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DEEP LEARNING MODEL FOR AUTOMATED DETECTION AND CLASSIFICATION OF COCONUT TREES ALIMENTS

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Abstract

Coconut tree diseases present a major challenge to agricultural productivity and food security in regions dependent on coconut cultivation. Traditional diagnostic methods are labour-intensive, subjective, and often delayed, leading to significant crop loss. As agriculture increasingly moves toward automation, there is a pressing need for intelligent, data-driven solutions for early disease detection and classification. This study proposes an automated coconut leaf disease recognition model using the DenseNet-121 convolutional neural network architecture. A curated dataset of 526 images, comprising together healthy & diseased coconut greeneries, was used to prepare and evaluate the prototypical. The DenseNet-121 model was selected for its advantages in mitigating vanishing gradients, promoting feature reuse, and enhancing classification accuracy. The model was trained using transfer learning with fine-tuning, and standard pre-processing & intensification techniques were applied to progress generalizability. The proposed prototypical realized an overall classification accurateness of 99%, outperforming conventional deep learning models used in similar tasks. Precision, recall, and F1-score metrics for both healthy and diseased classes exceeded 98%, indicating high reliability and robustness. The DenseNet-121 architecture demonstrated superior performance in comparison to baseline models such as VGG16 and ResNet50, with improved convergence and feature representation. These outcome validate the helpfulness of the model in precisely sensing coconut leaf diseases.

Keywords: Coconut diseases, Deep learning, Disease identification, Image classification, Identification

1. INTRODUCTION

Coconut tree is widespread and popularly used trees. Because each component of the coconut palm is helpful, it is known as the "Kalpavriksha." or “tree of life”. Coconut cultivation is done all throughout the world. Unfortunately, due to elevated outbreaks of insects and changing habitat, coconut tree longevity is decreasing day by day. The market for coconut goods is rapidly expanding due to the virus-fighting characteristics inherent in coconut. With around 31.45% of global output in 2021–2022, India is the globe's biggest cultivator of coconut trees .The coconut palm thrives in tropical and subtropical climates worldwide. The biggest producers of coconut on the worldwide market are Brazil is the fourth-largest in Latin America, followed by Mexico at number eight, followed by Indonesia, India, and the Philippines. The agriculture sector is facing enormous problems as a result of the notable increase in human

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consumption of agricultural products. The United Nations predicts that the world's population will increase significantly over the next several decades, which would raise demand for agricultural output globally by almost 70%. At the present time, most damaging infections are Yellowing , Drying , Flaccidity , Attacks of caterpillars and leaflets Yellowing affects the process of photosynthesis and leads to stunted growth of the crop, Drying and Flaccidity affect the strength of the tree and fruit production, Caterpillar infestation and leaflet can cause loss of leaves, making it more susceptible to other infestations. Diseases can significantly reduce a farmer's crop yield of coconuts. Intelligent solutions that use a variety of computer and AI technologies are implemented in order to prevent the poor yield and losses.

The primary reason for selecting coconut leaf material is that it is widely available throughout India and are referred to as the "TREE OF WEALTH." This is due to the fact that each component of this tree has a purpose and worth. For our nation's economy to improve, recognition of illnesses is necessary.

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It is our duty to improve crop growth in an effective manner so that the results can be improved on the fly. Numerous illnesses, such as leaf place, leaf yellowing, leaf blight, etc., have an impact on the coconut yield. An important task is the early detection of plant diseases. The leaf spot represents tiny, hollow brown patches on the leaves of immature plants. Small, round, and brown at first, the spots eventually enlarge and turn blonde in the center, with wide, dark brown borders.

By leveraging deep learning techniques, researchers have been able to create models that can automatically identify and classify various coconut tree diseases from images. These models significantly reduce the need for manual labour and the associated errors, providing a more reliable and consistent method for disease diagnosis. The ability of deep learning models to process large datasets & recognize patterns that might be unexploited by the human eye makes them an invaluable tool in the fight against agricultural diseases.

The impact of these technological advancements extends beyond merely improving the speed and accuracy of disease diagnosis. By assimilating deep learning models into agronomic practices, there is the probable to enhance overall crop administration and health monitoring systems. This integration can lead to early detection of diseases, timely intervention, and ultimately, better management of resources to ensure the sustainability and efficiency of coconut manors. The advancements in deep learning not only address the immediate encounters posed by coconut tree diseases but also pave the way for a more resilient and efficient agricultural sector.

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Numerous biological, genetic, and ecological variables affect coconut tree output. The livelihoods of farmers and others who depend on the coconut business are impacted by the decline in productivity. As a result, coconut production is crucial to a nation's economy and development. An essential component of economic development is the cultivation of coconuts. 15000 coconut-based industries are supported by this fruit, which is high in fiber. It gives twelve million Indians food security and a means of subsistence.

