Cassava Leaf Disease Classification: Deep Learning Using Convolutional Neural Network

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***Abstract*—This study uses the ResNet50 architecture of the Convolutional Neural Network (CNN) technique to solve prevalent problems associated with cassava leaf diseases in Indonesia, especially on Java Island. There is a 50-epoch training procedure in this experiment. The accuracy of the model rises steadily, reaching a maximum of 94.54% during the initial period. However, early halting at the 14th epoch is implemented due to worries about possible overfitting on training data. At 78.53%, validation accuracy is still quite poor. Consistent progress is seen in the loss graph, demonstrating convergence with actual values; nevertheless, validation loss varies, bottoming out at 0.7945 in the 14th epoch, which corresponds with the early halting trigger. Testing shows that the model's quality is not up to par, and that processing of the photos resulted in poor image quality, making it difficult to recognize cassava leaf images. The findings highlight the importance of giving model complexity and generalization due consideration. Preprocessing and data quality assurance measures must be taken further to improve the CNN model's performance in classifying cassava diseases.**

***Index Terms*—Leaf Disease Classification, Deep Learning, Convolutional Neural Network, ResNet50, Cassava Plant**

I. Introduction

Categorizing cassava leaf diseases using deep learning is an innovation to support cassava farming in Indonesia, especially on the island of Java. Cassava *(Manihot esculenta)* is a food crop that is widely grown in Indonesia and is an important commodity in the agricultural industry, especially on the island of Java. Cassava cultivation in Indonesia has a significant impact on the economy and food security. Even though cassava has high- productivity, the main challenge faced by farmers is disease attacks on the plants, which can cause a decrease in productivity and production quality. According to data from the Indonesian Central Statistics Agency in 2015, cassava production in Indonesia was 21,801,415 tonnes a year. [1]

This situation requires quick and accurate identification of plant diseases to take appropriate preventive measures. Traditionally, farmers have relied on agricultural experts to visually identify disease symptoms on cassava leaves. This process is not only time-consuming but also expensive and often cannot be carried out regularly. Therefore, the integration of deep learning technology in the classification of cassava leaf diseases can provide an efficient and effective solution.

Indonesia, as the third largest cassava producer in the world, can benefit significantly from the use of deep learning technology in agriculture. The cassava leaf disease classification system supported by deep learning can provide early detection of plant diseases, allowing farmers to take quick and timely control measures. By implementing this technology, cassava farming, in Java and throughout Indonesia can become more efficient, productive, and sustainable. Apart from that, this innovation can help improve the welfare of farmers and the contribution of the agricultural sector to national food security.

The research titled "Disease Detection System in Cassava Leaves Using Android-Based Deep Learning and TensorFlow" by Mirza Faturrachman, Indra Yustiana, and Somantri [6] aims to develop a disease detection system for cassava plants utilizing Android-based Deep Learning and TensorFlow. With a dataset comprising 21,367 cassava leaf images, the study achieves an 86 % accuracy rate in disease classification, highlighting the role of Image Processing technology. While Black Box Testing results indicate a well-performing system, Usability Testing shows a user satisfaction rate of 88.3 %. Suggestions for improvement involve employing more sophisticated algorithmic methods, enhancing UI/UX, and increasing accuracy through hardware optimization.

The research titled "Cassava Plant Disease Classification Using VGG16-Based Deep Learning Architecture" discusses the classification of diseases in cassava plants using deep learning methods with the VGG16 architecture. Conducted by Ardian Eka Nugraha, Syamsul Rizal, and Nor Kumalasari Caesar Pratiwi from the Faculty of Electrical Engineering, Telkom University, Bandung, Indonesia. [7] Cassava, as a staple food in Indonesia, has experienced a decline in production due to various factors, including plant diseases. The authors employed a Convolutional Neural Network (CNN) model based on the VGGNet architecture, specifically VGG16, with a dataset consisting of 9430 images categorized into 5 classes of cassava diseases. The testing results indicate that the model with a batch size of 32, SGD optimizer, and a learning rate of 0.001 achieved a training accuracy of 82.53 % and a validation accuracy of 75%. Despite an imbalance in the number of data instances per class, this model provided

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satisfactory precision, recall, and F1-score results for each cassava disease, demonstrating its potential for effective plant disease identification. However, a limitation in this research involves the lack of handling class data imbalance, which could impact the model's performance, especially for classes with fewer instances. Further efforts to address this imbalance could enhance the reliability of this model in practical situations.

