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Hybrid Diagnostic System for Groundnut Diseases

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Abstract: Groundnut (Arachis hypogea) is an important oilseed grown in the world, with China, Indian and Nigeria being the top three groundnut producing countries as of 2022/2023. However this crop is susceptible to various diseases, which significantly impact its productivity. Deep learning approach has been employed to detect groundnut leaf diseases, aimed to enhance the recognition and classification of these diseases. This method employed ResNet50 and VGG16 Convolutional Neural Network (CNN) models with Bayesian Optimization (BO). The dataset comprises images of both healthy and infected groundnut leaves, categorized into six distinct groups based on their condition. The dataset consist of 2380 training images and 818 testing images. Preprocessing of the image involves organizing them into their respective conditions. 1000 features are extracted from each image using the FC100 and F18 feature layers. In total 5940 images are used for feature extraction. The confusion matrix results indicate that ResNet50 and VGG16 models achieved accurate classification, with early rust and rust recorded 198 correct sample classifications with zero error. In the models performance the True Positive Rate (TPR) and False Negative Rate (FNR) graph demonstrate that both models achieved 100% accuracy in detecting early rust and rust. The adopted models ResNet50 and VGG16 achieved state_of_the_art accuracy of 98.7% and 97.0% respectively. The deep learning approach showcase the potential of high accuracy in detecting and classifying of groundnut leaf diseases, offering promising prospects for improving disease management in groundnut cultivation.

Keywords: Residual Network, Visual Geometry Group, Bayesian Optimization, Image Processing, MATLAB.

INTRODUCTION

Agriculture has provide a pivotal contribution to the global economy Hongkun et al. (2019) as the population continues to grow and urbanization leads to gradual reduction in cultivated land, the agricultural system faces increasingly pressure. Consequently, there is a growing need for efficient and secure agricultural methods to meet the rising demand for food production. To address this challenge, advanced sensing and driving technologies, along with improved information and communication technologies are being employed. Aichen et al. (2019) these advancements are essential for speeding up the increase in agricultural productivity with greater precision thus promoting the growth of high-quality and high-yield agricultural crops. Over the past decade computer vision inspection system have emerged as a vital tools in agricultural operations, expert and intelligent system based on computer vision algorithms are now commonplace in agricultural production management (Aichen et al. 2019).

Human perceive the world visually through their eyes and minds Pranav et al. (2021) in the realm of computer vision, the goal is to equip a system with comparable or enhanced visual capabilities, this technology involves the automatic retrieval, interpretation and understanding of valuable information from a single image or set of images using logical and algorithmic processes. Supriya and Kuricheti (2019) Computer vision which require a less subjective approach can efficiently analyze food characteristics with the benefit of speed, user friendliness and minimal sample preparation for training, this technology is particularly effective in categorizing food products, identifying flaws and estimating properties such as color, structure, size, surface irregularities and contamination.

Deep learning method, which utilize deep neural networks have gained popularity as a result of the rise in high performance computing resources, the strength and adaptability of deep learning stem from it capacity to handled numerous feature when working with unstructured data. Amitha et al. (2020) in deep learning algorithm data is processed through multiple layers with each layer progressively extracting features and transmitting them to the subsequent layers, various architecture such as unsupervised pre-trained network, convolutional neural networks, recurrent neural networks and recursive neural network can be utilized for the implementation of deep learning techniques. Sakshi et al. (2018) have shown a growing interest in deep learning, Convolutional Neural Network (CNN) have emerge as a widely adopted deep learning technique for addressing complex problems, surpassing the constraints of traditional machine learning methods. The study aim to enhance comprehension of CNN by presenting it fundamental concepts.

REVIEW OF RELATED WORK

The review of related and existing literatures is done. Diagnostic system for groundnut disease using image processing is rapidly growing increasingly in the field of research. And the feasibility of applying different type of application and techniques to evaluate fairly and compare systematically. Biswas and Moumita, (2019) six (6) plant diseases were pinpointed: Alternaria alternate, Anthracnose, Bacterial blight, Bacterial leaf scorch, Cercospora leaf spot and Downy mildew. They suggested a technique for classifying plant diseases using Back-Propagation Neural Network (BPNN) and Particle Swarm Optimization (PSO) to train the neural network using Back-Propagation and then employed PSO to refine the network weights and parameters. The outcome demonstrated an accuracy of approximately 96.42%.