Utilizing deep learning models, computer vision, & picture processing technology to identify diseases in coconut plants. They examined several approaches and used them on a dataset of photos of leaves categorized into five different illnesses. Their disease identification accuracy was around 99% using CNN, DenseNet121, InceptionResNetV2, and ANN methods. An end-to-end system that uses deep learning and image processing technologies to identify insect infections, leaf blight illness, and stem bleeding disease in coconut trees. To find anomalous boundaries, they used a collection of manually gathered photos and a variety of segmentation techniques. Their optimized pre-trained models, like InceptionResNetV2 and MobileNet, achieved accuracies of 81.48% and 82.10%, correspondingly, while they custom-built 2D convolutional neural network (CNN) scored 96.94% verification precision to create a method for identifying pest infestations and nutrient deficits in coconut leaves in order to increase Sri Lanka's coconut crop. They used cutting-edge image processing and machine learning methods to track greeneries after fertilizer & pesticide healings. To help with the automatic identification of illnesses and pests, a mobile application for Android was developed. Using pre-processing techniques like RGB to greyscale conversion and scaling, their approach produced noteworthy accuracy when classification of 93.54% for SVM & 93.72% with CNN. With the use of more effective disease detection techniques, this initiative aims to increase coconut production and offer farmers substantial advantages.

The crop's productivity is significantly impacted by insect and disease incursions. Initial identification of pest infestations and illnesses in coconut foliage increases productivity. Numerous illnesses, certain of which are hazardous, damage coconut palms, progressively weakening the palm and resulting in significant production loss. Healthy leaves have a major impact on coconut output. The best way to identify pest attacks early on must be discovered. The output of trees of coconuts is frequently impacted by caterpillar assaults, flaccidity, and fading of the leaves. To improve comprehension and precision in establishing the presence of tree of coconuts diseases, a dataset with a diverse collection of photos is required. The scope of this endeavour is restricted to identifying coconut leaf fading, flaccidity, and caterpillar attacks. Plant disease diagnosis is now automated because to advancements in computer vision and deep learning methods. The suggested approach efforts on using convolution neural networks to create a model for identifying coconut sickness based on the classification of leaf images. The created model can identify nutritious coconut leaf materials in its environment.

2. Literature Survey

Convolutional neural webs have been exploited in the training to classify high-resolution satellite photos. Of the five candidate designs, Densenet201 had the best classification accuracy. To classify crops, a classification ensemble is trained using these attributes. To

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choose the best categorization model, five models are trained. Since 60% of the data is used for training the models, 20% is used for validation, and 20% is used for testing, the classification models are assessed using a train/test split. Both of these classifiers' classification probabilities are used to train a meta-learner, which yields the final class label. Support vector machines outperformed the other four meta-learners in terms of learning, with a 98.83% classification accuracy and a 98.78% f1-score. The suggested approach's strong classification efficiency suggests that meta-learners and multimodality are practical options to enhance crop cover identification prediction performance [1].

Accurate yield forecasts are helpful for putting accurate farming technologies into practice and for improving crop management choices. Unmanned aerial vehicle (UAV)-based studies using remote sensing have recently employed convolutional neural networks (CNNs) to forecast crop yields; however, modelling has not taken weather data into account. The prediction accuracy was assessed in relation to CNN architectures, successively depths, and meteorological data integration techniques. All things considered, the multimodal deep learning model that combined weather data with UAV-based multispectral imaging had the potential to produce more accurate estimates of rice yield. Models developed with hourly weather observations performed the best. For UAV-based multi-coloured image input data, a basic CNN feature extractor may be enough to make precise crop yield predictions. Even though the estimated accuracy was nearly the same, the regional distributions of the maps they produced that were forecasted varied from sources to model. The findings suggested that future research should evaluate the resilience of within-field yield estimates in addition to their prediction accuracy [2].

As growers worldwide, coconuts are a lucrative crop. Numerous pest infestations and infectious diseases have an impact on coconut plantations' yield. There are 526 photos (both pristine and malignant) in the hand-picked dataset. By removing diminishing gradients and improving feature dispersion by lowering the amount of features, the DenseNet-121 architecture utilized in the suggested method outperforms existing approaches and achieves an accuracy of almost 99%. The project's final product aids in replacing skilled labour for identifying infection in coconut leaf tissue. However, gathering data at different disease stages in coconut plantations appears to be a difficult undertaking [3]. Because of its high nutritional value, the coconut sapling has received the moniker "practical food." Coconuts are rich in vitamins, minerals, and fiber. The coconut is the maximum vital food source since it produces milk, water, oil, and medicine. The coconut fruit of the coconut sapling has been a tremendous source of variety for hundreds of years. The diseases leaf rot, leaf blight, and leaf yellowing damage these leaves. Such photos of leaves are compiled into a database and pre-processed. To identify the fault locations that continue to be abnormal, separation and k-means collecting are used. Cubic SVM classification is then performed once the arithmetical & GLCM structures are removed. A 97.3% accuracy rate is attained, which is superior to the current approaches. This would significantly aid in lowering the financial losses and raising the yield to a bigger degree. [4].