Therefore, we aim to create a model that can be used to classify cassava and detect cassava diseases using CNN training techniques from scratch using a labeled dataset. This work describes the techniques we use to detect cassava diseases using an image dataset consisting of 5 categories of cassava leaf diseases and 12,595 labeled images.

II. Related Work

The exploration of Convolutional Neural Networks (CNNs) in the domain of cassava leaf disease detection has garnered significant attention, with researchers delving into innovative applications and methodologies to address the challenges of imbalanced datasets in the context of cassava disease classification. [2] One notable study was authored by G. Sambasivam and Geoffrey Duncan Opiyo from the Faculty of Information and Communication Technology at ISBAT University in Kampala, Uganda. The research addresses the challenges of small and imbalanced datasets in cassava plant disease detection, proposing techniques such as class weight, Synthetic Minority Over-sampling Technique (SMOTE), and focal loss to mitigate class imbalance in multi-class image datasets. The gap addressed involves the limited research on class imbalance in multi-class image datasets for cassava disease detection, and the study offers promising results while highlighting the need for further exploration in handling multiple co-occurring diseases and scaling the model for real-time monitoring in Sub-Saharan Africa's cassava farming.

Different strategies were required to counteract the class imbalance because the data was heavily biased towards the CMD and CBSD classes. To our knowledge, no research has been done for the classification of cassava mosaic or other cassava diseases by training CNNs from scratch using an unbalanced dataset, despite the positive results of our model's performance.

The research conducted by Rafi Surya and Elliana Gautama from Perbanas Institute, Jakarta, implements a Convolutional Neural Network (CNN) with MobileNetV2 architecture using TensorFlow to classify diseases in cassava leaves. [1] With a dataset collected from the Artificial Intelligence Lab at Makerere University and the National Crops Resources Research Institute (NaCRRI) in Uganda, the study identifies four types of healthy cassava leaves and their diseases. The experimental results demonstrate a high level of accuracy, with training accuracy reaching 0.8538 and validation accuracy at 0.7496. However, potential gaps may be associated with the model's generalization across various plant growth conditions, its reliability in handling image variations, and the need for a more extensive and representative dataset.

Another journal, titled "A Deep Learning Approach For Cassava Leaf Disease Diagnosis," [3] aims to develop a Convolutional Neural Networks (CNN) model for the early detection of cassava leaf diseases to assist farmers in efficiently diagnosing diseases. The primary author is Ambrose Azeta, accompanied by co-authors Kingsley Jonathan, Blessing Guembe, and Endurance Nwadoziokwu. The paper outlines the challenges in cassava farming, introduces the deep learning approach, and presents experimental results showing that the CNN model achieved a prediction accuracy 97.28.

The research conducted by Hema M.S., Nittesha Sharma, Y Sowjanya, Ch. Santoshini, R Sri Durga, V. Akhila, regarding plant disease prediction using the same method Convolutional Neural Network (CNN) talks a lot about India's loss in annual crop yield affected by unidentified diseases on the crop. [4] They proposed two methods Resnet34 and VGG16 in which the idea was to use CNN to identify the plant disease. The three processing steps are classification, image downsizing, and feature extraction. The performance metrics that were considered were specificity, sensitivity, and accuracy. Providing farmers with tailored advice based on soil characteristics, temperature, and humidity is beneficial.

Test-Time Augmentation: This technique can lower our models' generalized errors. We could also attempt image augmentation on test images to produce additional test data versions. Next, we predict those test images using the model, and the test images we created may have varying accuracies. We should obtain a more performance-oriented, more generalized model after averaging them. Modify random seeds: We can obtain multiple high-quality models by varying the random seeds. Our neural network's initialization can be affected by a variety of random seeds. However, concerning randomness, the optimizers, learning rates, and momentum can all be adjusted. Since reproducibility is a goal for the model.

The journal was written by two researchers Mrs. Kavita Krishnat Patil an M.Tech Student, and Mrs. Seema. S. Patil as assistant professor. In the paper, they had the same concern as the previous research in which seasoned farmers can have a difficult time diagnosing the diseases. Destructive insects and plant leaf diseases significantly threaten the agricultural industry. Thus, Convolutional Neural Networks [CNN] were utilized in the development of this system to process images. The suggested system can handle intricate situations from within a plant's vicinity and successfully identify various diseases. [5]

Convolutional neural networks were suggested and used to predict plant diseases. Plant disease prediction was done using the CNN architectures of Resnet34 and VGG16. Convolutional layers were used to extract features, pooling layers were used to reduce the size of samples, and dense layers were used to make predictions. In the convolutional layer, the ReLU activation function was employed. In the dense layer, the softmax activation function was applied. For testing, about 150000 plant leaves from 14 distinct species were collected. The suggested architectures demonstrated the ability to identify 38 distinct plant disease types.

