, where this kernel has the function of taking vector data and converting it into an optimal form. The results of the SVM classifier are presented in Table 2.

Table 2. Result Fc6, Fc7, and Fc8 with SVM Classification.

	Sensitivity	Specificity	Accuracy	F1-Score
Fc6	83.5%	93.7%	90.7%	83.5%
Fc7	82.5%	93.1%	90.1%	82.5%
Fc8	73%	89.7%	85.1%	73%

The results indicate that the fc6 layer achieved the best performance with a sensitivity of 83.5%, specificity of 93.7%, accuracy of 90.7%, and F1-score of 83.5%. This suggests that the fc6 layer, being closer to the input layer and capturing more general and discriminative features, is more effective in representing the essential characteristics of cassava leaves for classification. On the other hand, the fc7 and fc8 layers exhibited slightly lower performance, with fc8 performing the least. The SVM confusion matrix is depicted in Fig. 5.

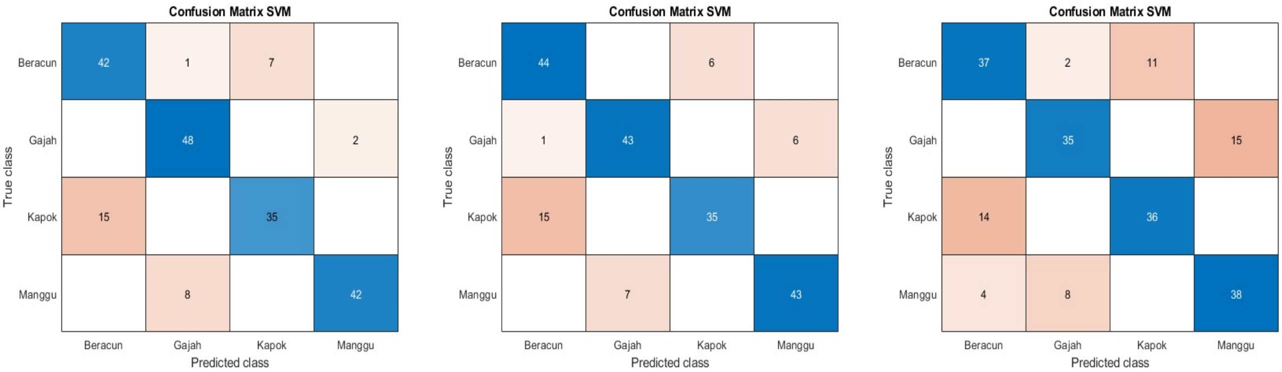

Figure 5. Confusion matrix of Fc6, Fc7, and Fc8 with SVM classifications.

Based on the SVM confusion matrix at the fc6 layer, it appears that 8 cassava leaves identified as non-poisonous are poisonous, while 15 leaves identified as poisonous are non-poisonous. The fc7 layer has identified 6 types of cassava that are non-poisonous and 16 types of non-poisonous cassava that are toxic. It was found in the fc8 layer that 13 poisonous cassava plants were mistakenly identified as non-poisonous, while 18 non-poisonous cassava plants were mistakenly identified as toxic.

Scenario 2: Alexnet (fc6, fc7, fc8) with KNN
In this scenario, the researcher aimed to assess the performance of KNN classification using the same feature extraction layers as in scenario 1. KNN is a different classification algorithm than SVM, and the researchers wanted to investigate how the extracted features from different layers (fc6, fc7, fc8) of AlexNet would affect the performance of KNN for cassava leaf classification. Table 3 displays the KNN classifier's results.

Table 3. Result Fc6, Fc7, and Fc8 with KNN Classification.

