Enhanced Coconut Tree Disease Classification Using ResNet50, EfficientNetB0, and DenseNet-201 with Comparative Analysis of Activation Functions

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***Abstract*—Accurate and timely prognosis of coconut tree diseases is essential for good crop health, high yields, and economic endurance in agricultural coconut trees, which are dominant in tropical economies. The paramount susceptibility of coconut trees to a variety of diseases can significantly reduce yields and impose a significant economic burden on farmers. Early pinpointing and intercession to protect the overall health of the trees is also important. To overcome symptomatic challenges and address the often unpredictable manifestations of coconut tree diseases, this study uses a novel approach employing advanced deep learning techniques.**

We used state-of-the-art image analysis techniques to extract key features from leaf images of coconut trees affected by various diseases like BudRoot Dropping,BudRot,Gray Leaf Spot,Leafrot ,StemBleeding. Specifically, we used DenseNet-201, ResNet-50, and EfficientNet B0 algorithms to encapsulate complex visual structures associated with different disease stages. To increase the discriminative power of the model, we trained models using four activation functions: ReLU, LeakyReLU, Swish, and ELU individually. Through a pervasive evaluation process, our model achieved a remarkable accuracy of 99.85% in classifying coconut tree diseases, demonstrating its exceptional performance in differentiating between disease types.

***Index Terms*—DenseNet-201, ResNet-50, EfficientNet B0 ,paramount,pinpointing,symptomatic,apprehension,pervasive evaluation, ReLU, LeakyReLU, Swish, and ELU**

I. Introduction

Coconut farming is an important source of income for lakhs of people in the tropics of the world. However, the survival of these farmers is being severely threatened by coconut diseases like BudRoot Dropping,BudRot,Gray Leaf Spot,Leafrot ,StemBleeding, that can severely reduce yields and crop quality. Recent estimates suggest that these diseases affect about 15-20%[1] of the world's coconut trees, causing significant economic losses. In major coconut-producing countries such as India, the Philippines, and Indonesia, this has reduced annual production by 10-15%[2], affecting smallholder farmers who rely heavily on coconut farming as their main source of income.

Coconut trees are susceptible to diseases such as deadly yellowing, branch rot, and leaf discoloration. Deadly yellowing, caused by certain plant chemicals, causes leaves to turn yellow, eventually leading to tree death if left unchecked[3]. Root rot, usually caused by fungal pathogens such as *Phytophthora palmivora*, leads to the loss of the apical shoot, resulting in stunted tree growth[4]. Leaf spot is another fungal disease that produces white spots on leaves, disrupting photosynthesis and weakening the tree over time[5].In addition to coconut disease diagnosis, advances in machine learning and deep learning are transforming the broader field of plant disease diagnosis[6,7]. Traditional methods, which often rely on expert manual testing, are not only time-consuming but also prone to human error and variability[8,9]. In contrast, systems powered by artificial intelligence, such as convolutional neural networks (CNNs), provide scalable and efficient solutions for plant disease diagnosis[10,11]. These systems can rapidly analyze images of plant leaves, stems, or fruits, identifying early symptoms of diseases with greater accuracy. Integrating such technologies into agriculture helps reduce crop losses and provides farmers with tools to prevent diseases earlier, ultimately helping to improve food security worldwide[12].

To combat these diseases, researchers have developed sophisticated disease identification systems using state-of-the-art deep learning models such as EfficientNet-B0, ResNet-50, and DenseNet-201[13,14]. These models are trained on large datasets of leaf images to distinguish between healthy and diseased leaves with remarkable accuracy.EfficientNet-B0 is known for its ability to balance accuracy and computational efficiency, making it ideal for use in real-time applications, even in resource-limited environments such as agriculture[15,16]. It is designed to optimize performance with fewer parameters. The performance of this model is further enhanced by the use of activation functions such as eLU(exponential linear unit), ReLU(rectified linear unit), Leaky ReLU, and Swish. ReLU is popular due to its simplicity and effectiveness in addressing nonlinearity in data[17,18], while the Leaky ReLU activation function addresses the issue of dying neurons by allowing small gradients when the neuron is inactive[19]. Swish provides smoother nonlinearity and better gradient flow[20].

II. Methodology

A. Dataset

For the purpose of this study, a dataset of 7,016 images is used (Dataset link: https://data.mendeley.com/datasets/gh56wbsnj5/1). These images used in this study belong to five different categories: Budroot dropping, Bud rot, gray leaf spot, leaf rot, and Stem bleeding, as shown in Fig. 1(a-e). The dataset is systematically divided into test, training, and validation sets in the ratio of 10:80:10. This phase assures that the model undergoes proper training on a robust dataset, tested on a different set for performance analysis, and validated on a new subset to refine it and prevent overfitting.

