International Journal of Electrical and Computer Engineering (IJECE)
Vol. 14, No. 2, April 2024, pp. 1544~1551
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i2.pp1544-1551

Guava fruit disease identification based on improved convolutional neural network

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Article Info

Article history:

Received Sep 4, 2023
Revised Sep 11, 2023
Accepted Nov 29, 2023

Keywords:

Agriculture
Automation
Deep learning
Guava fruit disease
Image processing

ABSTRACT

Guava fruit cultivation is crucial for Asian economic development, with Indonesia producing 449,970 metric tons between 2022 and 2023. However, technology-based approaches can detect disease symptoms, enhancing production and mitigating economic losses by enhancing quality. In this paper, we introduce an accurate guava fruit disease detection (GFDI) system. It contains the generation of appropriate diseased images and the development of a novel improved convolutional neural network (improved-CNN) that is built depending on the principles of AlexNet. Also, several preprocessing techniques have been used, including data augmentation, contrast enhancement, image resizing, and dataset splitting. The proposed improved-CNN model is trained to identify three common guava fruit diseases using a dataset of 612 images. The experimental findings indicate that the proposed improved-CNN model achieve accuracy 98% for trains and 93% for tests using 0.001 learning rate, the model parameters are decreased by 50,106,831 compared with traditional AlexNet model. The findings of the investigation indicate that the deep learning model improves the accuracy and convergence rate for guava fruit disease prevention.

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1. INTRODUCTION

The food and agriculture organization of the United States database shows that guava is grown on more than 2,515,970 ha of land and produces an average of 73,257 Hg/ha. The overall production of guava in the world in 2016 was 45,225,211 tons and the productivity was 80,153 hg/ha [1]. Regular crop monitoring and disease management systems are crucial for reducing production losses and ensuring the quality of guava fruit [2]. Machine learning (ML) methods like random forest, logistic regression, and artificial neural networks have been investigated by researchers as an approach to improve the accuracy of disease analysis [3]. In recent years, there has been significant progress in the development of the convolutional neural network method, which has the capability to autonomously identify and extract discriminative features for the task of image classification [4]. The convolutional neural network (CNN) is well recognized as an outstanding technique for recognition of patterns [5] and expression identification [6] in different fields.

Motivated by the significant advancement achieved by convolutional neural networks in the area of image-based recognition, the utilization of CNN for the identification of early disease has become known as a major area of research in the field of agricultural automation. CNNs have been extensively researched and applied in the discipline of crops and disease identification [7], [8]. According to the outcomes of previous investigations, the application of convolutional neural networks has not only decreased the necessity for image preprocessing but also increased the accuracy of recognition. This research introduces a novel methodology for evaluating guava fruit diseases. The CNN based methodology encounters difficulties in training model due to insufficient guava fruit diseased images and defining most effective network model structures. Here is a summary of the major contributions: i) To address the issue of insufficient images of guava fruit diseases, this work exhibits an image dataset constructed on the basis of image processing methods, which can improve the CNN-based model's adaptability and ensure against the overfitting. The initial process refers to the collection of natural guava fruit images, which are then put through to different digital image processing techniques, including data augmentation, contrast enhancement, image resizing and dataset splitting, in order to produce a sufficient amount of images; and ii) The initial step in identifying guava fruit diseases includes the utilization of a CNN. This end-to-end learning model has the ability to autonomously detect specific features that exist in guava fruit diseased images. Consequently, it can highly precisely describe the difference between the three most common types of guava fruit diseases. A novel improved-CNN model, which is based on AlexNet, is proposed in this study for the analysis of guava fruit diseases. The model includes several modifications, including adjustments to the convolution kernel size, replacement of fully-connected layers with a convolutional layer, and the use of Inception to enhance the feature extraction.

The findings of the experiment illustrate that the suggested improved-CNN model outperforms the other standard models with an accuracy of 98% on train data and 93% on test data. In contrast to the traditional AlexNet, the proposed model exhibits a decreased number of 50,106,831 parameters, which suggests an increased fast convergence rate. The recognition rate increases with using a dataset of 612 simulated images of guava fruit, which presents more effective generalization and robustness.

