CNN Design with AlexNet Algorithm for Diagnosis of Diseases in Cassava Leaves

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***Abstract* - Plant diseases play a significant role in reducing crop productivity. Nobody will be able to consume the crops because they have been contaminated with different illnesses. As a result, farmers may face huge losses. Cassava is a staple crop in some nations, so this issue may have severe impact on the economy. Detecting plant diseases manually takes time and is prone to errors. It is not always a reliable method for discovering and avoiding the propagation of plant diseases. In order to overcome these issues, cutting-edge technology like machine learning and deep learning may help with early plant disease identification. The main goal of the work is to use deep learning to image classification in order to accurately identify diseases that especially impact cassava plants. This identification may make it possible to implement early intervention measures like specific application of chemicals or confinement of contaminated crops. Each and every test and training image comes from a rural area in the natural world. Using a specific collection of data, the model has been verified to ascertain its true results. In a nutshell this work uses deep learning methods to combat cassava diseases, supporting agricultural practices and food security. The development of a precise disease detection and prevention model has the potential to significantly increase the capacity for recovery of the cassava crop, improving food production and the quality of life for those whose livelihoods depend on this paramount crop.**

Keywords- Cassava, Disease Identification, Intervention, Deep Learning, AlexNet.

I. INTRODUCTION

In several regions, cassava has been deemed as the most significant crop. Most people are familiar with cassava because of its capacity to thrive under challenging conditions. The majority of cassava is produced in Latin America, with Nigeria being the world's leading producer. Tamil Nadu is the main provider of it in India. Though their protein content level is not the highest, they are well recognized because they are the third-biggest supplier of carbohydrates in diet, beneath rice and maize [1]. Many people's nutritional demands can be satisfied by cassava. The sugary root and foliage are the essential parts that can be eaten. To prepare a nutritious supper, simmer the greens and fibrous roots. In conjunction with root and leaf matter, the starch extracted from cassava plants may be used in manufacturing processes and as feed for livestock. It also contains energy-boosting factors such as fatty acids, protein, antioxidant vitamin C, and a form of vitamin A [2]. Despite cassava's numerous benefits, infections caused by a variety of virus genomes and parasites have significantly reduced crop yield.

Given that the root system and foliage are fundamental components of a plant, various approaches can be employed to assess their condition. For instance, inspecting the leaves of cassava plants is a common method. Leaflet health, for example, can be evaluated by determining the proportion of leaf granules in the outermost layer and assessing its accessibility [3]. Once the issue is identified, farm owners can take measures to prevent the disease from spreading throughout the vegetation.

Problem Statement: Plant diseases pose a significant threat to farmers, often resulting in substantial harvest losses when multiple diseases afflict their crops. The prevalence of infections has notably reduced cassava output. Currently, experts primarily rely on visual assessment of leaves to detect symptoms of illness [4]. However, in some regions, farmers lack awareness of when to seek expert assistance, leading to inadequate diagnosis and treatment by plant pathologists or agricultural researchers [5]. To address these challenges, this investigation introduces a simple prototype designed to automatically detect plant diseases and alert agricultural workers to take necessary action.

II. LITERATURE REVIEW

According to R. Singh, et. Al [1], Research on agriculture has shown that Africa is the world leader in the production of cassava, with notable contributions from Asia and Latin America, particularly Thailand. Deep learning algorithms for disease identification such as DenseNet169 have emerged in response to these disorders. A recent study employed a dataset of 21,397 pictures encompassing five categories of cassava leaf disease: CBB, CBSD, CGM, CMD, and Healthy.

According to A. A. John, et. Al [2], Identifying plant diseases automatically is one of the biggest problems facing agriculture today, globally. An essential crop of carbohydrates, commonly farmed by smallholders in Sub-Saharan Africa, cassava is a hardy staple during droughts. Farmers currently mostly depend on specialized plant health inspectors for routine inspections. These inspections require labour-intensive laboratory testing and leaf sampling, which delays prompt disease action. The study made use of a dataset of 21,397 annotated photos that were obtained from routine surveys conducted in Uganda.