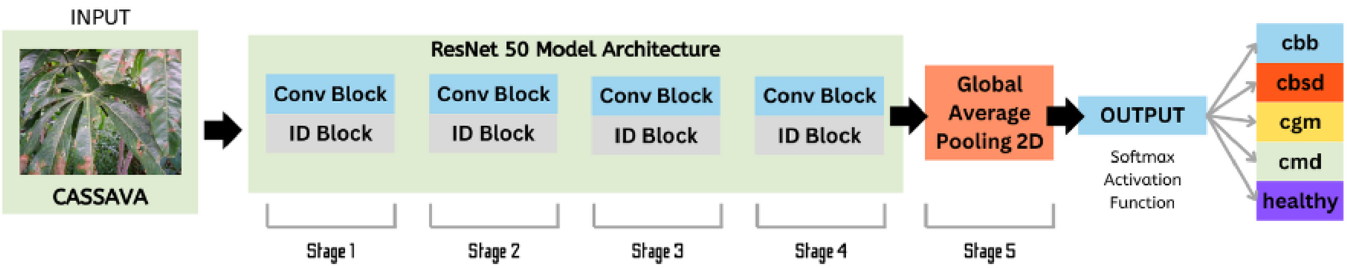

Fig. 1. Cassava Disease Classification Architecture

III. Proposed Method

A. Data Collecting and Preprocessing

Using a dataset of more than 12,595 annotated cassava leaf photos from Kaggle, the study applies a Convolutional Neural Network (CNN) in Python to the task of classifying diseases. The methodology, which is centered on identifying six distinct kinds of cassava illnesses, seeks to support early agricultural intervention and diagnosis. CNNs are an effective tool for image recognition, which emphasizes how well the method works for understanding complex patterns in photos of cassava leaves. Probably preparing the data helped the model learn better during the trial process, and performance was measured using metrics like accuracy and precision. In addition to demonstrating a strong Python implementation, the suggested method represents a significant advancement in the field by providing an automated method for precisely identifying and categorizing cassava diseases for effective crop management.

B. Model Architecture

Convolutional Neural Networks (CNNs), often referred to as ConvNets, stand as a formidable deep learning methodology widely acclaimed for its prowess in image analysis applications, particularly in tasks such as object categorization and recognition. What sets CNNs apart is their ability to operate directly on raw data, obviating the need for manual feature extraction—a distinctive departure from conventional methods. The success of CNNs is manifest in their exceptional performance across diverse computer vision applications.

Delving into the intricacies of CNN architecture reveals a meticulously designed framework comprised of multiple layers, each endowed with a specific function integral to the learning process. At the forefront of this design is the Convolutional Layer, a cornerstone component that employs filters to conduct convolution operations on the input image. This operation yields feature maps, effectively highlighting pertinent structures and patterns embedded in the data. The convolutional process plays a pivotal role in enabling the network to discern meaningful features autonomously.

The architectural prowess of CNNs is further augmented by the inclusion of the Rectified Linear Unit (ReLU) layer—an indispensable element enhancing training efficiency and speed. Operating as a critical element, the ReLU layer transforms negative values into zeros, imbuing the network with a heightened capacity for learning intricate relationships within the data. This non-linearity introduces a crucial aspect to the model, fostering more effective and rapid training.

Following the Convolutional Layer, the narrative of the CNN unfolds with the activation of the Pooling Layer. This layer, akin to its convolutional counterpart, serves to reduce the dimensionality of the convolutional feature matrix by spatially downsampling it. By preserving essential features identified during convolution, the Pooling Layer not only maintains the integrity of the learned patterns but also contributes to a significant reduction in the computational power required for subsequent data processing. Two prevalent pooling techniques, Average Pooling, and Max Pooling, are employed to compute the average and maximum values, respectively, from kernel-covered regions of the input image.

As the architectural journey progresses through the CNN, the Fully Connected Layer (FC) takes center stage as the final layer, succeeding the feature detection phase. Here, the primary function pivots towards classification, generating a K-dimensional vector where K corresponds to the number of classes the network can predict. Within this vector, probabilities for each class are encapsulated, offering a comprehensive insight into the likelihood of the input belonging to specific categories.