Coconut trees affected by various diseases show clear visual symptoms that aid in identification. ”Budroot dropping” as shown in Fig.1-a causes young branches to fall prematurely, often turning nearby leaves yellow or brown, with some signs of wilting or rot on the branches. ”Bud rot”as shown in Fig.1-b affects the tree’s growing point, leading to wilting young leaves and, in severe cases, the collapse of the top of the tree.

”Gray leaf”as shown in Fig.1-c spot appears as small black spots on the leaves that gradually enlarge and turn white, causing leaf wilting and a decline in the tree’s health. ”Leaf rot”as shown in Fig.1-d typically begins at the leaf edges with coarse spots, leading to further wilting and drying of the leaves, diminishing the tree’s vitality.Lastly,

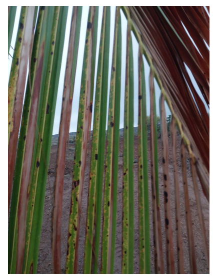
”Stem bleeding”as shown in Fig.1-e is marked by the oozing of a black, sticky sap from the trunk, often accompanied by cracks and discoloration, which weaken the stem and slow the tree’s growth. These visible symptoms leave the coconut trees more vulnerable to further diseases and health complications.

B. Hyperparameters

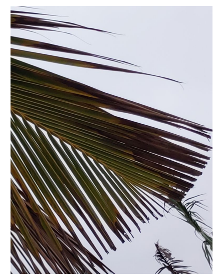
This study employed EfficientNet, ResNet, and DenseNet architectures, using a batch size of 32 and a dropout rate of 0.5 to prevent overfitting. The models were trained for 10 epochs with the Adam optimizer for adaptive learning. Binary cross-entropy was used as the loss function for EfficientNet, while categorical cross-entropy was applied to ResNet and DenseNet. The learning rate was set to 0.001 for balanced convergence during training.

(a) BudRoot Dropping

(b) BudRot



(c) Gray Leaf Spot



(d) Leafrot

(e) StemBleeding

Fig.1 Images of coconut tree diseases.

1) ResNet-50 Architecture

The ResNet-50 system is a deep convolutional neural network designed for solving missing vulnerability problem in deep networks using residual connections. The architecture is divided into five steps as shown in Fig.2, starting with the first convolutional layer followed by batch normalization, ReLU operation, and max pooling. Each subsequent step consists of more convolutional blocks (Conv Blocks) and identity blocks (ID Blocks) implementing the remaining combinations. Going through these parts, the network performs global average pooling, flattens the feature maps, and uses fully connected (FC) layer to produce final output. Because it can train very deep networks well, ResNet-50 is widely used in image classification applications.

In addition to ResNet 50, the algorithms EfficientNet B0 and DenseNet 201 are also used to improve the performance of the model. EfficientNet B0 considers model parameters such as depth, width, resolution etc. in a balanced manner, achieving high accuracy while maintaining the efficiency of low parameters On the other hand DenseNet 201 establishes dense layer connections, it promotes feature reuse and better information flow, and these models together with ResNet 50 addresses missing slopes improves overall accuracy in tree disease classification.

EfficientNet is a lightweight deep learning model that achieves high accuracy with fewer parameters using compound scaling, where depth, width, and shape are combined to scale EfficientNet-B0, with only 4.4 million parameters , compares favorably with ResNet50’s 24.1 million and DenseNet201’s

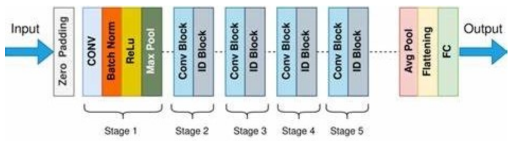


Fig.2 Resnet-50 Architecture. Source: ResNet-50

18.8 million parameters as mentioned in TABLE(I), it offers equal or better accuracy for its system is built around MBConv blocks and Squeeze-and-Excitation layers, which optimize feature extraction and reduce computational overhead so. Unlike ResNet50's reliance on residual connections and DenseNet201's dense connections, EfficientNet strikes a good balance between performance and compact design, optimizing applications requiring low computing power and fewer layers without sacrificing accuracy.

C. Activation functions

ReLU (Rectified Linear Unit): It returns the input directly if it is positive; otherwise, it returns zero. This simple and efficient activation function helps in preventing the vanishing gradient problem during backpropagation.

$$f(x) = \max(0, x) \tag{1}$$

Leaky ReLU: It is a variant of ReLU that allows a small, non-zero gradient when the input is negative.