	Sensitivity	Specificity	Accuracy	F1-Score
Fc6	63.5%	86.7%	80.5%	63.5%
Fc7	61%	85.7%	79%	61.5%
Fc8	63%	86.3%	80%	63%

The results showed that the fc6 layer outperformed fc7 and fc8, with an accuracy of 80.5%, a sensitivity of 63.5%, a specificity of 86.7%, and an F1 score of 63.5% with neighbor values or k = 5. KNN

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performance is lower than with SVM and can be associated with high dimensions of the feature vector extracted from the AlexNet layer, making distance-based KNN approaches less effective in this task. The KNN confusion matrix is depicted in Fig.6.

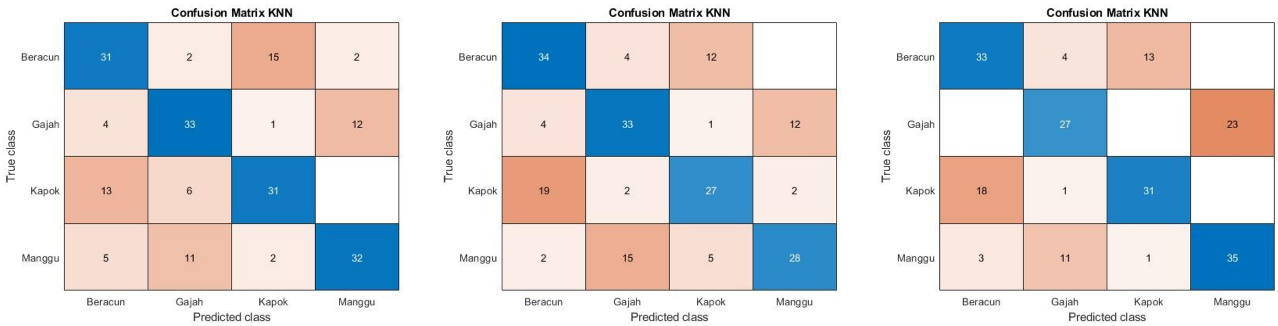

Figure 6. Confusion matrix of Fc6, Fc7, and Fc8 with KNN classifications.

In the FC6 layer, 21 cassava plants are classified as non-toxic but are poisonous, and 19 poisonous cassava plants are mistakenly classified as non-poisonous. Within the fc7 layer, 26 cassava samples that are not toxic are mistakenly labeled as poisonous, and 16 poisonous cassava samples are incorrectly labeled as non-poisonous. In the fc8 layer, there are 22 non-toxic cassava that are classified as poisonous cassava, while 17 poisonous cassava are classified as non-poisonous cassava.

Scenario 3: Alexnet (fc6, fc7, fc8) with Naïve Bayes

This scenario aimed to evaluate the performance of Naive Bayes classification using the three feature extraction layers (fc6, fc7, fc8) of AlexNet. Naive Bayes is a probabilistic classifier, and the researcher wanted to observe how it performed with features extracted at different levels of abstraction. The classification performance of Naive Bayes is displayed in Table 4.

Table 4. Result Fc6, Fc7, and Fc8 with Naïve Bayes Classification.

	Sensitivity	Specificity	Accuracy	F1-Score
Fc6	78%	91.3%	87.6%	78%
Fc7	79%	91.9%	88.4%	79%
Fc8	69%	88.4%	83.2%	69%

The results indicate that the fc7 layer achieved the highest quality results with an accuracy of 88.4%, sensitivity of 79%, specificity of 91.9%, and F1-score of 79%. Although Naive Bayes performed lower than SVM, it outperformed KNN, which suggests that its probabilistic approach was more effective in capturing the class distributions based on the features extracted from the fc6 and fc7 layers. Fig.7 shows the confusion matrix for Naïve Bayes.

In the fc6 layer, 23 cassava plants are incorrectly identified as non-toxic when they are, in fact, toxic. Additionally, 9 cassava plants are incorrectly identified as non-toxic when they are, in fact, hazardous. Within the fc7 layer, 14 cassava samples are not toxic that have been improperly labeled as toxic, and 11 cassava samples are poisonous that have been incorrectly labeled as non-poisonous. There is 15 poisonous cassava that are categorized as non-poisonous cassava in the fc8 layer, while there are 18 non-toxic cassava that are classed as poisonous cassava.