2. RELATED WORKS

The control of fruit diseases has become a topic of significant interest among researchers because it has a potential impact on both production and quality. In therefore, different solutions have been investigated in order to reduce this significant threat [9]. A deep learning approach was suggested for the classification and prediction of guava leaf diseases [10], utilizing a dataset consisting of 1,834 leaves categorized into five distinct groups. Four distinct pre-trained convolutional neural network (CNN) architectures were employed for training purposes. Among these architectures (VGG-16, Inception V3, ResNet50, and EfficientNet-B3), they observed that the EfficientNet-B3 architecture exhibited superior performance, achieving an accuracy of 94.93% on the test dataset. Another recent work provided an automated approach for detecting 12 kinds of guava leaf images [11]. Multiple ML classifiers utilized in this research, namely the instant base identifier, random forest, and meta bagging classifiers. The instant base identifier classifier outperformed other classifiers with an average overall accuracy of 93.01%.

The detection model for guava canker, dost, rust, and mummification diseases was proposed by Mostafa *et al.* [12]. The study utilized color-histogram equalization and unsharp masking technique for disease identification in guava trees. On this research, a group of five network systems, including AlexNet, SqueezeNet, GoogLeNet, ResNet-50, and ResNet-101, were employed to diagnose diseases across multiple guava plant species. The researchers worked with a dataset sourced from Pakistan. They asserted that their findings exhibited a remarkable accuracy rate of 97.74%. A combined collection of 321 images were utilized for the purpose of image processing. The researchers observed that ResNet-101 offered favorable outcomes in comparison to alternative models.

The studies mentioned above highlight the extensive application of CNNs in the field of fruit and plant disease recognition, generating advantageous results. However, it is important to note that those studies mainly utilize CNN-based models for the purpose of identifying diseases, without introducing any additional improvements to the current approach. However, the implementation of the CNN-based model for the purpose of identifying guava fruit disease has not been evaluated. In this study, we present an improve-CNN model that was used to identify guava fruit diseases.

3. METHOD

This study introduces improved-CNN model for accurately identifying diseases affecting guava fruit. The suggested workflow is represented in Figure 1. The processes of the suggested approach have been organized into several essential steps, each of them will be explained in more detail below.

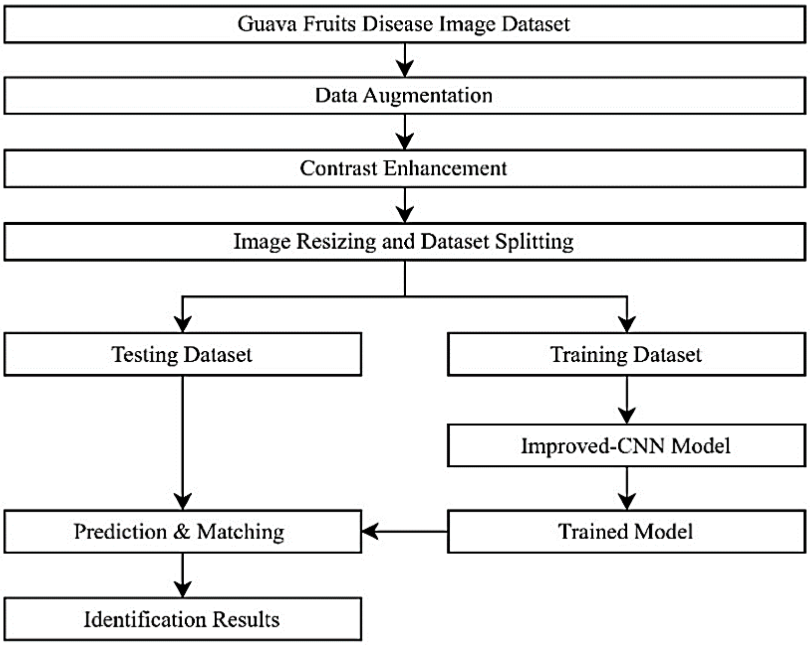


Figure 1. Proposed strategies for the guava fruit disease detection (GFDI) system

3.1. Data augmentation

The majority of the images consisting of the proposed dataset were captured by the researchers, but a portion of the collection was sourced from online repositories. The dataset was augmented through the use of affine transformations in standard image transformations [13]. The research utilizes the use of 612 images and a dataset repository that consists of three different diseases that might affect guava fruit: phytophthora, root, and scab [14]. Figure 2 illustrates the dataset of guava fruit images, while Table 1 provides a detailed summary of the image details. The fruits affected by Phytophthora exhibit a grayish brown color, which further darkens to a grayish black color upon immersion in water, as depicted in Figure 2(a). A discoloration under the persistent calyx that arises brown, black, and soft over time is one of the symptoms of root disease, as seen in Figure 2(b). Guava scab symptoms include lesions on fruit surfaces that are corky, ovoid, or spherical, as shown in Figure 2(c).