Thirumalaisamy and Vinod, (2016) studied comprehensively and outlines the primary diseases affecting groundnuts, their prevalence, distribution, associated losses, diagnostic symptoms, spread, survival, transmission and aflatoxin contamination. It encompasses disease management strategies such as host plant resistance, culture methods, employment of botanical control, chemical methods and biotechnological approaches

Hope el al. (2022) the utilization of image analysis and regression modeling led to the successful development of diagnostic algorithms for peanut foliar system. These algorithm represent a novel approach to automated diagnostic, not currently available through existing disease identification tools. The models were developed using field-based images providing a potential resources for farmers looking to quickly recognize leaf symptoms in the field. All the algorithms created for peanut foliar diagnostics demonstrated an accuracy of

Shanthini and Anna (2023) the study employed Progressive Groundnut Convolutional Neural Network (PGCNN) which focus on identifying groundnut leaf diseases using a self-collected dataset. The diseases targeted by the model include early spot, late spot, rust and rosette. Performance metrics were conducted to assess the models effectiveness and compare it with various deep learning architecture such as Alexnet, VGG11, VGG14, VGG16 and VGG19. The PGCNN demonstrate a training accuracy of 99.3% and a validation accuracy of 97.58%and an overall accuracy of 97.58%.

Shankumar et al. (2018) develop a system that utilized a neural network to identify crop diseases. Employed an image processing technique that can function as a smartphone app for detecting plant diseases. The support vector machine algorithm is implemented to reduce errors in unidentified patterns. The Graphical User Interface GUI of the system is developed using Java Jsp while MySQL was employed as the database. The development process was carried out in eclipse 3.3 indigo and the application was built using JavaScript and HTML.

Aishwarya and Padmanabha, (2023) Employ machine learning techniques and categorize groundnut leaves into six (6) distinct group based on their condition, the collected images undergo pre-processing and are organized into six folders. Using the Densenet frame work specifically Densenet-169 with RMSProp Optimization, the research achieves accurate detection and classification of infected groundnut plant leaves, with a success rate and accuracy of 99.83%. Building on this research, the study addresses issues related to groundnut plant leaf diseases by utilizing the dataset from Aishwarya and Padmanabha (2023). These study used Visual Geometry Group (VGG-16) and Residual Network (ResNet50) Convolutional Neural Network (CNN) are employ with Bayesian Optimization (BO) to enhanced the recognition performance in identifying and categorizing diseases affecting groundnut plant leaves.

METHODOLOGY

DATA COLLECTION

Gather a dataset of groundnut leaf image that contain both healthy and disease leaves. The dataset for this research are collected from (Aishwarya and Padmanabha 2023).

Table 1. Data Sample Description

Category	Number of Images
Healthy Leaf	1871
Early Leaf Spot	1731
Late Leaf Spot	1896
Nutrition Deficiency	1665
Rust	1724
Early Rust	1474
Total	10361

DATA PREPROCESSING

The image of groundnut leaves are divided into six separate groups based on their condition. These groups consist of 1871 healthy leaf images, 1731 early leaf spot images, 1896 late leaf spot images, 1665 nutrition deficiency images, 1724 rust images and 1474 early rust images. Out of which 2380 images are utilized for training the dataset while 818 are used for testing purposes. The images were first resized to suit the model input and convolutional layers. A [224, 224, 3] images sizes were used for both models. Next, features were extracted by the Resnet50 and VGG16 CNN models. The features extracted are 1000 features for each image using the FC1000 and F18 feature layers. A total of 5940 images were used.

CNN ARCHITECTURE DESIGN

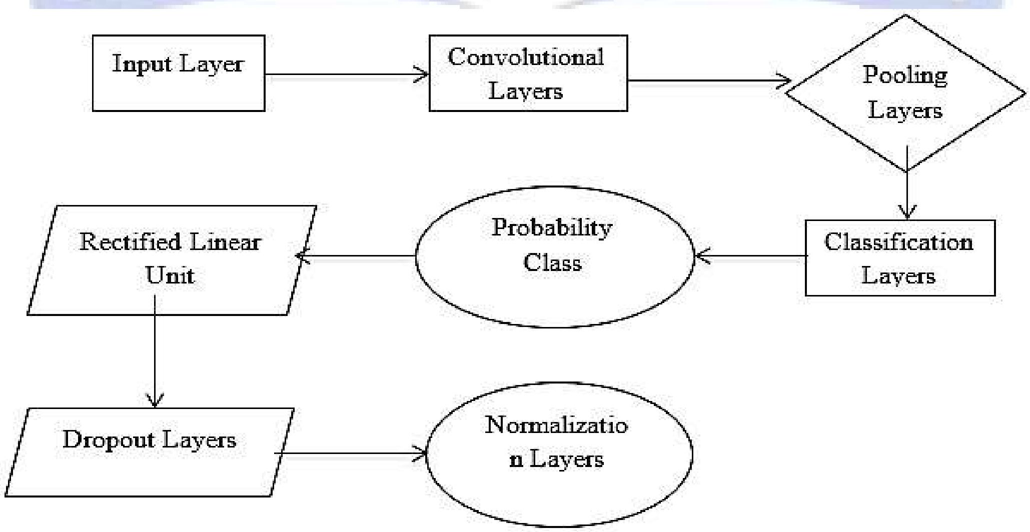

Figure 1: CNN Architecture

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RESIDUAL NETWORK (RESNET50)

ResNet50, a derivation of the residual network architecture, is a convolutional neural network (CNN) comprising 50 layers, incorporating 48 convolutional layers, one max pool layer and one average pool layer. It innovatively feature “shortcut connection” enabling more efficient back propagation of gradients to earlier layers, effectively addressing the challenge of vanishing gradients often encounter in deep neural networks. ResNet50 adopts a “bottleneck design” employing stacks of three layers.

