International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Developing of CNN Model for Disease Detection on Cassava Leaves Using VGG-16 Algorithm

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Submitted: 06/02/2024 **Revised**: 14/03/2024 **Accepted**: 20/03/2024

Abstract: Sub-Saharan Africa is home to many important crops, one of which being cassava. For many people, it is their staple meal. Although cassava leaves are full of health advantages, the illnesses that have been affecting it, have caused a significant reduction in productivity. The lab testing may need more time and resources from cultivators than they have. In order to meet these challenges, farmers therefore require a fast and efficient problem identification approach. In an effort to maximize model performance, the offered deep learning model utilizes the advantages of the EfficientNet-B0 architecture, which has been enhanced with k-fold cross-validation. The primary objective of the research is to use picture classification to precisely detect the illnesses that specifically affect cassava plants via deep learning. Early intervention steps, such as the targeted use of pesticides or the quarantine of infected crops, may be made feasible by this identification. Every one of testing and training image originates from a natural environment in a farming region. To determine the model's authentic outcomes, it has been validated by employing a particular set of data. To sum up, this study promotes the practices of agriculture and food security by utilizing deep learning techniques to fight Cassava infections. The resilience of the cassava crop may be substantially improved through the establishment of an accurate disease identification and prevention model, which will eventually enhance food production and the daily lives of those who depend on this important commodity.

Keywords: *Cassava Leaves, Disease Detection, Identification, Performance, Accuracy.*

I. Introduction

Cassava is regarded as most important crop in some areas [1]. Cassava is predominantly known for its ability to grow in difficult circumstances. Most cassava is grown in South America, while Nigeria being the largest producer in the world. In India, it is primarily produced in Tamil Nadu. They are not the greatest meals in terms of protein content, but they are well known for being the third-largest source of carbs in food, behind rice and maize. Cassava fits the dietary needs of a lot of people. The vital portions that are edible are the starchy root and leaves. If taken in a form that doesn't boil, it may be dangerous to humans. Thus, it is best to boil the leaves and starchy roots for a healthy meal. In addition to the leaves and roots, the starch that is taken from the cassava plants can be utilized in industrial applications and as animal feed. Additionally, it has some energy-boosting components like protein, lipids, vitamin C and vitamin A [2]. By nourishing the good bacteria in our stomachs, they may have even greater advantages for our digestive health. Despite the many advantages of cassava, illnesses brought on by several viruses and pests have severely decreased the crop's output. The health of the cassava leaves is where these illnesses mainly impact them. Certain natural mechanisms in the leaves are not going to function if they become affected by illnesses [3].

Since the roots and leaves of a plant are its most important components, there are numerous techniques like as monitoring the condition of the roots while observing the cassava plants' leaves [4]. A leaf's health, for example, can be ascertained by calculating the percentage of green particles present in the leaf and assessing its availability. Once the problem has been identified, the cultivator can take steps to stop the sickness from spreading to other plants. Some of the main diseases of Cassava leaves include:

- Bacterial Blight
- Anthracnose
- Pythium root rot
- Cassava vein mosaic
- Cassava green mottle

Bacterial Blight

Cassava Bacterial Blight is one of the bacterial and mycoplasma-like diseases [5]. Xanthomonas axopods pv.

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Manihotis is the primary cause of the Bacterial Blight in Cassava Leaves. It holds the ability to infect hundreds of plant members. It first came to limelight in Brazil, in 1912. It is also responsible for the largest loss in terms of yield.

Fig 1: Cassava Bacterial Blight

The symptoms include brown, wet lesions that are typically seen toward the base of the plant, as seen in fig 1.1 previously mentioned. A systemic infection is caused by it, since it enzymatically dissolves the barriers of the plant's vascular system.

Cassava Anthracnose

Significant losses have been incurred in the primary cassava-producing regions of Africa, South America, and Asia [6]. This disease is most commonly caused by Colletotrichum gloeosporioides f.sp. manihotis [7].

Fig 2: Symptoms of Anthracnose disease

The formation of cankers on the stem, necrotic patches on the leaves, and dieback at the tip of the shoot are the leaf withering,

and stem breaking, all of which reduce the quantity of premium cassava stem required for seeding the next growing season.

Cassava Pythium Root Rot

Fig 3: Cassava Pythium root rot observed on the cassava leaves

One characteristic of this form of illness is root necrosis, depicted in Fig. 3. earlier, which begins as a single dead spot and spreads across the whole root system. The main pathogens causing cassava root rot are found in the genera Phytophthora and Fusarium.

Cassava Vein Mosaic

Costa published the initial description of cassava vein mosaic disease in 1940. The scientific names for the cassava vein mosaic virus (CsVMV) are Kitajima & Costa (1966) and Lin & Kitajima (1980).

Fig 4: Cassava Vein Mosaic on cassava leaf

The virus has isometric particles with a diameter of 50 nm, which is apparent in Fig. 4 aforementioned, and its genome is composed of DNA [8]. The cytoplasms of infected cells have evident dense inclusion bodies. Brazil's northeastern states have reported cases of the virus, which is pervasive across the nation. Manihot esculenta is the only species that is known to be affected. Vegetative proliferation is the method used by viruses.

Cassava Green Mottle

In the late 1970s, a virus was discovered for the first time in Choiseul. Similar-symptom plants have been discovered recently on Malaita. The Cassava green mottle "nepovirus" is the scientific term. The shoots usually show signs of recovery and recovery from illness.

Fig 5: Green Mottle virus on Cassava Disease

From the depicted Figure 5, we can derive that, Young leaves have tiny to big yellow dots, green mosaic-like patterns, and twisted margins that are puckered. Plants can become extremely undernourished, and when edible roots are present, they are small and cook to a woody texture.