(a) (b) (c)

Figure 2. Guava fruit diseases: (a) phytophthora, (b) root, and (c) scab

Table 1. Number of guava fruit disease images

Guava fruit disease	Training	Testing	Total
Phytophthora	205	23	228
Root	162	18	180
Scab	183	21	204
Total	550	62	612

3.2. Contrast enhancement

The technique of histogram equalization is employed to enhance the contrast of the entire dataset. The contrast of the images is increased by using the histogram and the histogram equalization approach provided by (1) to assign a uniform intensity value to each pixel [15].

$$H(P_{(x,y)}) = round(\frac{f_{cdf}\left(p_{(x,y)}\right)-f_{cdf_{min}}}{(R\times C)-f_{cdf}} \times L-1) \quad (1)$$

where, f_{cdf} = cumulative frequency, $f_{cdf_{min}}$= cumulative distribution, $f_{cdf}(P_{(x,y)})$ = intensity, R = number of pixels in rows, C = the number of pixels in each column, and L = the total number of intensities.

3.3. Image resizing and dataset splitting

The process of scaling images facilitates the extraction of additional features and enhances the capacity for discriminating. All images are automatically cropped to 256×256 pixels before model training, utilizing the central square crop method [16], as given by (2).

$$def\,centeredCrop(img, new\_height, new\_width) \quad (2)$$

In order to enhance the performance of the improved-CNN, it is essential to split the dataset into training, and testing sets using the randomization method. The data has been split applying the random sub-sampling validation (RSV) method [17]. The size of each subsection for training and testing is determined as 90% and 10%, respectively.

3.4. Building improved-CNN

An improved-CNN model has been proposed for identifying guava fruit diseases, using traditional AlexNet [18], Inception [19], and their performance enhancements. The input image size is 256×256×3 pixel, batch size 16 for every epoch and the optimizer used is Nesterov's accelerated gradient (NAG) [20] with linearly scored categorical cross-entropy (LSCCE) [21] loss function for 30 epochs. The learning rate is crucial for deep learning models, as high rates result in longer jumps and low rates cause slow convergence [22]. The optimal learning rate is determined by applying learning rates 0.001. The improved-CNN model's structure is illustrated in Figure 3, and its associated parameters are listed in Table 2.

Initially, a structure known as Modified-AlexNet is developed, which is derived from the traditional AlexNet model. Higher-dimension convolution kernels offer enhanced macro information acquisition, resulting in 96 kernels in the first convolutional layer with dimensions of 9×9×3. This is not the same as the usual AlexNet, which consists of a first convolutional layer with kernels that are 11×11×3 in size. The noise is filtered by the second convolutional layer using 256 kernels of dimensions 5×5×48. The first two convolutional layers undergo normalization layers, followed by max-pooling layers. The third convolutional layer consists of 384 kernels, each with dimensions of 3×3×256. The outputs of the second convolutional layer are pooled and normalized, and the kernels are connected to those outputs. The fourth layer of the network is comprised of 256 kernels, each with a size of 2×2×192. In contrast to the traditional AlexNet architecture, a max-pooling layer is subsequently implemented. This configuration is designed to enhance the network's capability to extract small features.