The concluding layer of the CNN architecture employs the softmax function, facilitating a normalized transformation of the K-dimensional vector into a probability distribution across all possible classes. By assigning probabilities to each class based on the features detected and learned, CNN stands poised to provide thorough and accurate classification results. This intricate process significantly enhances the network's capacity to deliver insightful and precise predictions across a myriad of image recognition tasks, cementing the Convolutional Neural Network as a stalwart in the realm of deep learning.

For the architecture, we use a particular kind of convolutional neural network (CNN) known by the abbreviation ResNet was first described in the 2015 paper "Deep Residual Learning for Image Recognition" by He Kaiming, Zhang Xiangyu, Ren Shaoqing, and Sun Jian. [8] Computer vision applications are often driven by CNNs. A convolutional neural network with 50 layers, consisting of 48 convolutional layers, 1 MaxPool layer, and 1 average pool layer is called ResNet-

50. One kind of artificial neural network (ANN) that builds networks by stacking leftover blocks is called a residual neural network. The building block of the 50-layer ResNet is designed like a bottleneck. A bottleneck residual block minimizes the number of parameters and matrix multiplications by using 1×1 convolutions, also referred to as a "bottleneck." This makes training each layer much faster. Instead of using two layers, it employs a stack of three layers. The 50-layer ResNet architecture includes the following elements: '7x7 kernel convolution' with 64 additional kernels that have a stride of two sizes, 'max pooling layer' which has a 2-sized stride, '9 more layers' One convolution uses 3x3,64 kernels, another uses 1x1,64 kernels, and a third uses 1x1,256 kernels. There are three repetitions of these layers, '12 more layers' Four iterations were performed using 1×1,128 kernels, 3×3,128 kernels, and 1×1,512 kernels, '18 more layers' Six iterations were performed using 1×1,256 cores and 2 cores (3×3,256 and 1×1,1024), '9 more layers' utilizing three iterations of 1×1,512, 3×3,512, and 1×1,2048 cores.

ResNet50 has several arguments [9]that can be used to modify the architecture including 'include_top', 'weights', 'input_tensor', 'input_shape', 'pooling', 'classes', 'classifier_activation'. These arguments are going to be useful in classifying and adjusting the architecture model itself.

IV. Experiment

A. Training Process

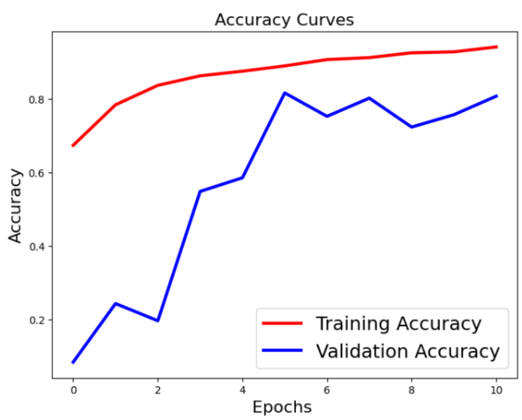

Fig. 2. Training accuracy and Validation graph

During the 50-epoch training process, the accuracy of the model steadily increased, reaching 67.44% in the first epoch. This percentage indicates the proportion of correctly classified samples within the training dataset. However, a potential concern arises as the validation accuracy remains significantly lower at 5.39%, suggesting that the model may be overfitting the training data and struggling to generalize to unseen examples. As training progresses, the accuracy fluctuates, peaking at an impressive 94.54%, while the validation accuracy hovers around 78.53%. The periodic fluctuations in both metrics suggest a dynamic learning process, and the early stopping mechanism is triggered in the 14th epoch, likely to prevent overfitting and ensure the model's generalizability.

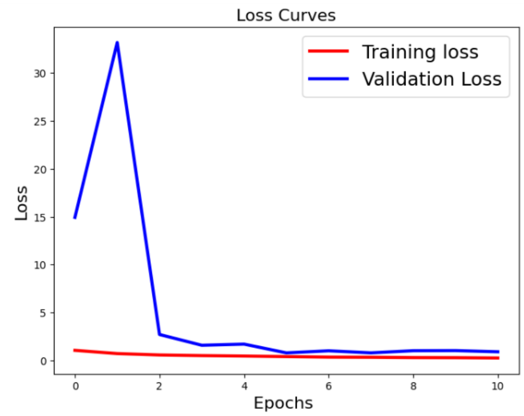

Fig. 3. Training and Validation loss graph

The loss metric, representing the difference between predicted and actual values, is a crucial indicator of a model's performance. In the initial epoch, the loss is relatively high at 1.0273, reflecting the model's early stage of learning. As training progresses, the loss consistently decreases, indicating improved convergence and alignment with the actual values. However, the validation loss, which measures the model's performance on unseen data, exhibits fluctuations, particularly during the later epochs. The lowest validation loss is achieved at 0.7945 in the 14th epoch, coinciding with the early stopping trigger. The patterns observed in both loss and validation loss underscore the iterative nature of training and the need for vigilant monitoring to strike a balance between model complexity and generalization.