Problem Statement: Plant diseases are a farmer's worst enemy. When numerous diseases begin to infect their plants, farmers may not be able to absorb the losses associated with the crop. The several illnesses have caused a dramatic decline in cassava productivity. Examining leaves with the unaided eye is still the most common way for professionals to find signs of illness. Even a tiny field requires a large team of researchers, to continuously monitor the condition of the plant. This cannot be done alone for huge fields; it requires more time and resources. In certain locations, farmers are unaware that they should seek professional assistance. Occasionally plant pathology experts or agricultural scientists fail to accurately detect the disease, which results in ineffective remedies. All of this creates a major hurdle for accurate identification of plant illness in order to give appropriate treatment and prevent crop damage. In order to solve all of these issues, we developed a straightforward model in this study, that will automatically identify the disease and thus by alerting the farmers to take appropriate action.

II. Related Work

Declining cassava production is mostly brought on by illnesses that harm cassava leaves and have a detrimental effect on farmers' earnings. Traditional methods of diagnosing illnesses are costly and time-consuming because they rely on laborious laboratory tests or expert consultation. To solve these challenges, the study proposes a novel lightweight deep learning model that combines a modified channel attention module with depth-wise separable convolution, channel attention, and spatial attention [9]. This model significantly increases accuracy while reducing parameters, with a notable validation accuracy of 98% and testing accuracy of 75%. Furthermore, a smartphone application is developed for immediate deployment in agricultural settings, aiming to promptly identify diseases on cassava leaves and fulfil the pressing needs of farmers.

Anand Shanker Tewari, et. al, It is imperative that the modern problem of automated plant disease detection be addressed, especially concerning cassava, which is vital for small-scale farmers in Sub-Saharan Africa. Prompt intervention is impeded by the existing dependence on expert inspections that occur periodically and require lengthy laboratory testing. A Convolutional Neural Network (CNN) model is proposed to improve early disease identification by analysing 21,397 tagged photos of cassava plants, including samples of healthy plants and four diseases (CBB, CBSD, CGM, and CMD). This information, collected in Ugandan fields, provides a genuine representation of the diagnostic difficulties faced by farmers. Working with specialists from Makerere University's AI lab and the National Crops Resources Research Institute, this study marks a significant advancement toward providing farmers with automated, effective disease detection tools.

M. K. Dharani, et. al, Africa currently leads the world in cassava production, although the crop is extensively cultivated in Asia and Latin America as well. Thailand, a major cassava exporter, holds the top spot globally in production due to cassava's ability to thrive in diverse climates and poor soil conditions. Despite the nutritional benefits of cassava, a significant decline in production has occurred since 2016 due to the widespread threat of cassava infections. Numerous strategies have been implemented to address this issue, with the primary objective being the enhancement of performance. This study utilizes the densenet169 deep learning pre-training model to identify and categorize cassava leaf diseases into five groups. The assessment of the model incorporates critical performance metrics such as loss, accuracy, specificity, and sensitivity. The dataset used for training and evaluation consists of 21,397 photos. This represents a substantial advancement in addressing the challenges faced by cassava growers in combating diseases affecting the crop.

Shiva Mehta,et. al, the growing global population has spurred an increasing demand for food, and India, heavily reliant on agriculture for both sustenance and economic stability, faces a significant challenge. In response, farmers are incorporating artificial intelligence (AI) into modern farming practices to enhance crop yield. AI applications encompass vital areas such as plant disease detection, weather and commodity price forecasting, and crop health monitoring. Deep learning techniques emerge as a potential solution, addressing the substantial threat that crop diseases pose to food safety and the complexities associated with manual detection, especially on large farms. This research review delves into the application of Efficient et for diagnosing cassava leaf diseases, emphasizing image-based automatic control and inspection.

Umesh Kumar, et. al, Evaluating the classification performance of renowned CNN models, including VGGs, ResNet, DenseNet, and Inception, is a key focus. The study aims to extend its scope by delving deeper into cassava disease identification in subsequent research. Through the implementation of brightness augmentation, DenseNet121 emerges as the most successful model, achieving an impressive F1-score of 92.13% and astounding classification accuracy of 94.32% in experimentation. Emphasizing the significance of utilizing cutting-edge CNN models, this literature review underscores the exceptional performance of DenseNet121 in classifying cassava diseases.

Seksan Mathulaprangsan, et. al, Image recognition holds significant importance in daily life, playing a vital role in applications such as surveillance, gaming, medical analysis, and agriculture—especially in the diagnosis of plant diseases. This research addresses substantial challenges in agriculture by employing machine learning algorithms for the early detection of leaf diseases in cassava plants, a crucial carbohydrate source in Africa. The study focuses on four common diseases—cassava green mottling, cassava mosaic disease, cassava brown streak disease, and cassava bacterial blight. EfficientNet-B0 is recommended for early detection, demonstrating superior accuracy and efficiency compared to current CNNs, significantly reducing FLOPS and parameters. This research, with an impressive 92.6% accuracy, represents a critical stride towards ensuring food security in Africa.

Yiwei Zhong, et. al, crucial for ensuring healthy cassava production by preventing the transportation and selection of contaminated stems. The use of HSV colour space in image preparation minimizes information loss during preprocessing, leading to increased detection accuracy in the target area. Subsequently, preprocessed leaf images undergo training with the EfficientNet model, extracting multi-dimensional features including depth, width, and resolution. This literature review outlines a comprehensive approach that integrates effective neural network models with colour space processing, offering a robust methodology for reliable monitoring of cassava diseases.

Charles Oluwaseun Adetunji, et. al, Early illness detection is crucial, and contemporary deep learning methods—in particular, Convolutional Neural Networks (CNNs)—offer highly accurate prediction skills. This paper presents a deep learning-based approach for distinguishing healthy leaves and the four common cassava leaf diseases using a "One-vs-All" technique. Using EfficientNet B4 as the foundational model, we train five binary classifiers for every class, and on skewed test data, we obtain an impressive 85.64% accuracy. In addition, the concept is implemented on Android to improve accessibility.