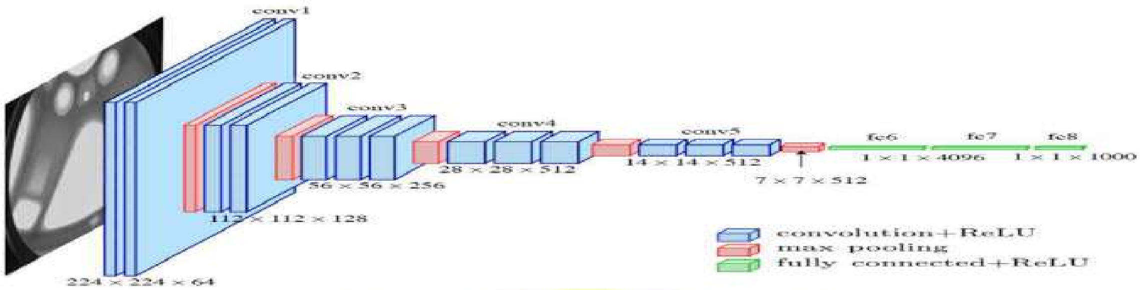

Figure 2: ResNet50 Architecture (Xinglong et al. 2021)

The ResNet50 architecture consists of four main elements: convolutional layers, identity blocks, convolutional blocks and fully connected layers. The 50-layer ResNet adopts a bottleneck design in its building blocks, incorporating convolutions, referred to as “bottlenecks” to decrease the number of parameter and matrix multiplication. This accelerates the training process for each layer significantly. It utilizes a stack of three layers instead of two. (Xinglong et al. 2021).

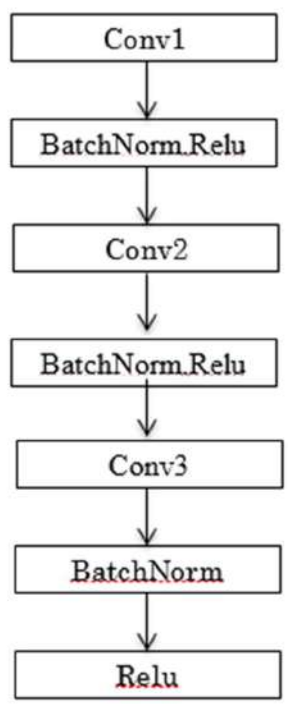

Figure 3: Bottleneck Flow chart (Xinglong et el., 2021)

ResNet50 is a widely used ResNet model due to its performance and efficiency. It has Floating points operations. The ResNet architecture adheres to two core design principles. Firstly, the number of filters in each layer remains constant relative to the output feature map size, secondly when the feature map size is halve, the number of filters is doubled to maintain the time complexity of each layer.

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ResNet50 architecture analyzes the input image and generates 1000-value vector, with each value denoting the probability of classification for a specific class. This model utilizes filters, ReLU activation and a convolution filters for input linear transformation. The mathematical formulation for ResNet50 varies according to the layer type. In convolution layers, the equation mirrors that of VGG16, but with the difference that ResNet50 employs and filters instead of filters. The difference is in the residual blocks equation which is.

$$y = F(X, W_i) + X \tag{1}$$

Where is the input feature map, is the output feature map, is the residual function and are the weight of the convolutional layers in the block. The residual function can be defined as:

$$F(X, W_i) = W_3 \sigma(W_2 \sigma(W_1 \times)) \tag{2}$$

Where is the activation function (ReLU), and , , and are the weights of the , and convolutional layers respectively. The skip connection combines the input with the output of the residual function, establishing a shortcut for the gradient to pass through. This enables the network to assimilate the identify function when the residual function is zero and the grasp the nonlinear function when the residual function is not zero.

VGG16 ARCHITECTURE DESIGN

VGG16 is a widely acclaimed convolutional neural network featuring 16 layers, including input and output layers, as well as several hidden layers. It is recognized as a high-performing advance computer vision model. It enhance depth by employing an architecture featuring small convolution filters, resulting in substantial advancements over previous configurations. By expanding to 16-19 weight layers, it achieves approximately 138 trainable parameter (Mustafa, 2023).