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha x & \text{if } x \leq 0 \end{cases} \tag{2}$$

Swish: It is a smooth, non-monotonic activation function that works better than ReLU in some cases.

$$f(x) = \frac{x}{1 + e^{-x}} \tag{3}$$

ELU (Exponential Linear Unit): It is similar to ReLU but tends to converge faster and produce better accuracy.

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha(e^x - 1) & \text{if } x \leq 0 \end{cases} \tag{4}$$

TABLE I Parameter counts for EfficientNetB0, DenseNet201, and ResNet50 architectures.

Parameters			
Model	**Total**	**Trainable**	**Non-Trainable**
EfficientNetB0	4,378,792	329,221	4,049,571
DenseNet201	18,821,662	493,061	18,328,601
ResNet50	24,113,541	525,829	23,587,712

III. Results

In our research, we employed Python 3.12.4 for coding and conducting experiments, utilizing Jupyter Notebook version 7.2.1 as the interactive platform for efficient data processing and visualization. Deep learning tasks were executed using TensorFlow version 2.17.0, which served as the core framework for building, training, and optimizing the neural network models. In coconut tree disease classification analysis, which involved five categories (Budroot drop, Bud rot, Gray leaf spot, Leaf rot, and Stem bleeding), we implemented different deep learning models using ResNet-50, DenseNet201, and EfficientNet-B0 architectures. Each model was trained with four activation functions—ReLU, Leaky ReLU, Swish, and ELU—evaluating classification accuracy through confusion matrices.

TABLE II Comparison of activation functions on different architectures with Test accuracy.

Accuracy (%)			
Activation Function	**DenseNet-201**	**ResNet-50**	**EfficientNet-B0**
ReLU	99.77	99.77	99.54
Leaky ReLU	99.55	99.20	99.77
Swish	99.20	99.85	99.65
ELU	98.52	99.55	99.77

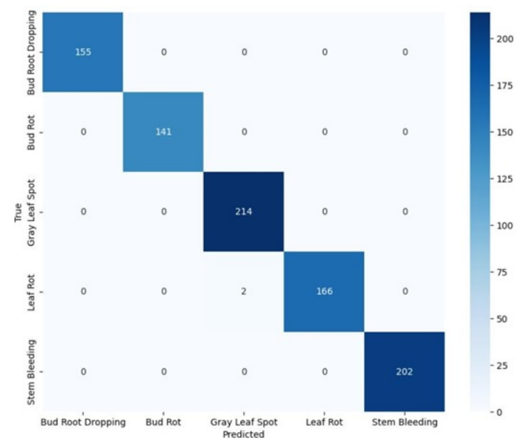


Fig.3 DenseNet architecture utilizing the ReLU activation function.

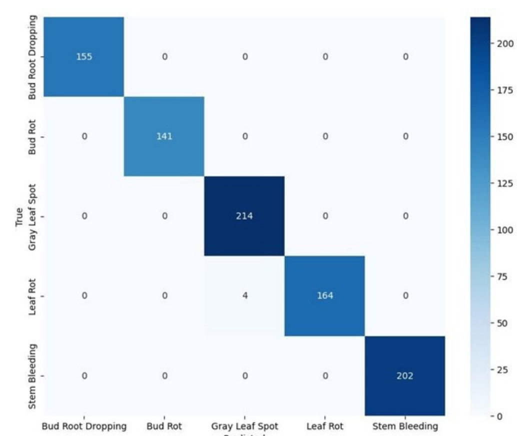


Fig.4 ResNet-50 with Swish Activation Function

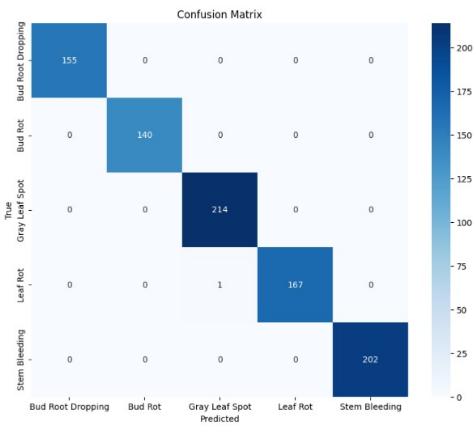


Fig.5 Efficientnet B0 architecture utilizing the LeakyReLU activation function.