Noor Ilanie Nordin, et. al, A popular cash and food crop grown all over the world, cassava is prized for its high vitamin and mineral content, making it a useful addition to diets during dry spells. Changes in the weather and problems with irrigation make it difficult to grow cassava in tropical regions and increase the risk of fungal diseases. The necessity for effective identification techniques stems from the time and money required for manual illness examination. The goal of this research is to use 21,375 photos of cassava plants to classify viral infections, such as cassava brown streak disease, cassava mosaic disease, cassava green mite, and cassava bacterial blight. which used the CNN models EfficientNetB4 and Inception-Resnet-V2, shows that Inception-Resnet-V2 performs better, enhancing the diagnosis of illnesses and enabling farmers to take timely preventative action.

T. Vijaykanth Reddy, et. al, Cassava is a popular commercial crop that is also a food crop that is rich in vitamins and minerals. It is vital as a nutritional supplement during dry seasons. In tropical regions, it has challenges from abrupt temperature changes and irrigation issues that might lead to fungal illnesses. Identification of fungal or viral illnesses by hand is costly, time-consuming, and inaccurate. This study addresses these problems by focusing on three viral illnesses: cassava brown streak disease, cassava bacterial blight, cassava mosaic disease, and cassava green mite. This makes it easier to identify infections. With 21,375 photos of cassava plants, the study uses Convolutional Neural Network (CNN) models to show that Inception-Resnet-V2 performs better

than EfficientNetB4, providing a practical way for farmers to take prompt preventative action and protect cassava crops.

The "Cassava-Leaf-Disease-Classification" dataset, a large and challenging collection published in 2020, is employed to address the significant task of identifying healthy and diseased Cassava plant leaves. The dataset, consisting of 21,397 images depicting both healthy and afflicted leaves, provides a robust foundation for training and evaluating deep learning models [10]. The study utilizes the Chan-Vese (CV) Segmentation technique, which operates within the MATLAB environment, to identify regions of interest within the leaf pictures, enabling more focused analysis. ResNet 50 and MobileNetV2, two well-known deep learning architectures, are used for feature extraction in the following steps [11]. These designs are great in gathering intricate patterns and representations from the chosen areas of interest, and they offer a rich feature set for categorization.

Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) techniques are used to categorize the gathered characteristics. Sophisticated deep-learning architectures combined with intricate classification techniques increase the precision and robustness of disease detection in cassava leaves. A K-fold cross-validation strategy with a value of 5 is used to split the dataset into training and testing sets in order to assess the model's performance [12,13]. This study shows notable success rates, with the ResNet50 architecture and SVM classifier achieving the highest average success rates of 85.4% in the training phase and 84.4% in the testing phase. This shows how effectively the ResNet50 architecture performs when paired with SVM to consistently classify cassava leaves into healthy and ill groups, particularly when the CV Segmentation approach is applied. [14]. The trained ResNet50 and MobileNetV2 networks are built using MATLAB Builder NE, which enables their online deployment, thus the study goes beyond only building and evaluating models. The result of this work is the development of an embedded web interface that manufacturers may use to easily access and utilize the deep learning-based decision-help system. [15]. This novel method simplifies the process of categorizing plant diseases, makes it easier for producers to incorporate the technology into their processes, and draws attention to the study's potential application in the agriculture industry.

A comprehensive approach that combines cutting-edge deep learning architectures, clever segmentation techniques, and trustworthy classification algorithms to classify cassava leaf illnesses [16]. The system's application in a web context emphasizes its practical relevance, making it a valuable tool for manufacturers searching for affordable and user-friendly plant disease detection and classification solutions. Thailand leads the world in the production and export of cassava, hence the crop has a significant economic impact there. However, infections with cassava frequently compromise the productivity of this significant industrial crop, putting farmers' livelihoods in jeopardy. To address this issue, the current work employs deep learning algorithms to offer a unique solution for automatically identifying cassava illnesses. The primary objective of the study is to examine the complexities associated with diagnosing cassava infections, with a particular focus on the severe cassava brown streak virus disease (cbsd). The illness's pronounced detrimental impact on cassava productivity led researchers to choose cassava mosaic disease (cmd) above the other five classes: healthy, cassava bacterial blight (cbb), cassava green mite (cgm), and healthy. [17]. The study aims to provide a customized solution to a prevalent and significant economic issue by concentrating just on CBT. The procedure comprises analysing a dataset of images of cassava leaves using deep learning techniques. The algorithm is trained to automatically classify these photographs into the appropriate sickness categories, paying particular attention to the very influential cbsd. [18]. To determine the efficacy of the proposed methodology, an experimental assessment is conducted. [19]. The findings show that the developed system functions satisfactorily, with an accuracy and F-measure of 0.96. This outstanding achievement suggests that the method is trustworthy and effective for classifying cassava diseases automatically, particularly the targeted cbsd. [20]. The high accuracy indicates that there may be practical uses for the recommended approach to classify cassava diseases automatically and effectively. [21]. The study's objective of looking for appropriate methods for classifying more cassava-related disorders indicates possible directions for future research. The study's commitment to ongoing research and development is demonstrated by its forward-looking approach, which attempts to expand the system's capabilities beyond the original focus on cbsd. This work therefore demonstrates the potential of automated cassava disease classification to significantly contribute to robust and sustainable cassava production systems, and it also lays the groundwork for future advancements in the area.[22].

III. Materials and Methods

Description

The identification and observation of the classification of various cassava leaf diseases and their detection is used in this work to make the discussion. The proposed work used the dataset which is present in Kaggle, an online platform for the datasets [23]. The dataset represents the cassava leaf pictures representing the four types of diseases, Cassava Bacterial Blight, Cassava Green Mite, Cassava Brown Streak Disease and Cassava Mosaic Disease. The article proposed a Convolutional Neural Networks (CNN) model for detecting the type of disease in the Cassava leaf in its starting phase from the picture of the Cassava datasets [24]. A well-organized solution for the identification of the type of disease based on the image is proposed in this article. To detect the plant disease, we have artificial intelligence method like deep learning to treat them in advance [25]. The proposed work CNN in deep learning with cloud computing help we can train CNN models and we can make the performance in detecting the plant disease with computer vision. Here with the prepared models of CNN method we can easily detect the plant disease in advance. In particular to detect the leaf disease In CNN we have two defined algorithms using advance CNN models we can train the model we some research to predict the accurate outcomes.