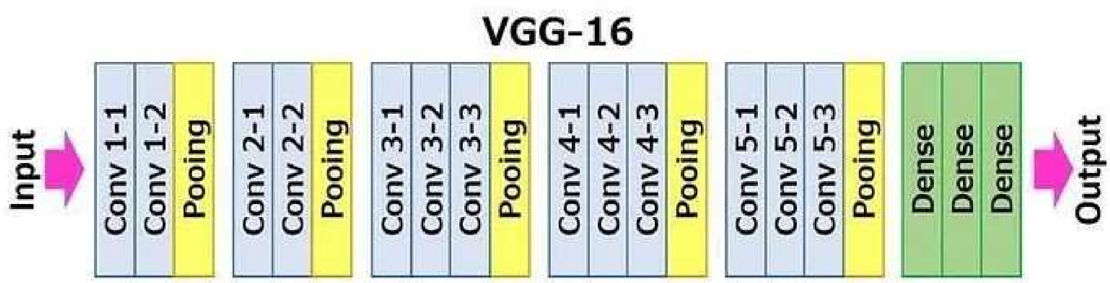

Figure 3: VGG16 Architecture (Mustafa, 2023)

The 16 in VGG16 signifies the inclusion of 16 layers with adjustable weight. Although VGG16 consist of 21 layers, encompassing thirteen (13) convolutional layers, five (5) Max-pooling layers and three (3) Dense layers, it specifically features only sixteen layers with trainable parameters. VGG16 focus on employing convolutional layers with a filter stride of 1 and consistently using the same padding along with Max-pool layers that have a filter stride 2. The architecture maintains a consistent pattern of convolution and Max-pool layers. For example Conv_1 layer comprises 64 filters, Conv_2 consist of 128 filters, Conv_3 features 256 filters and both Conv_4 and Conv_5 encompass 512 filters. The fully connected layers follow a sequence of convolution layers: the first two (2) have 4096 channels each, while the third performs 1000-way ImageNet Large Scale Visual Recognition Challenge (ILSVRC) classification and therefore contains 1000 channels. The final is the soft-max layer.

The mathematical equation for convolutional layer

$$Y_{i,j,k} = \sum_{1=0}^{C-1} \sum_{M=0}^{F-1} \sum_{N=0}^{F-1} W_{m,n,l,k} X_{i+m,j+n,l} + bk \tag{3}$$

The input feature map location, determine the output feature map, represent the filter weight, denoting the bias, indicating the number of input channels, is the filter size and is the output channel index.
For Max pooling equation

$$Y_{i,j,k} = \max_{m=0}^{P-1} \max_{n=0}^{P-1} X_{ip+m,\, jp+n,\, k} \quad (4)$$

Where is the input feature map, is the output feature map, is the pooling size and is the output channel index.
For fully connected layer

$$Y_K = \sum_{i=0}^{N-1} W_{i,k} \; X_i + b_k \quad (5)$$

Where is the input vector, is the output vector, is the weight matrix, is the bias vector, is the number of input neurons and is the output neuron index.

BAYESIAN OPTIMIZATION DESIGN

Bayesian optimization is a mathematical method that utilizes probabilistic models to effectively identify the best combination of hyperparameters for machine learning models. It is a sequential design approach that doesn't rely on a specific function forms and is commonly used to optimize functions that are costly to evaluate. The techniques involve smartly exploring the search space by using statistical models. (Frazier, 2018).

$$Arg \max_{XEX} E_{YEY}[F(X,Y)]$$

Where X is the search space for the hyper-parameters, Y is the search space for the features, $F(X,Y)$ is the objective function and $E_{YEY}[F(X,Y)]$ is the expected value of the objective function over the search space of the feature.

The process of Bayesian optimization involves the following steps:

- Define a search space for the hyper-parameters.
- Train a surrogate model using the objective function and the search space.
- Use the surrogate model to predict the performance of the objective function for new hyper-parameter.
- Use the acquisition function to determine the next hyper-parameters to evaluate.
- Evaluate the objective function at the new hyper-parameter.
- Repeat step iii to vi until the optimal hyper-parameter are found.

(Frazier, 2018)Bayesian optimization process involved modeling the unknown objective function the acquisition function directs the choice of the next point to assess, balancing exploration and exploitation. The acquisition functions include Expected Improvement (EI), Probability Improvement (PI), Upper Confidence Bound (UCB) and Gaussian Process (GP).
The acquisition function of expected improvement (EI) defined as:

$$EI = E\left[\max\left(F\left(X_{best}\right) - F(X), 0\right)\right] \quad (6)$$

Where (X) is the point to be evaluated, $(F(X))$ is the surrogate models predicted mean at (X), $F(X\_\{\backslash text\{best\}\})$ is the best observed value so far, $(\backslash mathbb\{E\}$ denotes the expected value.

The probability improvement (PI) is another acquisition function which is defined as:

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The acquisition function of expected improvement (EI) defined as:

$$EI = E\left[\max\left(F\left(X_{best}\right) - F(X), 0\right)\right] \tag{7}$$

Where (X) is the point to be evaluated, $(F(X))$ is the surrogate models predicted mean at (X), $F(X\_\{\backslash text\{best\}\})$ is the best observed value so far, $(\backslash mathbb\{E\}$ denotes the expected value.