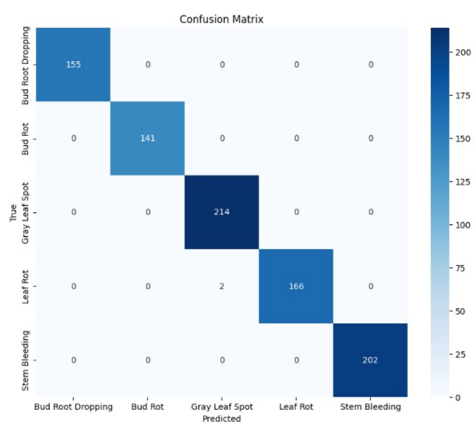


Fig.6 Efficientnet B0 architecture utilizing the eLU activation function.

Serial No.	Activation Function	Class	Precision	Recall	F1-Score	Support
1	ReLU	Bud Root Dropping	1.000000	1.000000	1.000000	155.000000
		Bud Rot	1.000000	1.000000	1.000000	141.000000
		Gray Leaf Spot	0.981651	1.000000	0.990741	214.000000
		Leaf Rot	1.000000	0.976190	0.987952	168.000000
		Stem Bleeding	1.000000	1.000000	1.000000	202.000000
2	Leaky ReLU	Bud Root Dropping	1.000000	1.000000	1.000000	155.000000
		Bud Rot	1.000000	0.992908	0.996447	141.000000
		Gray Leaf Spot	0.990741	1.000000	0.995349	214.000000
		Leaf Rot	1.000000	0.994048	0.997015	168.000000
		Stem Bleeding	1.000000	1.000000	1.000000	202.000000
3	Swish	Bud Root Dropping	1.000000	1.000000	1.000000	155.000000
		Bud Rot	1.000000	1.000000	1.000000	141.000000
		Gray Leaf Spot	0.986175	1.000000	0.993039	214.000000
		Leaf Rot	1.000000	0.982143	0.990991	168.000000
		Stem Bleeding	1.000000	1.000000	1.000000	202.000000
4	ELU	Bud Root Dropping	1.000000	1.000000	1.000000	155.000000
		Bud Rot	1.000000	1.000000	1.000000	141.000000
		Gray Leaf Spot	0.995349	1.000000	0.997669	214.000000
		Leaf Rot	1.000000	0.988095	0.994012	168.000000
		Stem Bleeding	0.995074	1.000000	0.997531	202.000000

Fig.7 Efficientent B0-Performance metrics

Serial No.	Activation Function	Class	Precision	Recall	F1-Score	Support
1	ReLU	Bud Root Dropping	1.000000	1.000000	1.000000	155.000000
		Bud Rot	1.000000	1.000000	1.000000	141.000000
		Gray Leaf Spot	0.990000	1.000000	1.000000	214.000000
		Leaf Rot	1.000000	0.990000	0.990000	168.000000
		Stem Bleeding	1.000000	1.000000	1.000000	202.000000
2	Leaky ReLU	Bud Root Dropping	1.000000	1.000000	1.000000	155.000000
		Bud Rot	0.990000	1.000000	1.000000	141.000000
		Gray Leaf Spot	1.000000	0.970000	0.980000	214.000000
		Leaf Rot	0.970000	1.000000	0.980000	168.000000
		Stem Bleeding	1.000000	1.000000	1.000000	202.000000
3	Swish	Bud Root Dropping	1.000000	1.000000	1.000000	155.000000
		Bud Rot	1.000000	1.000000	1.000000	141.000000
		Gray Leaf Spot	0.980000	1.000000	0.990000	214.000000
		Leaf Rot	1.000000	0.980000	0.990000	168.000000
		Stem Bleeding	1.000000	1.000000	1.000000	202.000000
4	ELU	Bud Root Dropping	1.000000	1.000000	1.000000	155.000000
		Bud Rot	0.990000	1.000000	0.990000	141.000000
		Gray Leaf Spot	0.990000	1.000000	1.000000	214.000000
		Leaf Rot	1.000000	0.980000	0.990000	168.000000
		Stem Bleeding	1.000000	1.000000	1.000000	202.000000