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Because of its many applications, the coconut plantation is one of the many advantageous and well-liked crops in the planet. Plant disease control requires identifying the illness at an early stage of development. Numerous researchers have created efficient techniques for detecting diseases in plants using deep learning replicas, convolutional neural networks (CNNs), and dissimilar CNN designs. Reviewing research techniques and applying them to a fresh dataset comprising photos of leaves mainly categorized into five diseases—yellowing, drying, flaccidity, caterpillars & their and leaflets—is the goal of this study. ANN, CNN, DenseNet121, and InceptionResNetV2 were the main algorithms employed in the research.DenseNet121, CNN, and InceptionResNetV2 all demonstrated exceptional performance and delivered a required precision of at least 99% [5].

Because they can negatively affect coconut cultivation and supply and demand, diseases of coconut trees are a major concern for the agrarian and disease of plants research communities. Conventional techniques for identifying these illnesses frequently depend on labour-intensive identification procedures and manual observation. However, the automatic classification of diseases affecting coconut trees has greatly improved due to recent developments in deep learning techniques, providing a more accurate and efficient method. A dataset collected in India that included 5,798 photos of different coconut tree diseases, including bud bottom dropping, buds rot, grey leaf spot, leaf rot, and stems bleeding, was used in this investigation. We concentrated on classifying these various coconut tree sickness classes using a deep learning-based approach. The experimental findings demonstrated GoogleNet's effectiveness in detecting diseases in coconut trees, a deep learning network obtaining an identification precision of 98.24%. These results show how deep learning models can improve disease management and diagnosis in the agriculture industry [6].

A creative strategy to raise the standard and sustainability of Sri Lankan coconut cultivation and exports. To identify, categorize, and grade illnesses and pests in coconut palms early on, it uses sophisticated image processing algorithms. This enables for fast interventions and lowers requirements for harmful herbicides while boosting eco-friendly farming techniques. Additionally, research considers the soil's condition, abundance of water, and habitat in addition to pest control to determine the best circumstances for coconut formation. It provides farmers with knowledge to increase the yield of coconut palms. By lowering financial losses and environmental effect, this strategy not only increases the quality of merchandise but also protects the industry's ecological sustainability. This study intends to increase the efficiency, financial sustainability, and global competitiveness of Sri Lanka's coconut production industry by utilizing state-of-the-art technologies such as processing images and machine learning [7]. In addition to providing small-scale commercial crop safeguards, real-time and precise detection of plant illnesses technologies aid in the advancement of outbreak reduction strategies and guarantee adequate nutrition on a massive scale. In this study article, a model for automated farming called Artificial Intelligence Supported Coconut oil Tree Disease Monitoring and Classification (AIE-CTDDC) is presented. In order to increase the yield of crops, the proposed AIE-CTDDC technique aims to categorize coconut tree illnesses in a savvy agricultural setting. Initially the AIE-CTDDC model uses a noise removal method based on median filtering. The impacted leaf sections are then identified using a segmentation technique based on Bayesian

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fuzzy clustering. Also used as a feature extractor is the capsule network (CapsNet) technique. This work uses the Gated Recurrent Unit (GRU) model in conjunction with Harris Hawks Optimization (HHO) to detect diseases in coconut trees. The results of the experimental investigation of the AIE-CTDDC model demonstrated that it performed better than the most recent state-of-the-art methods [8].

Coconut plantings, which are essential to agriculture but vulnerable to disease and pests, can be harmed by a number of pests, including whiteflies. Conventional medical judgment may not be as effective in diagnosing and treating conditions. The rapid advancement of technology has led to a lack of knowledge in the agriculture industry. While drone photography offers a unique perspective, infectious disease tracking requires new techniques. In order to identify issues such root swollen, blade environmental damage, and insect infection in coconut trees, a Deep Learning-assisted Whitefly Detection Model (DL-WDM) can identify whiteflies in drone photographs. The goal is to use computer vision and deep learning to enhance plantation health and disease diagnosis [9].