The probability improvement (PI) is another acquisition function which is defined as.

$$PI(X) = P\left(F(X) \geq F\left(X_{best} + \xi\right)\right) \tag{8}$$

Here $(\backslash Xi)$ is a tunable parameter that balance exploration and exploitation and $P(Icdat\ ))$ denotes the probability where the parameter control the trade-off between exploring new regions $((\backslash Xi. > 0)$ and exploiting the current best-known region $((\backslash Xi \backslash approx\ ))$ choosing an appropriate $(\backslash Xi)$ is problem dependent.

In practice the probability improvement acquisition function is often used with a Gaussian Cumulative Distribution Function (CDF) to estimate probability

$$PI(X) = \phi\left(\frac{F(X) - F\left(X_{best}\right) - \xi}{\sigma(X)}\right) \tag{9}$$

Where $(\backslash phi(\backslash dot))$ is the standard normal cumulative distribution function and $(\backslash sigma(x))$ is the predicted standard deviation of the surrogate model at (x).

The equation 3 express the probability that the surrogate function value at (x) is greater than current best plus $(\backslash Xi)$. If this probability is high, it suggests that (x) has a good chance of improving upon the current best making it a candidate for the next evaluation.

The Upper Confidence Bound (UCB) which is defines as.

$$UCB(x) = \mu(x) + k\sigma(x) \tag{10}$$

$(\backslash mu(x)$ Is the surrogate models predicted mean at (x), $(\backslash sigma(x))$ is the predicted standard deviation of the surrogate model at (x), $(\backslash kapp)$ is tunable parameter that controls the trade-off between exploration and exploitation.

Gaussian Process is used to model the unknown objective function the Gaussian equation.

$F(x) \sim GP(\mu(x), k(x, x))$ Where (11)

$f(x)$ is the unknown objective function, $(\backslash mu(x))$ is the mean function representing the expected value of $(f(x))$ at (x), $(k(x, x'))$ is the kernel function capturing the covariance or similarity between $(f(x))$ at (x) and $(f(x'))$ at (x'). The Gaussian process provides a probabilistic way to model the distribution of the objective function at different input point during the optimization process as more data point are observed, the GP is updated to better approximate the true underlying function.

PERFORMANCE EVALUATION METRICS

The optimize CNN-Bayesian model for groundnut leaf disease detection will be assessed using a confusion matrix, the performance metrics efficacy was assessed. It contain True Positive Rate (TPR) and False Negative Rate (FNR) with the following metrics: Accuracy, Classification error, Precision and Recall

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{12}$$

$$Classification\ error = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{13}$$

$$\Pr ecision = \frac{TP}{TP + FP} \tag{14}$$

$$\text{Re}\,call = \frac{TP}{TP + TN} \tag{15}$$

RESULT AND DISCUSSION

The development and execution of the models were conducted using Matrix Laboratory (MATLAB). The adopted groundnut leaf dataset was utilized to train and test the performance of the ResNet50 and VGG16 CNN models in recognizing, identifying and classifying various groundnut leaf diseases. The groundnut dataset comprises of 10361 samples of images, labeled into six (6) classes according to their condition: early leaf spot, early rust, healthy leaf, late leaf spot, nutrition deficiency and rust. Only infected leaves were selected from the dataset for the purpose of model training and testing. The training set includes 2380 images while the testing set comprises 818 images. The models were trained using images from the training set and subsequently used to classify images from the test set. Convergence curve for ResNet50 and VGG16 are depicted in figure 11 and 15. Training parameter and validation

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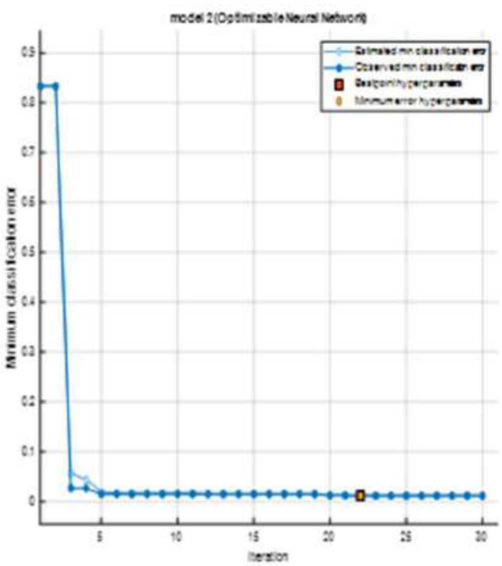
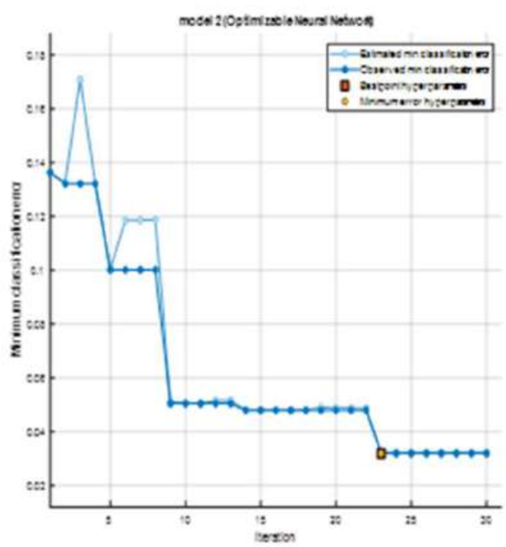
accuracy are illustrated in figure 12 and 16. Confusion matrix table were used to evaluate the classification model performance is shown in figure 13 and 17. True positive rate (TPR) and False negative rate (FNR) graphs are displayed in figure 14 and 18. Performance comparison is presented in figure 19 and 20. Therefore leveraging Bayesian optimization, the ResNet50 and VGG16 CNN models achieved an overall accuracy of 98.7% and 97.0% respectively. The result indicate that both models achieved 100% accuracy in identify early rust and rust. The finding demonstrate the robustness and high accuracy of the models in classifying groundnut leaf diseases, showcasing the potential of utilizing advance technology for efficient disease detection in agricultural system.