Convolution Neural Network

CNN model is a Deep learning architecture of neural network of a computer vision. CNN model is comprising with three types of sub layers and each layer represents it’s own work in a sequential order [26]. The sub layers are Convolution Layer, Pooling Layer, Output Layer. Convolutional neural networks function better with picture, speech, or audio signal inputs than other types of neural networks. Computer vision and image recognition activities are powered by convolutional neural networks. Computer vision is a branch of artificial intelligence (AI) that allows devices such as computers and systems to interpret and act upon digital photos, videos, and other visual inputs. It can make recommendations, which sets it apart from picture recognition tasks. Convolutional neural networks are made up of many layers of synthetic neurons. Artificial neurons are mathematical functions that approximate biological neurons by summing the weights of multiple inputs to get the activation value. Activation functions are generated by each layer in a ConvNet upon receiving an image input, and these functions are subsequently transmitted to the layer beneath it. Usually, the first layer is used to extract fundamental features like horizontal or diagonal edges. This output is sent to the next layer, which is responsible for identifying more complex characteristics such as corners or combinational edges. As we go further into the network, it can identify even more complex items, such as faces and objects.

The severity of the disease can be achieved by the specific intervals scaling of the collected various type of leaves and classifying the disease type to identify the Disease Severity Index (DSI). The prediction of the plants which is diseased can be started from 0% which refers to the symptoms as none and 100% which refers the high severity is a part of visual assessment. Considering the percentage of the diseased plant the data is collected of that particular area. The Disease Severity Index of the plant and be obtained by the equation (1).

$$DSI = \frac{Number\ of\ blighted\ plants \times Blight\ rating\ scale}{Total\ number\ of\ plants}$$

-(1)

The occurrence of the new instances of the disease which are observed periodically can be achieved through Incident Rate (IR). It helps foe monitoring the infected plants and aim to make the accurate decisions of proper growth in equation (2).

$$IR = \frac{Number\ of\ blighted\ plants}{Total\ number\ of\ plants\ observed} \times 100$$

-(2)

The quantitative measurement of severity of the particular type of disease on the plant and assess the intensity of the symptoms affecting on the leaves can be identified by Diseased Index (DI) in equation (3).

$$DI = \frac{Sum\ of\ all\ affected\ extremity\ ratings}{Total\ number\ of\ observations}$$

-(3)

The tool evaluates the disease in a certain time and make the comparisons by considering the rate, duration of the development of the disease in the leaves is achieved through the Relative Area Under Disease Progress Curve in equation (4).

Relative Area Under Disease Progress Curve (Raudpc):

$$r\,AU\,D\,PC = \sum_{i=1}^{n} \frac{Disease\ extremity\ at\ time\ i + Disease\ extremity\ at\ time \times (Time\ at\ i - Time\ at\ i-1)}{2}$$

-(4)

The Convolutional Layer

Convolutional layer is the first stage and also the crucial building block of CNN. The layer consists of kernels represents the filters comprises with height and width in a shape of square. The filters can be identified like a small spatial dimension with a volume of full depth. The input of the CNN is the depth of the channels of the images. The more the network is deeper, the more will be the applied filters in the existing layer. The idea of the convolutional layer is about convolving the filter of having the input volume large gives a name tag in CNN as local connectivity of the neuron in the respective field. The neuron count, or filters, in the CONV layer that are connected to a specific area of the input volume is determined by the depth of an output volume. Every filter generates an activation map that becomes active when oriented edges, blobs, or colors are present. Convolution is defined as sliding a tiny matrix across a large matrix, halting at each coordinate, multiplying and adding elements at a time, and storing the result.

The Pooling Layer

CNN architectures, which are the foundation of all cutting-edge deep learning models, frequently include pooling layers [27]. Convolutional layers are widely utilized in various Computer Vision applications such as Classification, Segmentation, Object Detection, Autoencoders, and many more. Because pooling layers have so many advantages, CNN designs frequently choose to use them. They are essential for controlling spatial dimensions and allowing models to pick up various aspects from the dataset. Incorporating pooling layers into your models has the following advantages:

Diminution of Dimensionality:

A subsample of values is chosen for each pooling operation from the entire convolutional output grid. One important advantage of convolutional architectures over fully connected models is that they down sample the outputs, which reduces the parameters and computation for following layers.

Translation Invariance:

Machine learning models that include pooling layers become invariant to tiny input changes like rotations, translations, or augmentations. Because of this, the model can recognize similar picture patterns and is hence appropriate for simple computer vision applications.

The Output Layer:

To transform the output of each class into its probability score, the fully connected layers' output is fed into a logistic function such as the sigmoid or softmax for classification tasks. In the absence of convolution and padding layers, we require a class as the output. It must be a fully connected layer to provide an output that equals the required number of classes in order to generate the final result. While convolution layers produce 3D activation maps, we just require the output to indicate if an image is a member of a specific class [28]. To calculate prediction error, the output layer uses a loss function similar to categorical cross-entropy. Backpropagation starts updating the weights and biases for error and loss reduction once the forward pass is finished.

In the fully connected layer also can be referred as the Dense layer, the input neurons for the formula can be taken as N_{in}, *and the neurons coming out is* N_{out} in equation (5)

$$OutPut = ReLU(Input \times Weights \times Biases) \qquad \text{-(5)}$$

The output layer obtains with the help of the softmax activation function for the multi-class classification of the fully connected layer at last in equation (6)

$$P(class_i) = \frac{c^z\mathrm{i}}{\Sigma_j \mathrm{e}^z j} \qquad \text{-(6)}$$

where z_i represents the softmax function for class i.