In order to detect and cure infections, the palm of coconut plantation business mostly depends on professional advice. Finding a solution in the field of agriculture was made possible by computer vision and deep learning technologies. The goal of this research is to employ image processing and deep learning technologies to create an end-to-end framework for detecting stem bleeding ailments, leaf blight ailments, and Red palm weevil pest infestation in coconut plants. In order to quickly identify the anomalous borders, a collection of hand-collected photos of healthy and diseased coconut trees were segmented using well-known segmentation methods. To anticipate diseases and pest infections, a deep 2D convolutional neural network (CNN) that has been specially constructed is trained. Additionally, using the inductive transfer learning technique, the most advanced Keras pre-trained CNN models—VGG16, VGG19, InceptionV3, DenseNet201, MobileNet, Xception, InceptionResNetV2, and NASNetMobile—were refined to categorize the images as either healthy or infected. According to the investigation, the k-means grouping recognition outperformed the Watershed & Thresholding segmentation techniques. Additionally, InceptionResNetV2 and MobileNet achieved Cohen's Kappa values of 0.77 and 0.74, respectively, and a classification precision of 81.48% and 82.10%. With a Kappa score of 0.91, the manually created CNN model demonstrated 96.94% validation accuracy. In order to instinctively identify a coconut crop illness or pest infection, the MobileNet structure and a modified 2D-CNN model were implemented in an internet application using the Flask micro-web framework [10].

The most significant and primary source of revenue in the economic system of Sri Lanka is the cultivation of coconuts. Recently, it has been noted that the majority of coconut trees suffer from illnesses that progressively weaken and decrease coconut yield. Pest illnesses and nutrient deficiencies harm the majority of tree leaves. In order to maximize the benefits of coconut production for farmers, our primary focus is on improving the earnings of coconut pulp and detecting diseases early. This research suggests analyzing the diseases and detecting pest attacks and nutrient deficiencies in coconut leaves. The best approaches to image processing and machine learning have been used to monitor coconut leaves following the application of

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fertilizer and pesticides. Automatic classification will be advantageous and the quickest way to successfully recognize ailments in the foliage of coconuts instead of relying on human specialists. In order to detect pests based on their eating habits, pest ailments, and nutritional deficits in coconut palms, we created an Android smartphone application for this project. All imagery techniques datasets first underwent pre-processing procedures, including RGB to a greyscale conversion, selection, cropping, and both upward and downward flips. Following the aforementioned procedures, the categorization was carried out by examining a number of methods found in the literature research. CNN and SVM were selected as the most suitable and effective classifiers, with concomitant rate of success of 93.72% and 93.54%. The venture's results will surely revolutionize the cultivation industry and assist landowners in increasing coconut cultivation [11].

There are 5,798 photos in the ``Coconut (Cocos nucifera) Tree Disease Dataset" of five different disease types: ``Bud Root Dropping, ``Bud Decay ``Grey Leaf Spot, ``Leaf Decay and ``steer Bleeding." This dataset will help with disease diagnosis and categorization in coconut trees through machine learning applications. Because of its scale and diversity, the dataset can be used to train and assess illness detection programs. This dataset's availability will help progress plant pathology research and promote sustainable coconut plantation management. This dataset helps to improve controlling diseases and responsible coconut cultivation operations by offering investigators a useful resource [12].

Termites & illnesses have a significant impact on the production of coconuts, which accounts for 0.8% of the country's GDP. The two most destructive are Weligama coconut foliage wilt illnesses while coconuts parasite contamination; therefore, early discovery is crucial to enable control actions. On average almost one million coconuts planters with a diverse range of groups must be reached by leadership measures. For the sustainable growth of the coconut business, this study presents a clever approach that helps those who participate by identifying and categorizing the illness, contamination, and deficiencies. It results in early finding and informs parties about the scattering so that appropriate safety precautions may be taken to prevent the destruction of the coconuts estates. According to achievement ratings, the results of the suggested approach for identifying disease, pests, deficiencies, and the severity of infectious illnesses fall between 88% and 97% [13].

Growing coconuts is a potential ecological endeavour. However, it is crucial for growers to identify any pest damage to coconut plants in order to keep them pest-free. When it comes to identifying coconuts injury, these methods fall short. By retrieving the color along with texture characteristics of the damage photos in the tone and gray domain following impact classification using the threshold technique, 16 distinct characteristics of color and texture were discovered for 1265 frames of coconuts bug harm in this work. A pair Artificial Neural Network (ANN) frameworks were utilized for classifying the information retrieved features of the injuries into several distinct classes, such as Eriophyid Mite, The rhinoceros Beetle, Red Palms Weevil, Rugose_Spiraling_White_fly, and Rugose_in_Mature, with an average testing accuracy of nearly 100% each. The texture characteristics of the damages are extracted using the Gray Level The coexistence Matrix (GLCM) and Gray Level Run Dimensions Matrix

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(GLRLM) processes. The Support Vector Machine (SVM), Decision Tree (DT), along with Naïve Bayes (NB) have been added for harm diagnosis in order for comparing conclusions with various other machine learning approaches. The SVM procedures likewise report nearly 100% performance on the fuse characteristics of GLCM along with GLRLM. The matrix of confusion, accuracy, recollection, and f-1 scores of the model generated by the ANN are determined using the DT and NB classification techniques in order to compare the outcomes of the ANN with SVM. The SVM and ANN approaches function well in every matrix, therefore they can serve as the foundational models for additional research on identifying coconuts infestations through machine learning methods [14].