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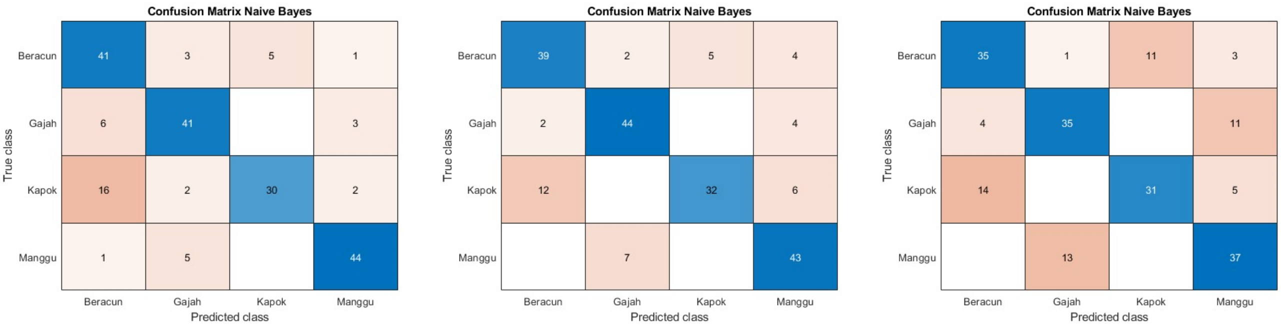

Figure 7. Confusion matrix of Fc6, Fc7, and Fc8 with Naive Bayes classifications.

Discussion

The study results showed that the AlexNet-based feature extraction method combined with the SVM classifier achieved the best performance in cassava leaf classification, with an accuracy of 90.7%, 90.1%, and 85.1% for fc6, fc7, and fc8, respectively. SVM is effective in many other image classification tasks, and its ability to handle high-dimensional feature spaces makes it well-suited for deep learning-based feature extraction methods. This indicates that the features extracted from the AlexNet images effectively captured the distinguishing characteristics of the different cassava leaf types. In contrast, the KNN classifier showed lower performance, with an accuracy of only 80.5%, 79%, and 80% for fc6, fc7, and fc8, respectively. This suggests that the KNN method may be less effective in classifying cassava leaf types based on the extracted features. In this study, KNN performed worse than SVM and Naive Bayes, which could be due to the high dimensionality of the feature vectors extracted from the AlexNet layers. Similarly, the Naive Bayes classifier also showed lower performance, with an accuracy of 87.6%, 88.4%, and 83.2% for fc6, fc7, and fc8, respectively. This indicates that the Naive Bayes method may be less effective than the SVM classifier in this specific task. In this study, Naive Bayes performed well on the fc6 and fc7 layers but not as well on the fc8 layer. This could be because the higher layers capture more complex features that violate the feature independence assumption.

The feature extraction layer comparison findings show that the fc6 layer is superior to the fc7 and fc8 layers. One possible reason is that the fc6 layer is closer to the input layer, which captures more general and discriminative features of the cassava leaf images that are important for classification. As a result, the fc6 layer may contain more relevant features for the cassava classification task. Another possible reason is that the fc6 layer has more neurons than the fc7 and fc8 layers. The fc6 layer has 4096 neurons, the fc7 layer has 4096 neurons, and the fc8 layer has only 1000 neurons. This means that the fc6 layer has a higher capacity to represent the features of the cassava leaf images and capture more relevant information compared to the fc7 and fc8 layers. Additionally, other studies[37–40], reported that the in-depth characteristic of fc6 is more discernible than that of fc7 and fc8, indicating that fc6 of AlexNet may achieve greater performance than fc7 and fc8 shown in Table 5.

Additionally, the fc6 layer is the last convolutional layer of AlexNet, which means it captures high-level features and semantic information. This makes it suitable for feature extraction in image classification tasks such as cassava classification. On the other hand, fc7 and fc8 are fully connected layers, which may capture less relevant information than the convolutional layer. Figs. 8, 9, and 10 show the accuracy of the overall classification results.