Proposed Model

The strategic and innovative adoption of technology in agriculture is reshaping the landscape, particularly when addressing pressing issues. A critical challenge in this context is the early detection and management of infections affecting cassava leaves. It is imperative to identify, categorize, and evaluate sick leaves during the growth phases of crops to ensure the continued advancement of agriculture [29]. The suggested article, which focuses on disease classification and detection with a particular emphasis on cassava leaves, is exactly focused on this. This work suggests applying a deep learning-based model to extract information from pictures in order to achieve a previously unheard-of level of precision in identifying healthy from unhealthy leaves. In this novel technique, the performance metrics for illness identification are improved by utilizing the CNN-based VGG (Visual Geometry Group) model, which is well-known for its effectiveness in image recognition problems [30].

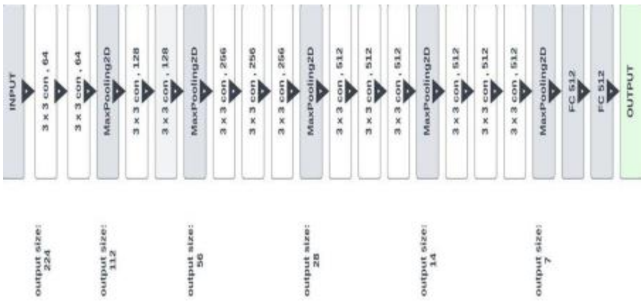

Fig 6: VGG-16 model architecture

As shown in Fig. 6, the model architecture has been built. The model goes through intensive training and testing as a crucial component of the experiment, using a large dataset of crop leaf pictures. The performance of the system is continuously monitored using key performance metrics, such as accuracy, sensitivity, specificity, precision, recall, and F1-score. A strong and dependable classification of disease-affected leaves is the ultimate goal, which will be achieved by continuously improving the model's performance. The model shows exceptionally high accuracy of 98.40% for cassava leaves. The consequences of this discovery go beyond the lab and directly affect the improvement and sustainability of agricultural food production. By seamlessly integrating cutting-edge AI approaches, especially the VGG model, into the agricultural environment, we open the door to a more robust and effective approach to disease control. This, in turn, contributes significantly to fulfilling the crucial mission of ensuring global food security [31].

Algorithm

Algorithm: Improved VGG-16 algorithm.

Input: Input pre-processed leaf images of diseased and healthy

Output: Classification of leaf disease

1: procedure DiseaseDetection(IMG, S)

2: BW ← Binarize(S)

3: Display IMG image

4: prop ← connected_region

5: size_k ← size(S, 1)

6: size_l ← size(S, 2)

7: region1 ← size_k ∗ size_l

8: while index < Number of elements in prop do

9: rectan = BoundingBox of prop[index]

10: region = region(rectan)

11: if region > region1/100 then

12: hold_on

plot Centroid of prop[index] in red color

hold_off

plot rectangle of prop[index] in red color

index ← index + 1;

IV. Experiments and results

Experimental environment and Methodology

This experiment is focused on the classification of cassava leaves diseases, the dataset plays a pivotal role, encompassing a diverse array of over 20,000 images meticulously curated to represent various states of cassava leaf ailments. Through an initial visual examination, the dataset provides a comprehensive foundation for training a robust classification model, capturing the intricacies and nuances of different disease manifestations [32].

As for the workspace and tools employed in this endeavour, Google Colab has been chosen as the primary platform, providing a dynamic environment equipped with GPU resources that significantly expedites the training process. The selected toolset incorporates the BEST KERAS CNN architecture, a state-of-the-art deep learning framework known for its efficacy in image classification tasks [33]. This strategic combination of workspace and tools ensures an efficient and powerful approach to accurately classify cassava leaf diseases.

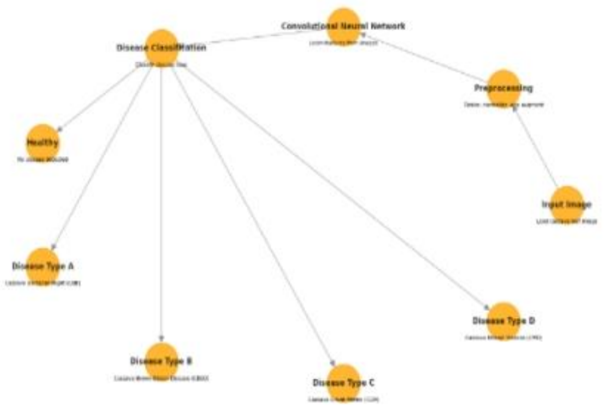

Fig 7: Flow of work

The work flow will be as illustrated in Fig. 7, mentioned previously. The input image is first taken, after which it is preprocessed and the CNN model is used to teach the machine the features needed for image classification. The leaf's condition and illness can then be categorized. This methodology for cassava leaf disease detection employs a systematic process that begins with the intake of a cassava leaf image. This image is subjected to preprocessing steps, including resizing, normalization, and potential augmentation to standardize and enhance the dataset. Following this, a CNN is engaged to autonomously learn intricate characteristics from the preprocessed images. The primary objective is disease classification, where the model distinguishes between a healthy cassava leaf and various disease types (labelled from 0 to 4). In case the model deems the leaf as healthy, the workflow concludes, signifying that no disease is detected. On the other hand, if a disease is identified, the path leads to a specific disease type classification (from 0 to 4), providing detailed information about the nature of the detected disease

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 256, 256, 32)	896
activation_1 (Activation)	(None, 256, 256, 32)	0
dropout_4 (Dropout)	(None, 1024)	0
dense_2 (Dense)	(None, 15)	15375
activation_7 (Activation)	(None, 15)	0
Total params:	5,81,02,671	0
Trainable params:	5,80,99,791	0
Non-trainable params:	2,880	0

Fig 8: Model Architecture

Model architecture consisting of the layer, output shape, and parameter feature with a thorough computation utilizing the aforementioned, figure 8. It is also possible to analyse total parameters with unique features.