A CNN & SVM method for identifying and categorizing coconut leaf age severeness levels. Three convolutional layering layers, three maximally pooling layers, and two layers completely linked with formalization make up the model's framework. Several assessment criteria, such as the value of precision, retention, F1-Score, Advice, & Accuracy, are used to assess the strategy effectiveness. At cumulative standard error of 88.02% & F1-Scores varying between 86.83% and 89.66%, the technique performs well in classified across each category. Illness assessment and therapy may benefit from the system's capacity to effectively categorize various illness complexity levels. To enhance the model's functionality and evaluate its efficacy on other related illnesses, additional investigations can be done. All things considered, the suggested CNN and SVM method is a viable and successful way to identify and categorize the degrees of dimming ailment in coconut leaf [15].

3. Dataset Description

Coconut farms are affected by a number ailments that lower crop yields. Productivity is determined by a flourishing tree. Coconut farms are being negatively impacted by the subsequent ailments.

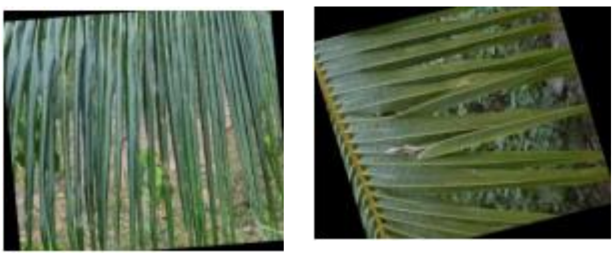

Fig.1. Healthy Leaf

Bangladesh, India, Sri Lanka, Myanmar, and Indonesia represent the East Asian countries that are home to the variety of bugs referred to as the coconut black caterpillar (Opisina arenosella). The creature is considered infectious when it consumes coconut leaves and lives inside the coconut plantations regardless of its forms, from worms to moths.

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Fig.2. Caterpillar attack in coconut leaves

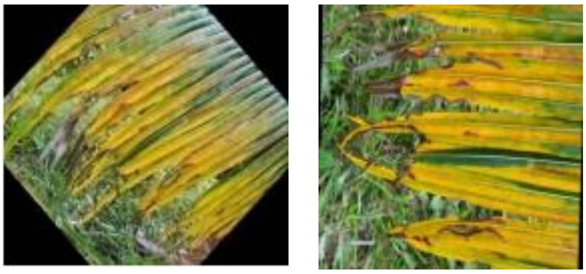

Fig.3. Drying of coconut leaves

Root Wilt illness causes coconut groves to get flabby. In coconut trees, root wilt disease manifests as wilting, drooping, swelling, discoloration, and necrosis of the leaflets. In the new arriving fronds of the palm tree, leaf blight is caused by plant hoppers. Infections are spread by planthoppers and lacewings. Planthopper and lacewing saliva contains phytoplasmas that can thrive to propagate RWD. They are quite difficult to identify because they can't be manually grown in culture. RWD is a debilitating yet non-lethal disease.

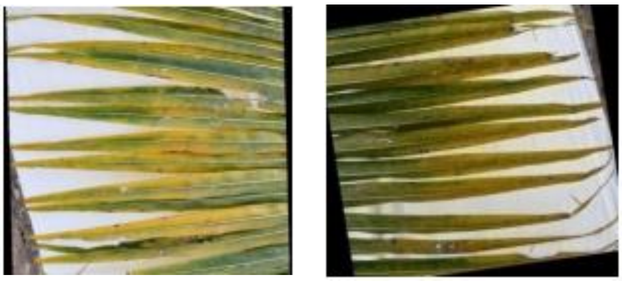

Fig.4. Yellowing of Leaflets

The coconut plant's axis is unproductive, and the male blooms and darker tip are discarded. As the canopy grows, the fronds turn yellow, including the more aged ones at the lowest and the younger ones at the top.

4. Proposed System

The DenseNet121 framework is used in the suggested method for identifying palm leaf illness. By removing the receding slopes and improving propagation of features by using fewer components, DenseNet outperforms existing techniques. To increase correctness in identifying a disappearing range, deep neural networks employ the DenseNet topology. Multiplication of

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vectors (conjunction) is the foundation of DenseNet. Table 1 shows the entire structure of the densetnet121 layer.