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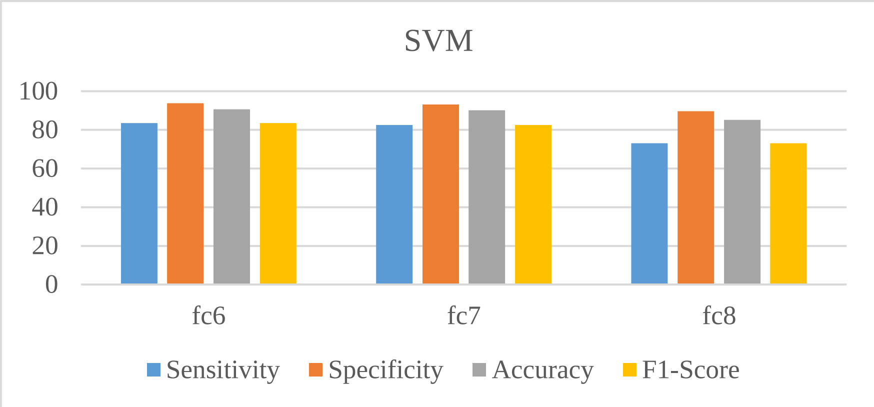

Figure 8. Overall accuracy result of SVM.

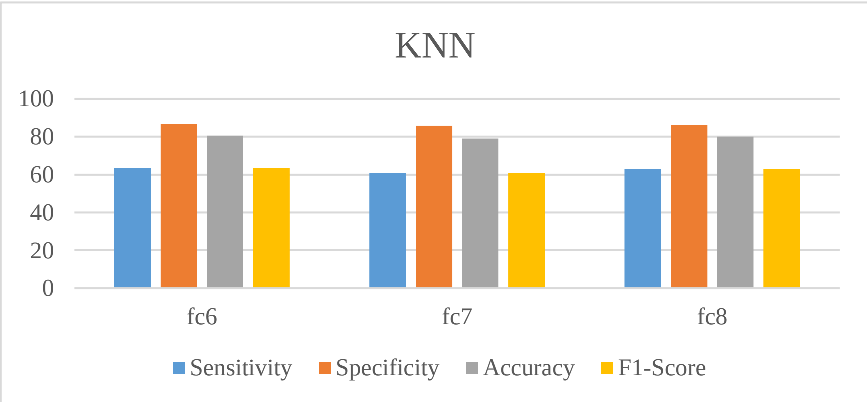

Figure 9. Overall accuracy result of KNN.

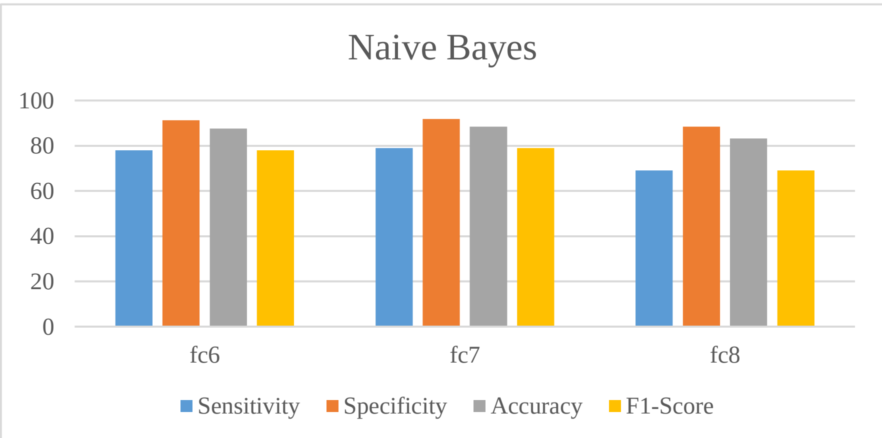

Figure 10. Overall accuracy result of Naive Bayes.