Database Overview

In the initial phase of this investigation, we focus on the crucial task of package loading, which lays the groundwork for a seamless progression of our analysis. We import a series of fundamental libraries, including NumPy, Pandas, Matplotlib, Seaborn, and the datetime module, to facilitate numerical computations, data manipulation, and visualization, respectively. Additionally, we leverage scikit-learn to access tools for model evaluation, such as train-test splitting and accuracy assessment. The integration of TensorFlow and Keras enables the implementation of a Convolutional Neural Network (CNN) for predictive modeling.

To initiate the process, we inspect the working directory to gain insights into the structure and contents of our dataset, which is derived from the 'cassava-leaf-disease-classification' repository. The directory contains relevant elements such as 'train_tfrecords', 'target.csv,' 'test_tfrecords,' 'train_images,' 'train.csv,' 'label_num_to_disease_map.json,' and 'test_images.' Of particular note is the 'label_num_to_disease_map.json' file, which encodes a mapping of numerical labels to corresponding cassava leaf diseases. The dataset, comprising a total of 21,397 images, is categorized into five classes: "Cassava Bacterial Blight (CBB)," "Cassava Brown Streak Disease (CBSD)," "Cassava Green Mottle (CGM)," "Cassava Mosaic Disease (CMD)," and "Healthy." This structured representation enables a deeper understanding of the dataset's composition and lays the groundwork for subsequent data preparation and modeling endeavors. Following the preparatory steps, we advance to the pivotal stage of model training, where we aim to discern patterns within the cassava leaf dataset. To gain a visual understanding of the images corresponding to each class, we extract and display sample photos for the various cassava leaf diseases and the "Healthy" category. This visualization process facilitates our comprehension of the dataset and sets the stage for the development of accurate predictive models category.

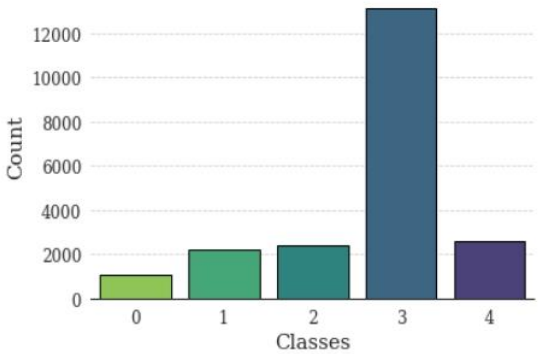

Fig 9: Dataset containing 5 classes

Ah, an exciting development! The dataset has been divided into five categories, as depicted in Figure 9. Now, we proceed to the most crucial stage of the study: training the model to recognize patterns within the cassava leaf dataset. To gain a better visual understanding of the images associated with each class, we extract and display sample photos of cassava leaf diseases and the "Healthy"category.

Let's begin with "Cassava Bacterial Blight (CBB)" (Class 0), a subset of three images has been randomly selected from the training dataset and labeled as CBB. These images are now arranged in a visual array to offer a brief, illustrative representation of this particular disease category [35].

Some photos of "0": "Cassava Bacterial Blight (CBB)"

Fig 10: Some photos of "0": "Cassava Bacterial Blight (CBB)

Fig 11: Some photos of "1": "Cassava Brown Streak Disease (CBSD)"

Fig 12: Some photos of "2": "Cassava Green Mottle (CGM)"

Fig 13: Some photos of "3": "Cassava Mosaic Disease (CMD)"

Fig 14: Some photos of "3": "Cassava Mosaic Disease (CMD)"

According to the dataset, various diseases affecting cassava leaves are depicted in Figures 4.4, 4.5, 4.6, 4.7, and 4.8. These images provide improved precision for the model to identify and diagnose different cassava leaf diseases, which is essential for effective disease management.

Creating and Visualizing CNN

To construct a robust Convolutional Neural Network (CNN) for cassava leaf disease classification, we leverage the EfficientNetB0 framework [3] as the foundation of our model. By modifying the EfficientNetB0 architecture, we create a custom model that efficiently extracts relevant features from input images. Specifically, we exclude the top layer of the EfficientNetB0 and adjust the input shape to match the target size of (TARGET_SIZE, TARGET_SIZE, 3). This design enables the network to learn spatial features with high efficiency and accuracy for better results.

Subsequent layers of the model are designed to capture global spatial information through a Global Average Pooling 2D layer. This operation condenses the learned features, providing a compact representation of the spatial characteristics of the input images. The final layer consists of a Dense layer with a softmax activation function, producing a probability distribution over five target classes [12]. This output layer aligns with the cassava leaf disease classification task, where the goal is to assign each input image to one of five distinct categories.

To train the model, we use the Adam optimizer with a learning rate of 0.001 and sparse categorical crossentropy as the loss function. Model accuracy is monitored as a performance metric during training. Our well-structured CNN architecture, implemented through the Keras framework, forms the core of our predictive model. By training this model on the labeled cassava leaf dataset, we aim to develop an accurate and efficient classification system for various diseases affecting cassava plants.

Evaluation Metrics

Image classification can be designed with the VGG-16(Visual Geometry Group) wis of the convolutional neural network (CNN) architecture. The object detection can be obtained through one of the CNN modes like VGG-16 with the techniques Region Proposal Networks9RPN) and the Region of Interest (ROI) for the pooling of the detection of the bounding boxes. The actual implementation can also include the considerations of the specific framework used.