B. Testing Process

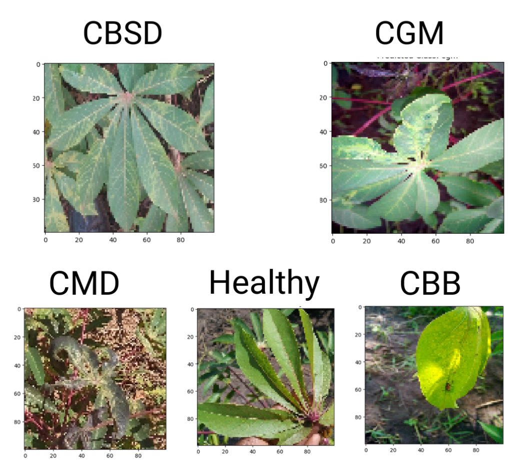

Fig. 4. Testing Result

In the context of this experiment, it seems that the results of the model that has been created show an unsatisfactory level of quality. After going through a series of tests, the model was able to guess the image of a cassava leaf, but unfortunately, several images did not match the classification. This problem can be traced back to the quality of the images processed in the process. The graphics in the images input into the modeling tend to be less than optimal, and as a result, the model's accuracy is hampered by this condition.

V. Conclusion

Convolutional Neural Networks (CNNs), namely the ResNet50 architecture, exhibit potential in the classification of cassava leaf diseases, according to the research's experiments. The accuracy of the 50-epoch training procedure shows a consistent climb, peaking at 94.54%; nevertheless, worries about possible overfitting prompt the 14th epoch to introduce early stopping. At 78.53%, the validation accuracy is still quite low, suggesting that careful attention must be paid to striking a balance between generalization and model complexity. The iterative nature of the learning process is highlighted by the loss metric, which shows increased convergence and alignment with actual values throughout training with oscillations in validation loss. However, the ensuing testing procedure highlights the impact of inferior image quality on model performance by revealing difficulties in correctly identifying photos of cassava leaves. As a result, the research indicates that in order to increase the overall efficacy of the created CNN model for cassava disease classification, better preprocessing and data quality assurance procedures are required.

References

[1] R. Surya and E. Gautama, 'Cassava leaf disease detection using convolutional neural networks', in 2020 6th International Conference on science in information technology (ICSITech), 2020, pp. 97–102.

[2] G. Sambasivam and G. D. Opiyo, 'A predictive machine learning application in agriculture: Cassava disease detection and classification with imbalanced dataset using convolutional neural networks', Egyptian informatics journal, vol. 22, no. 1, pp. 27–34, 2021.

[3] A. Azeta, K. Jonathan, B. Guembe, and E. Nwadoziokwu, 'A Deep Learning Approach For Cassava Leaf Disease Diagnosis', Available at SSRN, 2023.

[4] M. S. Hema, N. Sharma, Y. Sowjanya, C. Santoshini, R. S. Durga, and V. Akhila, 'Plant disease prediction using convolutional neural network', EMITTER International Journal of Engineering Technology, vol. 9, no. 2, pp. 283–293, 2021.

[5] M. K. K. Patil and M. S. S. Patil, 'CONVOLUTION NEURAL NETWORK FOR LEAF DISEASE DETECTION', Open Access Repository, vol. 9, no. 6, pp. 129–136, 2022.

[6] M. Faturrachman, 'SISTEM PENDETEKSI PENYAKIT PADA DAUN TANAMAN SINGKONG MENGGUNAKAN DEEP LEARNING DAN TENSORFLOW BERBASIS ANDROID', Nusa Putra, 2022.

[7] A. E. Nugraha, S. Rizal, and N. K. C. Pratiwi, 'Klasifikasi Penyakit Pada Tanaman Singkong Menggunakan Arsitektur VGGNET Berbasis Deep Learning', eProceedings of Engineering, vol. 9, no. 6, 2023.

[8] Datagen Team, "ResNet-50: The basics and a quick tutorial," Datagen, https://datagen.tech/guides/computer-vision/resnet-50/ (accessed Dec. 19, 2023).

[9] K. Team, "Keras Documentation: Resnet and RESNETV2," Keras, https://keras.io/api/applications/resnet/ (accessed Dec. 19, 2023).