This study accomplished several noteworthy successes in classifying cassava plants by utilizing the AlexNet model as a feature extractor and analyzing the performance of several classification algorithms. The key achievements and their significance are discussed below:

1. Accurate Classification: The study successfully classified various cassava plant species. Using the AlexNet model for feature extraction in conjunction with classification algorithms like SVM, KNN, and Naive Bayes proved successful in this study.

2. Comparison of Classification Algorithms: Classification algorithms for cassava plants were evaluated, with SVM, KNN, and Naive Bayes all receiving some attention. SVM was superior to KNN and Naive Bayes across all AlexNet model layers for feature extraction in terms of accuracy, sensitivity, specificity, and F1 score. These results show that SVM is optimal for cassava plant classification tasks.

3. Evaluation of Different Layers: The research compared the effectiveness of the AlexNet model's feature-extracting fc6, fc7, and fc8 layers. Overall, fc6 was shown to be the most effective classification method. This discovery highlights the significance of fc6 in capturing the most discriminative traits for the classification of the cassava plant, suggesting its value in achieving accurate and dependable results.

4. Contribution to Automated Plant Classification: The research creates automated systems for classifying cassava plant species, reducing reliance on manual and subjective approaches. Through the utilization of deep learning models and pre-trained networks, the research presents a potentially valuable strategy for simplifying the classification procedure, cutting down on time spent on it, and providing accurate and reliable findings. This accomplishment sets the door for future breakthroughs in automated plant classification, not just for cassava but also for other plant species. Specifically, this work focuses on the classification of cassava.

The algorithm suggested in this research is not just applicable to cassava but can be applied to recognize other plants as well.

Comparison with the state-of-the-art:
In this section, the performance of the model made will be compared with the state-of-the-art ones. Specifically, focus on the feature layers fc6, fc7, and fc8.

Table 5. Comparison of state-of-the-art methods.

References	Feature Layer	Classification	Accuracy (%)
Peng[37]	Fc6	SVM	86.30
	Fc7		81.50
	Fc8		79.30
Suh[38]	Fc6	SVM	93.92
	Fc7		88.21
	Fc8		81.23
Sethy[39]	Fc6	SVM	96.20
	Fc7		94.40
Our proposed model	Fc6	SVM	90.70
	Fc7		90.10
	Fc8		85.10

According to the findings, the proposed model delivers results that are on par with those produced by the most advanced approaches now available. When compared to Peng[37] and Sethy[39], it obtains a greater level of accuracy for all of the feature layers. On the other hand, it does not attain the same level of accuracy as Suh[38], which had the highest level of accuracy among the procedures that were examined.

In general, the performance of the proposed model in image classification is impressive and shows promise, particularly for the feature layers fc6 and fc7. On the other hand, additional research and testing might be required if the performance is to be improved upon and the gap with Suh[38] is to be closed in terms of accuracy.

Limitations of This Work:
The research on cassava species classification using leaf images and the Alexnet architecture has limitations. One challenge is the model's ability to generalize, which may result in suboptimal performance when the images have noise or are not taken under ideal conditions. Additionally, the model may give incorrect results when tested with images that differ significantly from those in the training data. Furthermore, the model is only trained to recognize four types of healthy cassava, which may lead to inaccurate classification results when tested with images of diseased plants. To achieve optimal

results, modifications to the existing Alexnet architecture are necessary.

Conclusion

This study involved conducting a range of experiments to categorize various types of cassava. AlexNet was used for the extraction feature with three fully connected layers (fc6, fc7, and fc8) and three classifiers (SVM, KNN, and Naive Bayes). After analyzing the results, the best overall performance was achieved by utilizing fc6 as the fully connected layer and SVM as the classifier. This combination provided impressive metrics with a sensitivity of 83.5%, specificity of 93.7%, accuracy of 90.7%, and F1-score of 83.5%.