Based on the research study proposed by R. Surya, et. Al [3], In Indonesia, cassava is very important, especially as a rice alternative. The Indonesian Central Statistics Agency recorded a large amount of cassava production in 2015. Despite output losses in 2016 brought on by common diseases, Lampung Province emerged as a major cassava grower in the nation. Utilizing deep learning innovations, including Convolutional Neural Network (CNN) techniques, presents viable paths for cassava plant disease diagnosis. CNNs are good at classifying images; thus they can tell healthy cassava leaves from damaged ones. H. C. Choi, et.al [4] proposed a new approach to solve the limitations of conventional visual inspection methods for cassava leaf disease identification. It does this by utilizing an image classification algorithm based on Residual Network (ResNet). E. Gautama, et. Al [5] states that in Indonesia, cassava is an essential crop that replaces rice; the main producer of cassava is Lampung Province.

R. Aruna, et.al [6] mentions the significance of supervised machine learning in agricultural solutions, particularly in the context of plant pathology, this work provides a comprehensive approach to the detection of diseases on cassava leaves. A. Methil, et. Al [7] reveals that over 500 million people worldwide rely on cassava as a critical tropical root crop to provide them with the energy they need to survive. Even though it is resilient, cassava can get several bacterial and viral illnesses; the Cassava Mosaic Disease alone results in large annual losses. Modern deep-learning approaches are being adopted because accurate prediction depends on early disease identification.

Umesh Kumar Lilhore, et.al [8] proposed a novel method emphasizing the practical applicability through mobile deployment, enhancing disease detection in cassava plants, and shown how deep learning techniques may be used to address agricultural difficulties.

As mentioned by Yiwei Zhong, et. Al [9], plant features are gathered from different locations using the deep learning architectures of ResNet 50 and MobileNetV2. Following the collection of characteristics, K-nearest neighbour (KNN) and Support Vector Machine (SVM) approaches are applied to classify the data.

N. Sharma, et. al [10] split data into training and testing sets using the K-fold cross-validation procedure. With accuracy rates of 85.4% and 84.4% for training and testing, respectively, the results demonstrate that the ResNet50 architecture and SVM classifier combination yields the highest success rate.

As mentioned by M. K. Dharani, et. Al [11], A vital industrial crop, cassava is grown and exported extensively across the nation. However, the frequency of cassava infections drastically lowers output and has a detrimental effect on farmers' revenue. The Cassava brown streak viral disease

(CBSD) is the subject of this investigation due to its significant effects on productivity.

A. Saini, et. al [12] proposed a smart way to use a Python graphical user interface (GUI) to identify cassava leaf disease. The system uses the deep learning model MobileNetV2. The five disease types that are included in the approach are healthy leaves, cassava Mosaic Disease (CMD), cassava Green Mite (CGM), cassava Brown Steak Disease (CBSD), and cassava Bacterial Blight (CBB).

The assessment carried out by Huy-Tan Thai, et. al yielded an overall accuracy of 65.6%, demonstrating the system's effectiveness in classifying different diseases. The GUI program is designed to be user-friendly and efficient, even for inexperienced users, and is specifically tailored to fulfil the needs of cassava farmers in the field.

Priya Kumari, et. al [14] mentioned that Recently, deep learning has demonstrated potential in image-based applications, particularly in the identification and categorization of plant diseases. This study uses a dataset with unbalanced samples to give a thorough comparative analysis of deep learning models for cassava leaf disease detection and classification.

Shiva Mehta, et. Al [15] utilized deep convolutional neural networks (CNNs) and other strategies including attention mechanisms and transformers to analyse Transformer-Embedded Res Net, EfficientNetV2 with visual attention, and mobile-based deep learning models with the goal of improving accuracy and efficiency.

A. A. John, et. Al [16] analyse the serious risks faced by cassava, a crucial source of carbohydrates, especially in sub-Saharan Africa. This puts food security at risk. To combat this challenge, new approaches to illness detection are required. Image recognition emerges as a scalable and affordable option, and deep learning models enable deployment that is compatible with mobile devices.

III. METHODOLOGY

A. CNN Model Construction

The goal of the CNN model is to simulate the biological processes that underlie human vision. Convolutional network architecture consists of numerous layers that are configured differently to produce diverse network topologies. It falls under several categories of layers.

B. Layers of Convolution

Two-dimensional convolutional layers can carry out convolution operations using filters or trainable kernels, with each kernel having a trainable bias. During convolutional procedures, kernels can travel in the direction of the input as "strides." The kernel can skip additional space during the convolution period if there is a possibility that the stride will be large [7]. Output size can be calculated by using equation (1).

$$Output\ Size = \frac{M-T+2K}{C} + 1 \tag{1}$$

C. Subsampling layers

The features in the two-dimensional subsampling layers are down-sampled using non-trainable kernels, also referred to as windows. This is evident in the decreased dependency on the network's location and is also beneficial in the lowering of feature count. There are two categories of subsampling: maximal pooling and average pooling [8].