RESNET50 AND VGG16 CONVERGENCE CURVE

The convergence curves for ResNet50 and VGG16 depicting the training of the classifier for groundnut leaf disease detection are presented in figure 4 and 5. Bayesian optimization was employed to optimize the model using the classification error as the fitness function over a maximum of 30 iterations. The initial classification error for ResNet50 was 0.83 gradually decreasing to 0.02 while for VGG16 it started at 0.13 and decreased to 0.037 representing the optimal convergence point for all parameters.



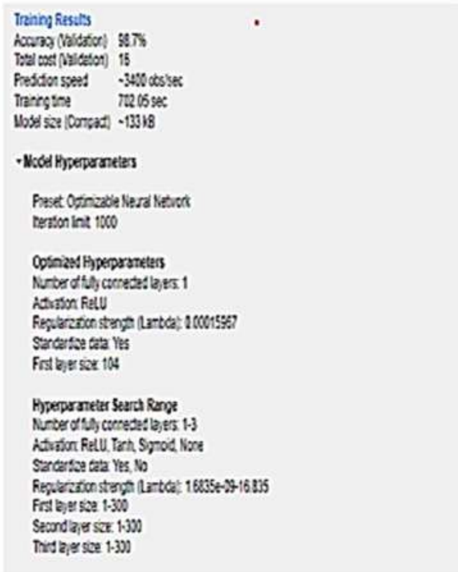
Resnet50 Convergence curve



VGG16 Convergence curve

SNAPSHOT OF TRAINING PARAMETERS FOR RESNET50 AND VGG16

The training result of ResNet50 and VGG16 models are depicted in figure 6 and 7 respectively. The optimal hyperparameter for ResNet50 model determined by the bayesian optimizer consist of a single fully connected neural network, ReLU (1) activation function, a lambda value of 0.00015967 and a layer size of 104. Similarly, the optimal hyperparameters for the VGG16 model also chosen by the bayesian optimizer include two fully connected neural networks, ReLU (2) activation function, a lambda value of 0.0000028079 and a layer size of 288.



Training Results
Accuracy (Validation) 98.7%
Total cost (Validation) 15
Prediction speed ~3400 obs/sec
Training time 702.05 sec
Model size (Compact) ~133 kB

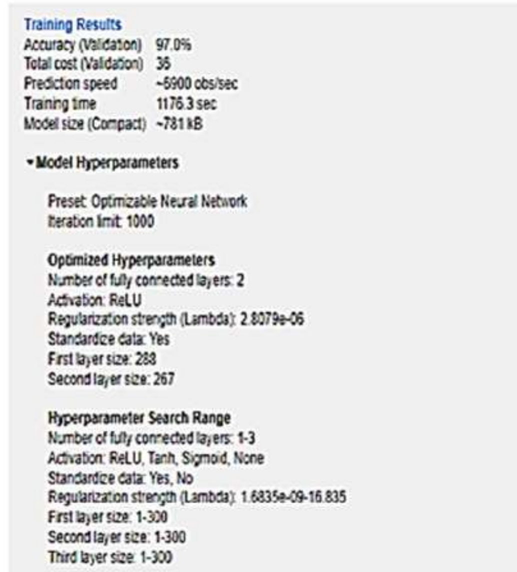
▾Model Hyperparameters

Preset: Optimizable Neural Network
Iteration limit: 1000

Optimized Hyperparameters
Number of fully connected layers: 1
Activation: ReLU
Regularization strength (Lambda): 0.00015967
Standardize data: Yes
First layer size: 104

Hyperparameter Search Range
Number of fully connected layers: 1-3
Activation: ReLU, Tanh, Sigmoid, None
Standardize data: Yes, No
Regularization strength (Lambda): 1.6835e-09-16.835
First layer size: 1-300
Second layer size: 1-300
Third layer size: 1-300

Snapshot of Training Parameters for Resnet50



Training Results
Accuracy (Validation) 97.0%
Total cost (Validation) 36
Prediction speed ~6900 obs/sec
Training time 1176.3 sec
Model size (Compact) ~781 kB