The study showcases the efficiency of transfer learning using pre-trained AlexNet for the classification of plant species. The accurate classification of various cassava types highlights the potential of deep learning models in addressing difficult agricultural issues related to crop identification and diversity analysis. Our findings have significant implications for the practical application of cassava leaf classification. The use of fc6 and SVM yielded exceptional levels of accuracy and sensitivity, indicating that this approach could be utilized in automated systems to swiftly and precisely identify various cassava variants. This research contributes to computer vision and plant species classification by showcasing the efficacy of fine-tuning a pre-trained AlexNet on a specific agricultural dataset. Analyzing different fully connected layers and classifiers enables researchers to identify the most suitable combination for classifying cassava leaves

Although our approach has shown promising results, it's important to recognize the limitations of this study. The dataset used in the experiments may be limited in size and diversity, which could affect the model's ability to generalize to unseen cassava variants.

It would be helpful for future research to explore ensemble learning techniques in order to enhance the accuracy of classification. Additionally, it would be beneficial to extend this research to include the classification of multiple plant species, not just cassava.

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Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee in University of Universitas Islam Lamongan and University Tun Hussein Onn Malaysia.

Authors' Contribution Statement

Conception, design, and drafting the manuscript, M.S.; interpretation, revision, proofreading, and results discussion, M.F.M.F.; worked on revision and proofreading, M.N.I.

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استخراج الميزات المستندة إلى AlexNet لتصنيف الكسافا :نهج التعلم الآلي

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الخلاصة

تعتبر الكسافا محصولًا مهمًا في أجزاء كثيرة من العالم، لا سيما في إفريقيا وآسيا وأمريكا الجنوبية، حيث تعمل كغذاء أساسي لملايين الأشخاص. يعتبر استخدام ميزات اللون والملمس والشكل أقل كفاءة في تصنيف أنواع الكسافا. وذلك لأن أوراق الكسافا لها نفس لون مورفولوجيا بين نوع وآخر. بالإضافة إلى ذلك، فإن أوراق الكسافا لها شكل مشابه نسبيًا لنوع واحد من الكسافا، وبالمثل، مع قوام أوراق الكسافا. إلى جانب ذلك، هناك أيضًا المنيهوت السامة. الكسافا السامة وغير السامة لها لون وشكل وملمس أوراق متطابق نسبيًا. يهدف هذا البحث إلى تصنيف أنواع الكسافا باستخدام طريقة التعلم العميق مع AlexNet المدربة مسبقًا كمستخرج للميزات. تم استخدام ثلاث طبقات مختلفة متصلة بالكامل لاستخراج السمات، وهي fc6 و fc7 و fc8. كانت المصنفات المستخدمة هي Support Vector Machine (SVM) و K-Nearest Neighbours (KNN) و Naive Bayes. تتكون مجموعة البيانات من 1400 صورة لأوراق الكسافا تتكون من أربعة أنواع من الكسافا: Gajah و Manggu و Kapok و Beracun. أوضحت النتائج أن أفضل طبقة استخلاص كانت fc6 وبدقة 90.7٪ للطبقة المتناهية الصغر (SVM). كان أداء SVM أيضًا أفضل مقارنةً بـ KNN و Naive Bayes، بدقة 90.7٪، وحساسية 83.5٪، ونوعية 93.7٪، ودرجة F1 83.5٪. ستساهم نتائج هذا البحث في تطوير تقنيات تصنيف النباتات، وتوفير رؤى حول الاستخدام الأمثل للتعلم العميق وطرق التعلم الآلي لتحديد الأنواع النباتية. في النهاية، يمكن للنهج المقترح أن يساعد الباحثين والمزارعين وعلماء البيئة في تحديد الأنواع النباتية ومراقبة النظام البيئي والإدارة الزراعية.

الكلمات المفتاحية: اللون ، استخراج الميزة ، KNN، Naïve Bayes ، الشكل ، SVM ، الملمس.