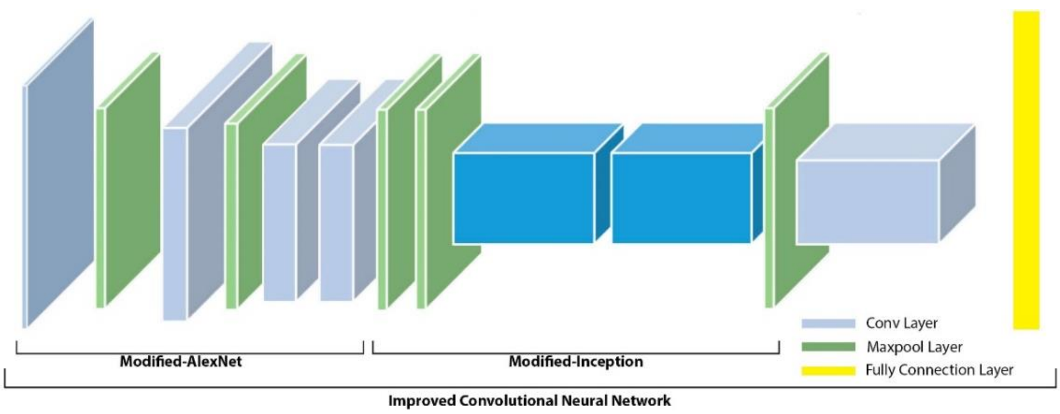


Figure 3. The structure of improved-CNN model

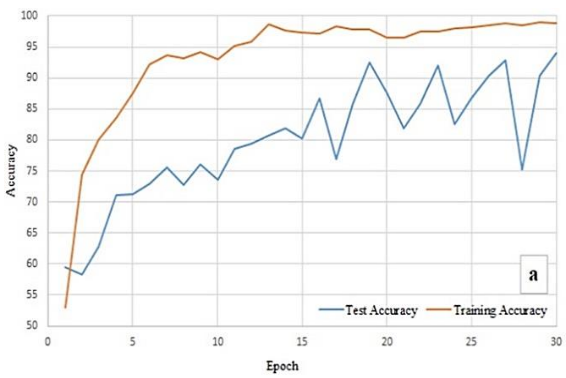
Following the development of the modified-AlexNet, the modified-Inception architecture is constructed. The architectural design encompasses a configuration comprising of two max-pooling levels and two Inception elements. The first max-pooling layer removes the noise in the feature maps that modified-AlexNet generates. Then, the two Inceptions utilize the best classification features from the multidimensional evaluation. To avoid having some features filtered out, the output of the first Inception is sent into the concatenation layer of the second Inception. The standard AlexNet has been replaced with a fifth convolutional layer and a modified-Inception with 4,096 kernels of size 1×1×736. The fully connected layer has been adjusted to make predictions for three different types of diseases that impacts guava fruit. The last layer is realized as a three-way Softmax layer in its implementation.

Table 2. Model configuration and accuracy for train and test set [Epochs: 30, Batch Size: 16, optimizer: NAG, loss function: LSCCE]

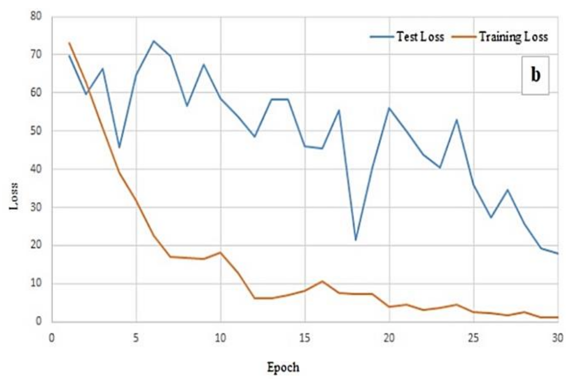
Model configuration				Train accuracy	Test accuracy
Layer	Patch size	Output size	Learning rate		
Conv	9×9	96×55×55	0.001	98%	93%
Maxpool	3×3	96×27×27			
Conv	5×5	256×27×27			
Maxpool	3×3	256×13×13			
Conv	3×3	384×13×13			
Conv	2×2	256×14×14			
Maxpool	3×3	256×7×7			
Maxpool	3×3	256×3×3			
Inception	-	256×3×3			
Inception	-	736×3×3			
Maxpool	3×3	736×1×1			
Conv	1×1	4096×1×1			
Fully Connection	-	3			
Softmax	-	3			

4. RESULTS AND DISCUSSION

This section contains an exposition of the results obtained through the investigation. The research is carried out on a personal computer platform, particularly an Acer Nitro 5 with 16 GB RAM and a 4 GB NVIDIA Graphics card. The experiment is performed using Google Colab, which utilizes a 12 GB NVIDIA Tesla K80 GPU. The performance of the improved-CNN model is evaluated by the accuracy graph, Figure 4 depicts the comparison graphs derived from the training and testing datasets. Figure 4(a) compares accuracy curves for the training set and the test set throughout epochs, demonstrating that both sets achieve similar accuracy levels but that the test set's accuracy is always lower. This observation suggests that the improved-CNN model successfully reduced the issue of overfitting in both the training and testing datasets. Figure 4(b) illustrates the loss curve for both the training set and the testing set respectively. The improved-CNN model exhibits a lower error rate on the test set compared to the training set, which can be considered a positive indicator of the model's classification ability.



(a)



(b)

Figure 4. Curves for comparison for the train dataset and the test dataset: (a) accuracy and (b) loss

In order to conduct a comprehensive analysis, the efficacy of the model is further examined through the measurements of precision, recall, and F1-score [23]. Based on the findings of the identification process, it was determined that the phytophthora class had the highest precision rate of 92%, as shown in Table 3 for details. However, phytophthora has the highest recall value of 95% and the highest F1-score of 93%.