▾Model Hyperparameters

Preset: Optimizable Neural Network
Iteration limit: 1000

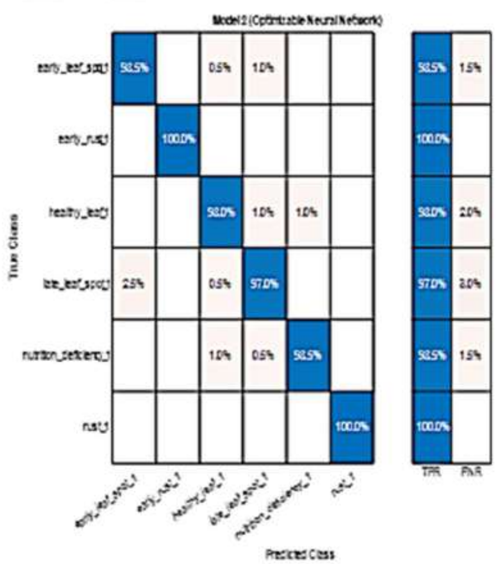
Optimized Hyperparameters
Number of fully connected layers: 2
Activation: ReLU
Regularization strength (Lambda): 2.8079e-06
Standardize data: Yes
First layer size: 288
Second layer size: 267

Hyperparameter Search Range
Number of fully connected layers: 1-3
Activation: ReLU, Tanh, Sigmoid, None
Standardize data: Yes, No
Regularization strength (Lambda): 1.6835e-09-16.835
First layer size: 1-300
Second layer size: 1-300
Third layer size: 1-300

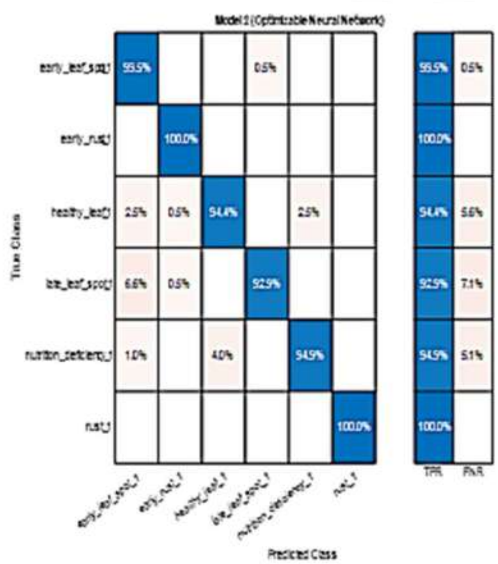
Snapshot of Training Parameters for VGG16

RESNET50 AND VGG16 CONFUSION MATRIX

The confusion matrix visualization in figure 8 and 9 represent classification validation of the ResNet50 and VGG16 models. These matrices provide a detailed breakdown of the accurate and inaccurate classification counts for all disease classes. The model indicates a high level of precision with nearly all samples correctly classified. Notably, both models achieved exceptional performance in identifying the Early Rust and Rust disease classes with 198 correct samples classification with zero errors



Resnet50 TPR and FNR graph



VGG16 TPR and FNR graph

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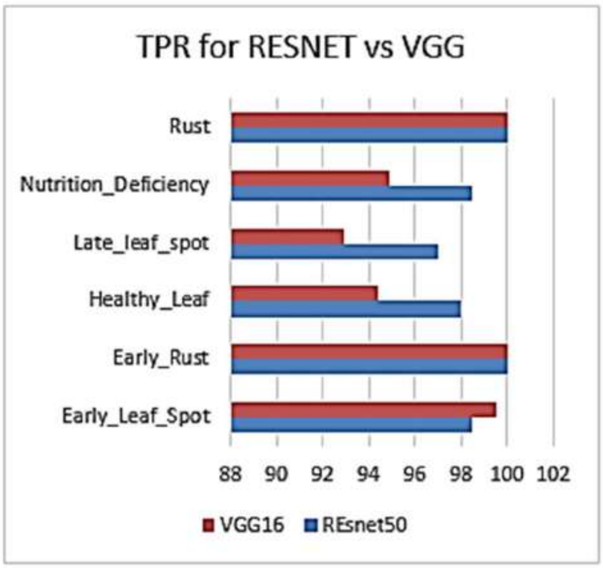
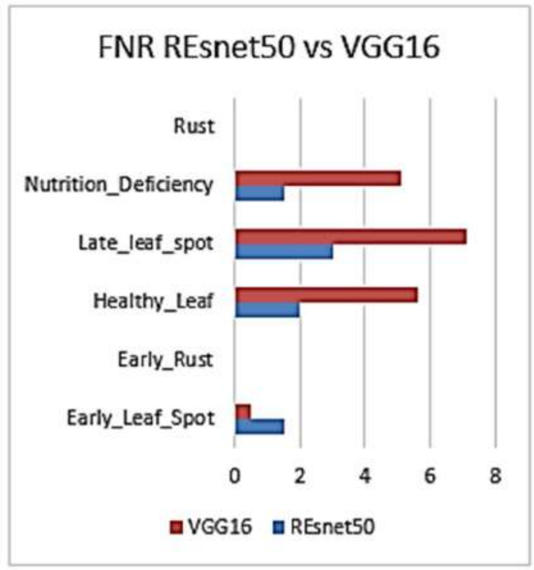
TPR FOR RESNET50 VS VGG16 AND FNR FOR RESNET50 VS VGG16