D. Fully Connected Layers

Only CNN's can contain fully connected layers. The majority of the completely linked layers in CNN's are often found in the last layers, which can occur after numerous convolutional and subsampling operations. The fully linked layer consists of numerous hidden layers, including the activation function, output layer, and loss function [9]. This layer uses a trainable bias, outcomes summing, and multiplication of the inputs with the use of weight vectors that may be trained. In the past, outputs were delivered by activation functions that are identical to those of convolution layers [10].

E. Dataset separation

The test data, which is derived via CNN training, and training data make up the two segments of the dataset. CNN uses training data to create its educational materials [11]. Test data and training data have distinct compositions. Using the 10-fold cross-validation method, the training data is split into training and validation subsets once it has been entered into the program [12].

F. CNN Learning

CNN learning is essential to determine which type of CNN architecture is best for initiating the learning process [23]. The optimal architecture will be one that works with the dataset. In essence, the CNN model employed in this study is an AlexNet design [14]. The neural network is the most often used algorithm in the learning process, and it's combined with a method known as gradient descent [13]. This approach makes it possible to calculate the weight of each neuron [6]. Similar to momentum, Adam maintains an exponential decay rate on the preceding gradient p_k:

$$\hat{p}_k = \frac{p_k}{1-\beta_1^k} \tag{2}$$

$$\hat{S} = \frac{s_k}{1-\beta_2^k} \tag{3}$$

$\hat{p}_k$ and $\hat{s}_k$ are the estimates of the first and second moment of each gradient, respectively, derived from equations (2) and (3). The final formula looks like this in equation (4).

$$\theta_1 + 1 = \theta_t - \frac{\eta}{\sqrt{\hat{s}_k - \epsilon}}\ \hat{p}_k \tag{4}$$

IV. IMPLEMENTATION BY USING ALEXNET WITH CNN MODEL.

A. AlexNet

The AlexNet architecture consists of five convolutional layers, three pooling layers, and two dropout layers, and three fully connected layers. The convolutional layers are responsible for feature extraction from the input image [22]. The pooling layers are used to reduce the size of the feature maps [15]. There are two types of pooling layers: average pooling and max pooling. The fully connected layers are used to make predictions based on the extracted features.

Layer	Filters	Size	Stride	Padding	Activation
Input	-	224x224x3	-	-	-
Conv1	96	11x11	4	2	ReLU
Pool1	-	3x3	2	-	-
Conv2	256	5x5	1	2	ReLU
Pool2	-	3x3	2	-	-
Conv3	384	3x3	1	1	ReLU
Conv4	384	3x3	1	1	ReLU
Conv5	256	3x3	1	1	ReLU
Pool5	-	3x3	2	-	-
FC6	4096	-	-	-	ReLU
Dropout1	-	-	-	0.5	-
FC7	4096	-	-	-	ReLU
Dropout2	-	-	-	0.5	-
FC8	1000	-	-	-	softmax

Table 1: AlexNet Architecture Details

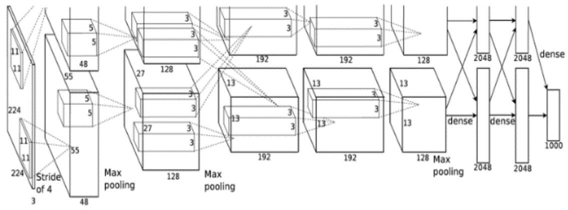

Figure 1: AlexNet Architecture

The architecture of AlexNet can be seen in Figure 1 and the details of the layers can be seen in Table 1

This research uses the MATLAB programming platform. MATLAB can perform matrix manipulation operations, function plotting with data, algorithm application, and Graphical User Interface (GUI) creation. MATLAB has toolboxes for various needs such as Simulink, Neural Network, Fuzzy Logic Toolbox, and others [16]. A confusion matrix is a useful tool for analysing how well a classifier/model recognizes tuples from different classes. There are four terms that represent the results of the classification process on the confusion matrix: True Positive (TP) means positive data predicted correctly, True Negative (TN) means negative data predicted correctly, False Positive (FP) means negative data predicted as positive, and False Negative (FN) means positive data predicted as negative [17].

B. Experiment

This study has developed a successful research project. It uses an algorithm, a set of instructions, to categorize diseases on cassava leaves. This tool uses AlexNet, a type of Convolutional Neural Network (CNN). You can run this program on Google's Colab platform.