For Image classification:

Convolutional Layer:

Input can be taken as $W_{in}, H_{in,} D_{in}$ represents width, height, depth of the input tensor of having the size of the convolutional filter as F × F, number of filters can be represented as K with the Padding as P and Stride as S. The output can be defined with the width, height and depth of the output tensor represent $W_{out}, H_{out,} D_{out}$ in the equations 7,8 and 9 below.

$$W_{out} = \frac{W_{in} - F + 2P}{S} + 1 \qquad \text{-(7)}$$

$$H_{out} = \frac{H_{ik} - F + 2P}{S} + 1 \qquad \text{-(8)}$$

$$D_{out=K} \qquad \text{-(9)}$$

By applying the rectified linear unit activation function in element- wise, the output of the $W_{in}, H_{in,} D_{in}$ convolutional layer is obtained in equation (10)

$$Re\,LU(x) = max(0, t) \qquad \text{-(10)}$$

Max Pooling Layer:

The equations in the max pooling layer can be obtain like same as of the taken input $W_{in}, H_{in,} D_{in}$ of having the pooling size F × F, with the Stride S and the output can be obtain as $W_{out}, H_{out,} D_{out}$, in the equations 11,12 and 13 below.

$$w_{out} = \frac{W_{in} - F}{s} + 1 \qquad \text{-(11)}$$

$$H_{out} = \frac{H_{in} - F}{S} + 1 \qquad \text{-(12)}$$

$$D_{out} = D_{in} \qquad \text{-(13)}$$

The previously mentioned formulae have been used to determine a range of values. Additionally, these values can be employed to the assessment of graphs and tables.

Visualization of the first layer:

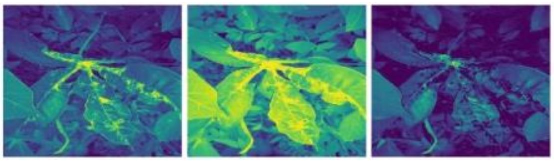

Fig 15: First Layer Visualization

Visualization of the layers:

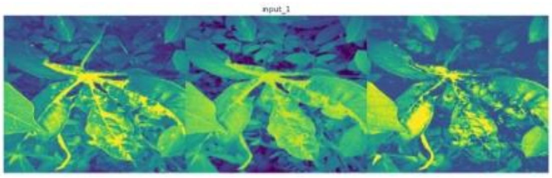

Fig 16: input

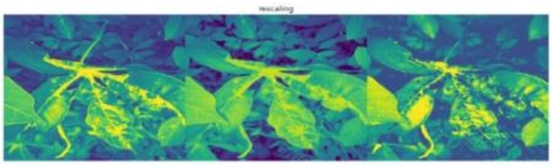

Fig 17: Rescaling

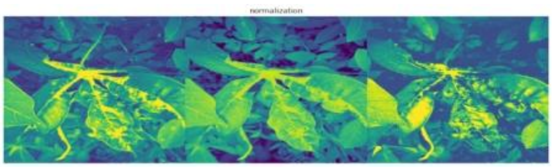

Fig 18: Normalization

Fig 19: Stem_conv_pad image

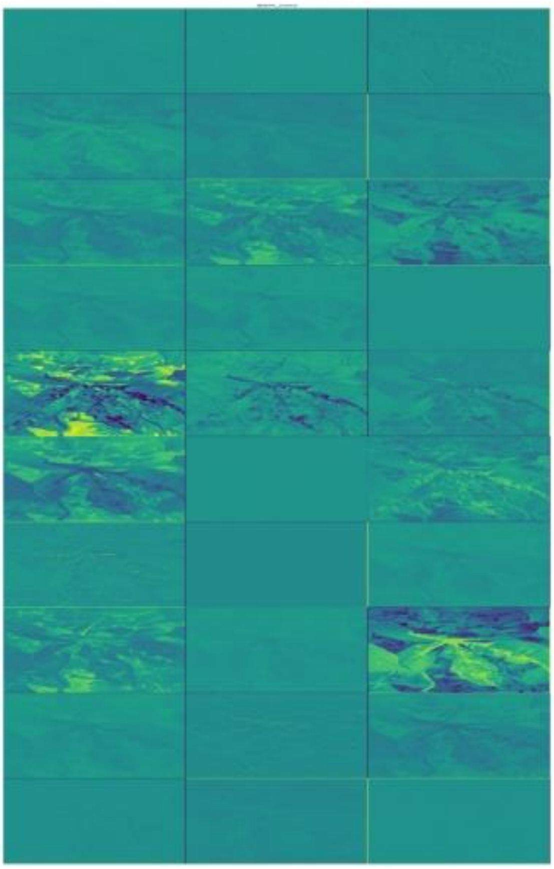

Fig 20: Stem_conv image

Various photographs have been visualized, highlighted in Figures 15, 16, 17, 18, 19 and 20. Visualizing intermediate activations provides a step-by-step view into the operational dynamics of Convolutional Neural Networks (CNNs), resulting in a thorough grasp of how they function.

Epoch	Loss	Accuracy	Validation Loss	Validation Accuracy	Learning Rate
1	0.6477	0.7721	0.6571	0.7871	0.0010
2	0.5273	0.8182	0.4997	0.8364	0.0010
3	0.4861	0.8317	0.4933	0.8387	0.0010
4	0.4604	0.8403	0.4658	0.8444	0.0010
5	0.4442	0.8465	0.487	0.8341	0.0010
6	0.4295	0.8537	0.4214	0.8556	0.0011
7	0.4207	0.8577	0.5324	0.8264	0.0013
8	0.4063	0.8582	0.4133	0.8602	0.0012
9	0.4004	0.866	0.4298	0.8579	0.0015
10	0.3916	0.866	0.4281	0.8591	0.0003

Fig 21: Values while training

A variety of values have been assessed using the above figure 21, including learning rate, validation accuracy, validation loss, and validation accuracy values. This data allows for additional improvements to be made, greatly enhancing the model's accuracy and performance.