In figures 12 and 13 both models RESNET50 and VGG16 demonstrate strong performance exhibiting high True Positive Rate (TPR) and low False Negative Rate (FNR). Overall ResNet50 appears to outperform VGG16 marginally across various disease classes. The model exhibit exceptional effectiveness in accurately classifying disease such as Early_Rust and Rust, achieving flawless classification. Notably, VGG16 demonstrate superior performance to ResNet50 in detecting false negative rate across different disease.



TPR for ResNet50 vs VGG16



FNR for ResNet50 vs VGG16

PERFORMANCE EVALAUATION AND VALIDATION

i. **Early Leaf_Spot:**
- RESNET50: TPR of 98.5%, FNR of 1.5%
- VGG16: TPR of 99.5%, FNR of 0.5%
- Both models perform well for Early_Leaf_Spot, with high TPR and low FNR.

ii. **Early_Rust:**
- RESNET50: Perfect classification with 100% TPR and 0% FNR
- VGG16: Similarly, perfect classification with 100% TPR and 0% FNR
- Both models perform excellently for Early_Rust.

iii. **Healthy_Leaf:**
- RESNET50: TPR of 98%, FNR of 2%
- VGG16: TPR of 94.4%, FNR of 5.6%
- RESNET50 performs slightly better than VGG16 for Healthy_Leaf.

iv. **Late_leaf_spot:**
- RESNET50: TPR of 97%, FNR of 3%
- VGG16: TPR of 92.9%, FNR of 7.1%
- RESNET50 outperforms VGG16 for Late_leaf_spot.

v. **Nutrition_Deficiency:**
- RESNET60: TPR of 98.5%, FNR of 1.5%
- VGG16: TPR of 94.9%, FNR of 5.1%
- RESNET50 performs slightly better for Nutrition_Deficiency.

vi. **Rust:**

- RESNET50: Perfect classification with 100% TPR and 0% FNR
- VGG16: Similarly, perfect classification with 100% TPR and 0% FNR
- Both models perform excellently for Rust.

FINDINGS

The comparison showcases variation in the number of classes in the dataset, choice of models and achieved accuracies, indicating difference approaches and outcomes in two studies.

In this study the aim is to improve the recognition performance of detecting and classifying groundnut leaf disease using RESNET50 and VGG16 CNN model with Bayesian optimizer using the dataset obtained from (Aishwarya & Padmanabha, 2023) the result shows that not only Densent-169 can achieve a remarkable performance and accuracy. Numerous machine learning techniques can be applied to yield impressive outcomes. The occurrence of diseases in groundnut varieties is heavily influenced by the environmental condition and genetic composition, varying from one season to another and across diverse agro-ecological setting.

The study indicates that planting groundnut early significantly reduces the occurrence of spot disease compared to planting it late. Late-planted groundnuts experienced early leaf shading due to severe disease infection and attacks on the tender leaves, leading to higher incidence of disease and consequently lower yield. Therefore the timing of planting and plant spacing are crucial factors to consider. It is important to allow a clear break in time between successive groundnut crops, and crop roation is essential for preventing early season infection.

CONCLUSION AND FUTURE RESEARCH

The aim is to enhance the detection and classification performance of groundnut leaf diseases by employing deep learning models, specifically the ResNet50 and VGG16 CNN models with Bayesian optimizer. Both models exhibit high True Positive Rate (TPR) and low false negative rate (FNR) across different disease, achieving 100% accuracy for early rust and rust. The adopted model has set a new benchmark, achieving a state_of_the_art accuracy of 98.7% for ResNet50 and 97.0% for VGG16 respectively. The evaluation of the RESNET50 and VGG16 models for disease classification demonstrates commendable performance, with both models exhibiting high True Positive Rates (TPR) and low False Negative Rates (FNR) across various disease classes. RESNET50 consistently outperforms VGG16, showcasing its efficacy in capturing relevant features for disease identification. The models excel in early disease detection, particularly evident in the perfect classification of Early_Rust and Rust. However, there are variations in performance across specific classes, with RESNET50 demonstrating superior accuracy for Healthy_Leaf and Late_leaf_spot. Overall, the results underscore the potential of deep learning models in agricultural disease diagnosis, with RESNET50 emerging as a preferred choice for its nuanced performance.

The findings of this research mark the initial steps towards the recognition, detection and classification of groundnut leaf disease. Given the ever-changing nature of agriculture and the progressing domain of machine learning, it is advisable to explore hybrid methodologies. Combining the present approach with other advanced machine learning techniques would enhance robustness and prediction accuracy.

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