There are two parts to this program: training and validating and identifying diseases on images [19]. During the training stage, you can use the Colab platform. It lets you train and validate with a big dataset of cassava leaf diseases. The program will tell you how accurate it is against the validation data [18]. The goal is to hit more than a 70% accuracy mark. In the image classification phase, the program facilitates the input of cassava leaf images, offering users the ability to obtain swift and accurate classification results [20].

Utilizing Google Colab, this version promotes easy access, quick calculations, and team effort for those trying to identify diseases in cassava leaves [21].

C. Dataset

In this study, we will examine cassava leaves. The goal is to recognize and group different health issues that impact the plant. The information we will use comes from a competition on Kaggle about classifying diseases in cassava leaves.
You can find the competition here: https://www.kaggle.com/competitions/cassava-leaf-disease-classification. The data contains pictures of cassava leaves with various problems. This includes Cassava brown streak disease, healthy leaves, damage from green mites, Cassava mosaic disease, Brown leaf spot, and healthy leaves. The purpose of the analysis is to correctly identify and categorize the diseases based on visible changes in the cassava leaves.

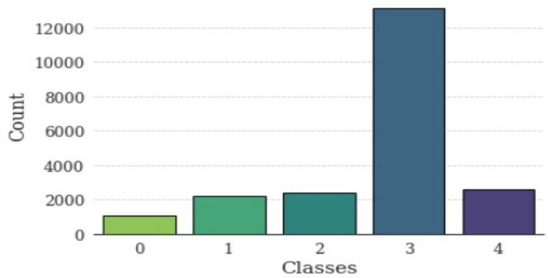

Figure 2: dataset containing 5 classes

The above graph (fig 2) shows the dataset containing 5 classes, that the cassava leaf diseases are associated.

D. Training process

The training process encompasses several stages, starting with the input of training data, followed by the division of data into training and validation sets [24]. The subsequent steps involve configuring parameters and initiating the training and validation procedures. The calculation of training accuracy and validation values is determined using equation (5).

$$Accuracy = \frac{Correct\ amount}{Total\ data} \times 100 \qquad (5)$$

This process is implemented on the training page. The training process flowchart can be seen in Fig. 3

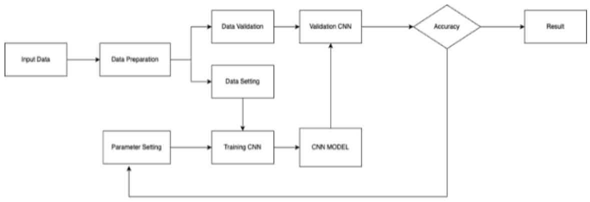

Figure 3: training process

Input Requirements	Description	Input Requirements	Description	Input Requirements	Description
Training Data	A dataset of cassava leaf images	Training Data	A dataset of cassava leaf images	Training Data	A dataset of cassava leaf images
Epoch	The number of times the learning algorithm will work through the entire training dataset	Epoch	The number of times the learning algorithm will work through the entire training dataset	Epoch	The number of times the learning algorithm will work through the entire training dataset
Mini-batch	A subset of the training data used for each update of the model weights	Mini-batch	A subset of the training data used for each update of the model weights	Mini-batch	A subset of the training data used for each update of the model weights
Learning Rate	The step size for each update of the model weights	Learning Rate	The step size for each update of the model weights	Learning Rate	The step size for each update of the model weights
Momentum	A hyperparameter used to accelerate gradient descent in the relevant direction	Momentum	A hyperparameter used to accelerate gradient descent in the relevant direction	Momentum	A hyperparameter used to accelerate gradient descent in the relevant direction

Table 2: input needs of the training process

Details of the input needs of the training process can be seen in Table 2.

Output Requirements	Description	Output Requirements	Description	Output Requirements	Description
Detailed Training Data	File names, actual class labels, and predicted outputs for each image in the training set	Detailed Training Data	File names, actual class labels, and predicted outputs for each image in the training set	Detailed Training Data	File names, actual class labels, and predicted outputs for each image in the training set
Detailed Validation Data	File names, actual class labels, and predicted outputs for each image in the validation set	Detailed Validation Data	File names, actual class labels, and predicted outputs for each image in the validation set	Detailed Validation Data	File names, actual class labels, and predicted outputs for each image in the validation set
Accuracy	The percentage of correctly classified images in the validation set	Accuracy	The percentage of correctly classified images in the validation set	Accuracy	The percentage of correctly classified images in the validation set
Model Network	The trained CNN model with Alexnet architecture for detecting cassava leaf diseases	Model Network	The trained CNN model with Alexnet architecture for detecting cassava leaf diseases	Model Network	The trained CNN model with Alexnet architecture for detecting cassava leaf diseases

Table 2: output requirement of the training process

Details of the output requirement of the training process can be seen in Table 3.