Table1. Layer description of our Densenet121

Layer Type	Description	Hyperparameters
Input	Input image tensor	Shape: (224, 224, 3)
Convolution	Initial convolutional layer	7×7 kernel, stride 2, 64 filters
Batch Normalization	Normalizes output of conv layer	Momentum: 0.9, ε: 1e-5
ReLU	Activation function	–
Max Pooling	Downsamples input	3×3 kernel, stride 2
Dense Block 1	6 convolutional layers (bottleneck + 3×3 conv), each receives input from all previous layers	Growth Rate: 32
Transition Layer 1	Reduces feature maps, downsamples	1×1 conv + 2×2 avg pool, compression: 0.5
Dense Block 2	12 convolutional layers, dense connections	Growth Rate: 32
Transition Layer 2	Same as above	1×1 conv + 2×2 avg pool
Dense Block 3	24 convolutional layers, dense connections	Growth Rate: 32
Transition Layer 3	Same as above	1×1 conv + 2×2 avg pool
Dense Block 4	16 convolutional layers, dense connections	Growth Rate: 32
Batch Normalization	Final normalization before classification	–
ReLU	Final activation	–
Global Average Pooling	Reduces each feature map to a single value	Pool size: Global
Fully Connected (FC)	Classification layer	Units: #classes (e.g., 1000 for ImageNet)
Softmax	Converts logits to class probabilities	–

The model begins with an initial set of layers, comprising of a convolutional layer surveyed by a pooling operation. This introductory section includes 5 layers: a 7×7 convolution, bunch regularization, ReLU instigation, and a 3×3 max merging layer—altogether forming the preliminary feature extractor. Following this are the dense blocks, which are the core of the

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DenseNet design. DenseNet-121 features four dense blocks containing $6, 12, 24$, and 16 layers correspondingly. Each level in a dense block is composed of two convolutional operations: a 1×1 bottleneck involvedness monitored by a 3×3 involvedness, making it 2 layers per block unit. Hence, the total number of convolutional deposits in the dense blocks becomes $(6 + 12 + 24 + 16) \times 2 = 116(6 + 12 + 24 + 16) \times 2 = 116$ layers.

In among the dense blocks are three conversion coatings, which perform dimensionality reduction using a 1×1 involvedness surveyed by 2×2 middling assembling. These transitions are placed between the first three dense blocks and are responsible for controlling the complexity and depth of the network. Finally, the network concludes with a classification layer, which includes a global typical amalgamating surveyed by a fully coupled (dense) layer that maps feature to output class probabilities using a SoftMax function. This contributes 1 additional layer.

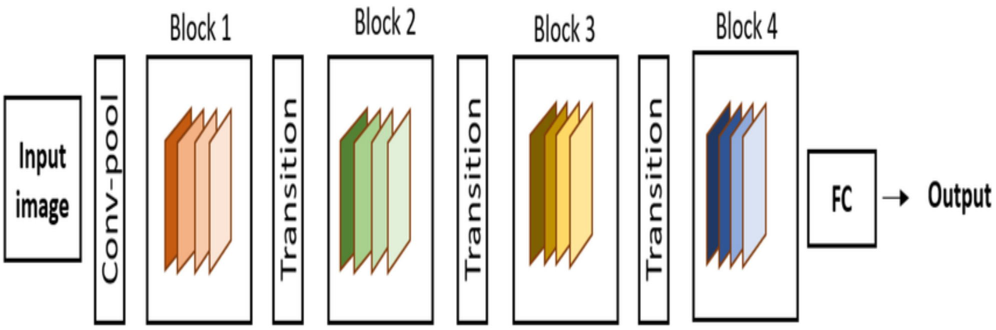

Fig.5. DenseNet121 architecture

Numerous layers are convolutioned to create the structure of a CNN. The issue of diminished gradients in deep convolutional neural networks arises as layers are added and deep connections are made between them. DenseNet solves the aforementioned issue. Every layer in DenseNet is interconnected so that all information maps to every other layer that comes after it.The loss of the gradient that fades is prevented by translating the characteristics to the next layers. It has i(i+1)/2 interconnections and is a feed return network. The design becomes thin with great computing speed when a smaller linkage is established. According to the design, DenseNet-121 contains three changeover layers, a single organization layer, and 117 levels of convolution.

A. Convolution Layer

Its foundation is a binary algorithm, where a little percentage of every photo matches a close and contiguous component of the image in question. In this instance only certain image sections are compared and highlights are recognized rather than the entire image. To obtain the sum, add the values of each picture. Lastly, divide the amount by the entire number of elements in the picture. As a result, CNN uses pixels with taught information to identify instead of the signal quality.