Fig.8 Resnet 50-Performance metrics

Serial No.	Activation Function	Class	Precision	Recall	F1-Score	Support
1	ReLU	Bud Root Dropping	1.000000	1.000000	1.000000	155.000000
		Bud Rot	1.000000	1.000000	1.000000	141.000000
		Gray Leaf Spot	0.990000	1.000000	1.000000	214.000000
		Leaf Rot	1.000000	0.990000	0.990000	168.000000
		Stem Bleeding	1.000000	1.000000	1.000000	202.000000
2	Leaky ReLU	Bud Root Dropping	1.000000	1.000000	1.000000	155.000000
		Bud Rot	1.000000	1.000000	1.000000	141.000000
		Gray Leaf Spot	0.990000	0.990000	0.990000	214.000000
		Leaf Rot	0.990000	0.990000	0.990000	168.000000
		Stem Bleeding	1.000000	1.000000	1.000000	202.000000
3	Swish	Bud Root Dropping	1.000000	1.000000	1.000000	155.000000
		Bud Rot	1.000000	0.980000	0.990000	141.000000
		Gray Leaf Spot	0.980000	0.990000	0.980000	214.000000
		Leaf Rot	0.990000	0.990000	0.990000	168.000000
		Stem Bleeding	1.000000	1.000000	1.000000	202.000000
4	ELU	Bud Root Dropping	1.000000	1.000000	1.000000	155.000000
		Bud Rot	1.000000	1.000000	1.000000	141.000000
		Gray Leaf Spot	1.000000	0.940000	0.970000	214.000000
		Leaf Rot	0.930000	0.990000	0.960000	168.000000
		Stem Bleeding	1.000000	1.000000	1.000000	202.000000

Fig.9 Densnet 201-Performance metrics

The models demonstrated strong performance, with certain combinations significantly reducing misclassifications. To assess model efficiency, we used metrics such as accuracy as shown in TABLE II, precision, recall, and F1-score. Notably, ResNet-50 with ReLU and EfficientNet-B0 with Leaky ReLU achieved the highest accuracies, offering valuable insights into how different models and activation functions affect the precision of disease classification.

In our coconut tree disease classification , Budroot drop, Gray leaf spot, and Stem bleeding were consistently classified with high accuracy across all models—ResNet-50, DenseNet201, and EfficientNet-B0—and activation functions like ReLU, Leaky ReLU, Swish, and ELU. This consistency demonstrates strong generalization across these disease categories, indicating that they are well-represented and easily distinguishable by the models regardless of the function or architecture used. For Bud rot, the ReLU activation function performed particularly well, delivering robust results across all architectures, as shown in Fig.3, which depicts the confusion matrix of DenseNet201 with ReLU. The ResNet-50 model, when paired with the Swish activation function, also demonstrated high accuracy in classifying several diseases, as shown in Fig.4. EfficientNet-B0 showed consistent performance with the Leaky ReLU activation function, as shown in Fig.5.

On the other hand, Leaf rot was best classified by DenseNet201 across all activation functions, showcasing the model's ability to capture complex patterns specific to this class. The EfficientNet-B0 architecture, utilizing the ELU activation function, exhibited robust results in detecting various diseases, as shown in Fig.6. Performance metrics for EfficientNet-B0, covering all activation functions, as shown in Fig.7. The overall performance of ResNet-50, highlighting its generalization capability across all disease categories, as shown in Fig.8. DenseNet201's performance metrics, reflecting its strength in distinguishing between different disease categories, especially Leaf rot, as shown in Fig. 9. These findings suggest that while some diseases are effectively classified across multiple models and functions, others, like Bud rot and Leaf rot, benefit from specific model-function pairings. The effectiveness of ReLU for Bud rot and DenseNet201's strength in detecting Leaf rot highlight the importance of selecting the right combinations to achieve optimal disease detection. This analysis provides deeper insights into how different models and functions contribute to classification accuracy.

Conclusion

ResNet-50 with the Swish activation function excels due to its smooth, non-monotone behavior, which, combined with ResNet-50's residual connections, ensures effective gradient flow and efficient learning across layers. This synergy allows the network to capture complex information and achieve an impressive accuracy of 99.85% in coconut disease classification. DenseNet-201 benefits from its dense connections, which facilitate feature reuse and mitigate gradient issues. However, the limitations of ReLU in very deep layers can slightly hinder performance, resulting in an accuracy of 99.77%. EfficientNet-B0, utilizing Leaky ReLU and ELU activation functions, leverages its efficient scaling along with these activation functions to maintain gradient flow and enhance convergence, also achieving an accuracy of 99.77%. Activation functions such as ReLU, Leaky ReLU, Swish, and ELU played crucial roles in model performance. ReLU's simplicity and effectiveness in avoiding vanishing gradients made it consistently effective. Leaky ReLU helps prevent "dying" neurons, optimizing learning. Swish's smooth behavior supports effective learning, while ELU accelerates convergence and maintains average activation close to zero.

Furthermore, careful dataset preprocessing reduced noise and highlighted important features, which improved model accuracy. The diversity and quality of the datasets contributed to the models' generalization capabilities, and meticulous hyperparameter tuning optimized the study design. This combination enabled the models to accurately detect coconut tree diseases.

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