E. Classification Process

In the classification process, the user will use the network obtained from the training process. Input in the form of images will be classified by the network so that they can be obtained, including which class of the image. This process is implemented on the image processing page. The classification process flowchart is shown in Fig. 4

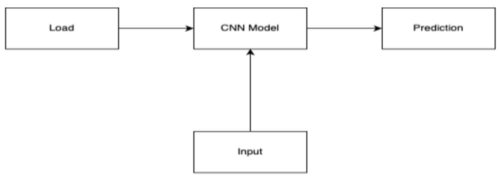

Figure 4: Classification flow chart

F. Testing

Testing is carried out using confusion matrix to get accuracy, precision and recall values. The confusion matrix image is shown in Fig. 5

		Predicted class		
		Yes	No	Total
Actual class	Yes	TP	FN	P
	No	FP	TN	N
	Total	P'	N'	P + N

Figure 5: Confusion matrix

The accuracy value is calculated with equation (6), precision with equation (7) and recall with equation (8).

$$Accuracy = \frac{TP + TN}{P + N} \tag{6}$$

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

$$Recall = \frac{TP}{P} \tag{8}$$

V. ALGORITHM

input: I: Input Image, k=4.

output: Icrop (Incremental k-means segmented Image)

functions: imresize: resize input image I to 256x256.

rgb2hsv: Convert Input RGB Image to hsv

IncK means: Incremental k-means clustering

mask: mask label image.

1: initialize I;

2: I= imresize (Input image (I) 256X256);

3: I_hsv= rgb2hsv (I);

4: s= hsv _transform (select s-channel);

5: RGB = label2rgb(mask);

6: bk=RGB(1,1, :); select all rows, column;

7: for eachi= 1: size (RGB, rows) inbk

8: for eachj= 1: size (RGB, column) inbk

9: if RGB (i, j,1) ==bk (1,1,1) &&RGB (i, j,2) ==bk (1,1,2) &&RGB (i,j,3)==bk(1,1,3)

10: Icrop (i, j,1) =0;

11: end

12: Output: Icrop; Incremental k-means segmented Image

13: Iconv=hsv2rgb (Hsv);

14: Ir=Iconv(:,:,1); Ig=Iconv(:,:,2); Ib=Iconv(:,:,3);

15: Rmean=mean2(Ir)

16: Gmean=mean2(Ig); Extract Rmean, Gmean, and Bmean features

17: Bmean=mean2(Ib);

18: AIr=Ir(:); select Red channel, Green channel, Blue channel

19: Rstd=std(double (AIr));

20: Gstd=std (double (AIg)); Extract Rstd, Gstd, and Bstd features

21: Skewness = skewness (double (Icrop (:))); Extract Kurtosis and Skewness

22: return Icrop;

VI. CONCLUSION

Pre-trained Convolutional Neural Networks (CNNs) were created to achieve optimal results for disease detection and classification in photos of cassava leaves. The current study examines convolutional neural networks, specifically AlexNet, using a transfer learning strategy to identify plant leaf diseases [25]. The CNN also confirms the accuracy and training effectiveness for cassava leaf diseases. With AlexNet retrained using CNN, suggested adjustments to weights and biases enabled correct identification of the leaf disease category. Based on the experimental results, AlexNet achieves a maximum accuracy score of 96.4%. The suggested methodology was applied to various types of photos featuring leaf diseases. Based on the extracted features, leaf diseases were categorized into four distinct classes utilizing PNN, KNN, and SVM classifiers. The accuracy of the proposed PNN, KNN, and SVM algorithms was evaluated using the following five performance metrics: i) Sensitivity

(SE), ii) Specificity (SP), iii) Precision (Pr), iv) Correctness, and v) F-measures. The findings indicated that in accurately predicting the three types of leaf diseases, including healthy ones, the PNN and KNN Classifier approaches exhibited the lowest accuracy. The evaluation results clearly indicate that deep CNN architecture outperforms traditional classifiers such as Probabilistic Neural Networks (PNN), K-Nearest Neighbours (KNN), and Support Vector Machines (SVM) in terms of classification accuracy.

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