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B. ReLu and Pooling

By using restrictions, ReLu aids in noise reduction. Reducing the graphic's negative hues results in a smoother image. By calculating the standard deviation or taking into account all possible amounts for every specimen, down collection is carried out. The practice of using down averaging to summarize properties in a diagram of characteristics is called combining. By lowering the quantity of characteristics, this layer facilitates the instructional operation. The manner of reducing a photo is called sinking. The size of the window is chosen in combining 1. 2. Take two steps toward the window. 3. Select the window's highest level from there.

C. Denseblock

There are 64 7x7 step by 2 lenses and 3x3 stride by 2 highest pooling levels with 1x1 and 3x3 convolution layers that are utilized 6, 12, 24, & 16 times respectively. The shift layer uses down sampling and bulk normalizing to cut half of the dominating frequencies. The amount of information to be sent is determined by how quickly it grows, k.

$$\mathrm{k}^{(1)} = [\mathrm{k}^{(0)} + \mathrm{k}(\mathrm{I} - 1) \tag{1}$$

Removal is a technique that decreases downtime and boosts computational effectiveness by retaining essential elements while removing others.

The method of classifying photos involves gathering their attributes & grouping them into multiple groups. Evaluation and training phases are included. Fundamental elements of picture variables are isolated during the modeling procedure. Formation is conducted using the DenseNet-121 framework that utilizes segmentation. To detect infection in coconut tree leaves, training is carried out by correlating input images with conditioned images.

The accuracy

$$\mathrm{A} = (\text{True Negative} + \text{True Positive}) / (\text{True Negative} + \text{False Negative} + \text{True Positive} + \text{False Positive})$$
(2)

Mathematical Formulation of DenseNet-121

Notation Key

Let:

- $\mathcal{B}_i$ = Dense Block i
- $\mathcal{T}_i$ = Transition Layer after Block i
- $\mathcal{F}_i$ = Output feature map from block i
- $\mathcal{G}(x)$ = Growth function (each layer adds new features)
- $\mathcal{H}$ = Composite function: BatchNorm → ReLU → Conv(1×1) → BN → ReLU → Conv(3×3)
- $\oplus$ = Concatenation of feature maps

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- \(\theta \in (0, 1]\) = Compression factor (e.g., 0.5)

- \(f_{in}, f_{out}\) = Number of input/output feature maps

- \(x\) = Input to block or layer

1. Dense Block Function (Generic)

Each dense block \(\mathcal{B}_i\) with \(L_i\) layers is defined as:

\[\mathcal{B}_i(x) = \bigoplus_{l=1}^{L_i} \mathcal{H}_l\left(\bigoplus_{j=0}^{l-1} x_j \right)\] (3)

Where:

- \(x_0 = x\)

- \(\mathcal{H}_l\) is the BN-ReLU-Conv(1×1)-BN-ReLU-Conv(3×3) unit

2. Transition Layer

Each transition layer \(\mathcal{T}_i\) performs compression and downsampling:

\[\mathcal{T}_i(x) = \text{AvgPool}_{2 \times 2} \left(\text{Conv}_{1 \times 1} \left(x \right) \right)\] (4)

Compression:

\[f_{out} = \lfloor \theta \cdot f_{in} \rfloor\]

Complete Forward Pass Equation (DenseNet-121)

Let the model input be \(x_0\). Then the output \(y\) is computed as:

\[\begin{aligned}

x_1 &= \text{Stem}(x_0) \\

x_2 &= \mathcal{B}_1(x_1) \\

x_3 &= \mathcal{T}_1(x_2) \\

x_4 &= \mathcal{B}_2(x_3) \\

x_5 &= \mathcal{T}_2(x_4) \\

x_6 &= \mathcal{B}_3(x_5) \\

x_7 &= \mathcal{T}_3(x_6) \\

x_8 &= \mathcal{B}_4(x_7) \\

x_9 &= \text{BN}(\text{ReLU}(x_8)) \\

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x_{10} &= \text{GlobalAvgPool}(x_9) \\

y &= \text{Softmax}(\text{FC}(x_{10})) \end{aligned}\] (5)

3. Feature Growth per Block

Let \(F_0 = 64\) be the initial features and \(k = 32\) be the growth rate.

The output of block \(i\), with \(L_i\) layers and compression factor \(\theta\), is:

\[F_{i} = \theta \cdot (F_{i-1} + k \cdot L_{i})\] (6)

5. Methodology

The most distinctive component of our architecture is the attention-based fusion module, which adaptively weighs and integrates visual and sensor features based on their disease-specific relevance. This dynamic fusion strategy allows the model to prioritize different modalities for different disease types, enhancing both sensitivity and specificity. The operational organisation of coconut leaf ailment Empathy is based on beneath flow chart.