We compared the model performance with AlexNet [24] using proposed dataset [14]. Images were scaled down to 120×120 pixels. Table 4 displays a comparison between improved-CNN and AlexNet in terms of accuracy. We can observe that the improved-CNN is capable of an accuracy of up to 98% for training, whereas the AlexNet has a maximum accuracy capable of 92%. The results show that improved-CNN does better than the AlexNet on small dataset, when the same training and testing conditions are used.

In order to deploy proposed improved-CNN model, Figure 5 exhibits a web application aimed at the identification of diseases in guava fruit. Figure 5(a) shows a hypertext markup language (HTML) page that is designed with input. The submitted image is sent as part of a 'POST' request to the application programming interface (API), which was programmed in Python Flask [25]. The provided image was translated into a NumPy array, which was subsequently transformed into a dataframe. Subsequently, the model was employed for predicting guava fruit disease utilizing the dataframe. Based on the predicted results, the output was employed to generate an additional HTML page that illustrates the actual result, as depicted in Figure 5(b).

Table 3. Performance evaluation of the improved-CNN model

Disease name	Precision	Recall	F1-score
Phytopthora	0.920	0.958	0.939
Root	0.882	0.789	0.833
Scab	0.913	0.945	0.923

Table 4. Comparison between improved-CNN and AlexNet

Models	Accuracy	
	Train	Test
AlexNet [24]	92%	84%
Improved-CNN	98%	93%

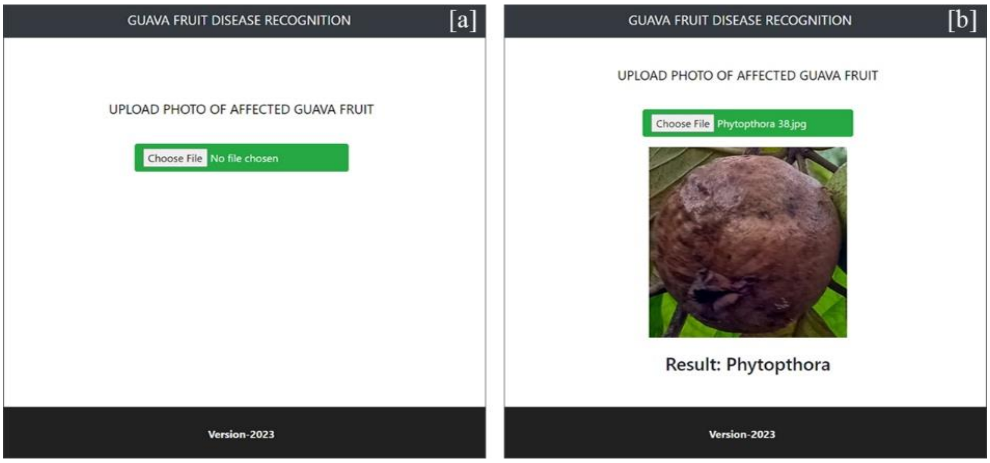


Figure 5. Web application: (a) screenshot of the webpage and (b) predicted result

5. CONCLUSION

The main objectives of this research work were to find out the limitations of existing GFDI systems and apply probable solutions to overcome the limitations. A comprehensive set of 612 images had been generated by the utilization of techniques for image processing such as data augmentation, contrast enhancement, image resizing, and dataset splitting. The above steps were taken to ensure a sufficient number of guava fruit images depicting various diseases. Furthermore, a novel improved-CNN model was constructed by integrating the architectural components of AlexNet and Inception. The obtained findings are considered satisfactory, as the improved-CNN model exhibits a higher overall training accuracy of 98% compared to other models. The NAG algorithm and LSCCE loss function have been applied to optimize network parameters for accurate guava fruit diseases identification and it can be used on a regular computer without a GPU and takes less time to train the dataset.

The proposed method could be used in robotics, where human-computer interactions (HCI) are extremely crucial. Another possible application could involve the development of a real-time system for automatically identifying and recognizing diseases. Adding more guava fruit diseases to the existing dataset is one way to further developing our research. Additionally, we can expand proposed dataset to include more guava images in order to build better models for the future. Additionally, it is recommended to incorporate a wider range of data augmentation techniques, in order to enhance the robustness and reliability of the results obtained from the proposed guava disease dataset.

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