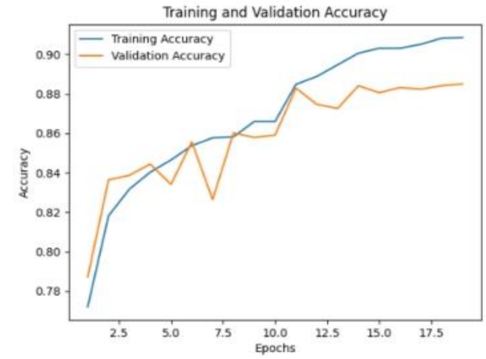

Fig 22: training and validation accuracy

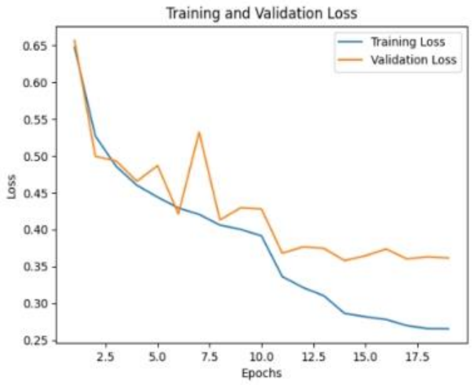

Fig 23: training and validation loss

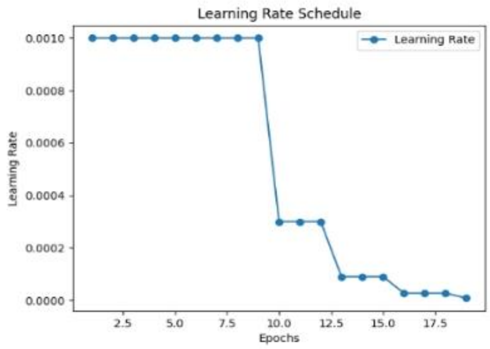

Fig 24: learning rate schedule of model

Using the previously provided data, the graphs in Figs. 22, 23, 24 above illustrate the model's performance. The values are simply expressed in the format shown above. Figures depict training and validation accuracy, training and validation loss, and a learning rate schedule.

Prediction

In the prediction phase of this research, the model's efficacy in classifying cassava leaf diseases is assessed. Commencing with the reading of the sample submission file, denoted as ss, the Data Frame structure outlines the anticipated format of the prediction results. As the model traverses through each 'image_id' entry, it loads the corresponding test image from the 'test_images' directory, resizing it to the specified dimensions (TARGET_SIZE). Subsequently, the image is preprocessed and utilized for prediction, with the resulting class label being appended to the 'preds' list.

The 'ss' DataFrame is then updated to reflect the predicted labels for each 'image_id,' and this comprehensive summary is stored in a new CSV file, 'submission.csv.' The final Data Frame showcases the 'image_id' alongside the corresponding predicted labels, providing a clear snapshot of the model's classifications.

Discussion on result

In this extensive study aimed at predicting cassava leaf diseases, a rigorous methodology was employed to guarantee a comprehensive understanding of the dataset, model development, and performance evaluation. The investigation began with the crucial step of data preparation, involving the collection and preprocessing of a dataset comprising cassava leaves to train a Convolutional Neural Network (CNN) using the Keras framework. This meticulous preparation laid the groundwork for a robust modeling phase, where an efficient CNN architecture was designed using the EfficientNetB0 model. The model's architecture was tailored to accurately classify cassava leaf diseases into five distinct categories, which helps in better precision.

Subsequent steps included installing necessary packages, examining the working directory, and visualizing samples from each disease class for qualitative assessment. The model was then trained on the prepared dataset, allowing it to learn intricate patterns and features vital for disease classification. Upon completion of the training phase, predictions were made on a set of test images, providing valuable insights into the potential diseases affecting cassava plants. The prediction results were organized and stored in a submission file ('submission.csv'), offering a comprehensive summary of the model's classifications for further analysis and operations which are going to be useful.

In evaluating the overall research outcome, careful consideration was given to specific disease classes, enabling a detailed examination of predictions related to labels 0, 1, 2, and 3. This nuanced analysis revealed the model's performance across various disease categories, allowing researchers to identify areas of strength and potential improvement. The research's best-case scenarios emerged when the model demonstrated exceptional accuracy in distinguishing between cassava leaf diseases, particularly in correctly classifying healthy leaves. This achievement highlights the model's proficiency in identifying normal plant conditions, a critical aspect for accurate disease diagnosis.

V. Conclusion

The primary goal has been to develop effective methods for classifying diseases using Deep Learning techniques. Despite the fact that there are numerous Convolution Neural Networks in the literature, and they have been shown to be incredibly successful in overcoming the 1000 class classification issue; nevertheless, these CNN are impractical for everyday tasks like identifying plant diseases. Several lightweight CNN architectures are employed to identify disease. Data from the dataset, which includes a different number of samples in each class, has been used for the experiment. Therefore, data augmentation techniques have been used to balance the quantity of samples in each class. It has been noted that models that have already been trained can be used for classification. However, because of their large and intricate construction, they require a lot more storage space and processing time. These models can't be used in edge computing devices because of storage capacity and inference time issues. Furthermore, the continued advancement and enhancement of these technologies promise a steady rise in the precision of illness identification. Overall, cassava disease detection systems should become more successful as more data becomes accessible and machine learning models are improved. Working together, researchers, agronomists, and technology specialists will be essential to the advancement of these technologies and to guaranteeing their usefulness throughout a range of farming circumstances.

Machine learning techniques have made it possible for large datasets to be examined rapidly and scalable in illness detection systems. This enables the detection of subtle patterns and symptoms indicative of various cassava ailments. These technologies assist in the early diagnosis of infections, reduce yield losses, and halt the spread of diseases throughout agricultural landscapes. Adopting targeted treatments that might significantly lessen the impact of illnesses on cassava yields requires early disease detection. Crop management techniques and the proper use of pesticides are two examples of these interventions.

Conflicts of Interest:

The authors indicate they have no competing interests.

Research involving human participants and/or animals:

This article does not contain any studies involving animals and human participants performed by any of the authors.

Funding Information:

There is no funding for this research article.

Inform Content:

There is no animal and human samples use in this manuscript.

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