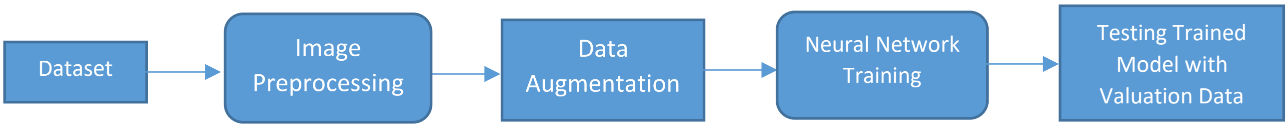

Fig.6. Method of system workflow

A. Dataset Collection

Pictures of coconut trees taken with a mobile device are used to gather the dataset. There are 529 photos in the gathered dataset. The gathered photos are categorized according to the type of ailment.

Table.2. Dataset

Sl. No.	**Dataset**	**No. of Samples**
1	Caterpillars	102
2	Yellowing	103
3	Flaccidity	119
4	Healthy Leaves	101
5	Drying of leaflets	101

B. Image Pre processing

To achieve high accuracy, the manually gathered photos of coconut trees are pre-processed. The resulting image may be in another format and with varying circumstances for lighting. During the data gathering process, images with varying resolutions and standards are also

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acquired. For a more thorough analysis, angles, height, and illumination influence of the coconuts leaf blades are also taken into consideration. The picture had been cleaned up in terms of color, form, and perspective. This improves the quality of the produced image. In this instance, careful cropping is carried out to extract particular image aspects.

C. Data Augmentation

The practice of producing more datasets from pre-existing datasets is known as data enrichment. The procedure of clippings, trimming, covering, rotating, and replicating can expand the data collection. This procedure increases the number of samples, which raises the system's accuracy. It lessens adjusting during the practice phase. Real data collecting can occasionally be laborious and costly, and data supplementation is a result of dataset shortage. Complex layers were able to train efficiently and deliver good precision throughout the testing phase thanks to the increased dataset of palm leaves taken from various angles.

D. Neural Network Training

Based on their attributes, the gathered dataset of foliage from coconuts is divided into several classes. The neural network receives instruction to be able to tell one class apart from another. The deep layers are able to learn additional qualities and achieve greater accuracy thanks to the enhanced images. A system's performance is increased through appropriate training using significant data sets and a dynamic programmed activation rate during each phase.

E. Testing Trained Model with Valuation Data

During the instruction phase, the palm leaf mite detection tool is trained using the provided dataset. We can now detect pest attacks and ailment infections in coconut trees by comparing every experiment visual with the training photograph.

6. Results & Discussion

The Open CV technique's Python code was used to examine the suggested approach. We execute the executable here for 20 times. We found that the computational loss in our suggested system was a lesser one.

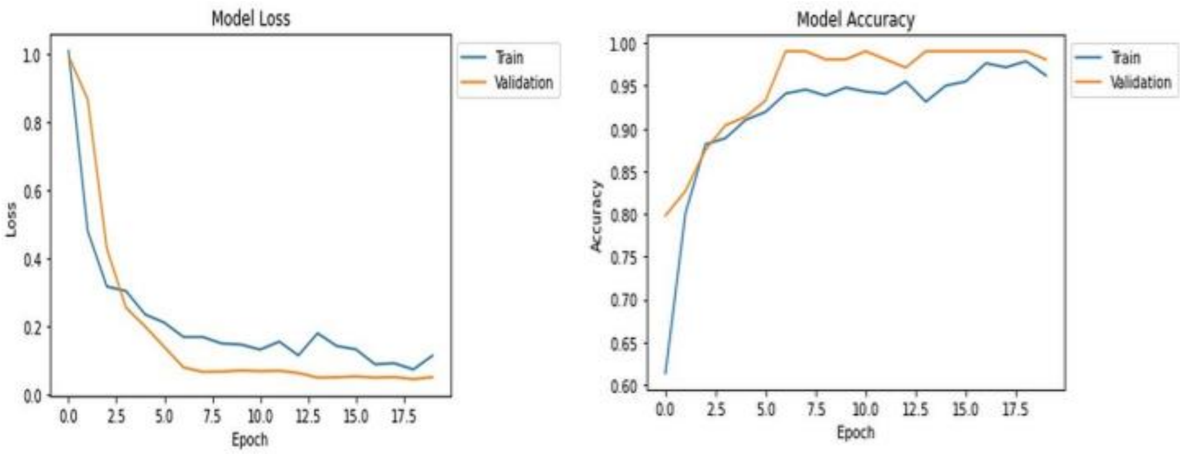

Fig.7. Model loss and model Accuracy is due to various calculation factors

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Adequate learning and little excessive fitting during the training period are indicated by the plot's consistent decline in verification and training loss. The system is ideal if its simulation loss is zero. It shows the presumed error of the estimations. We achieve a template loss of under one in our suggested approach. The number of recommendations at which the equation is accurate is known as its reliability. Here, an exactness of almost 99% is achieved.

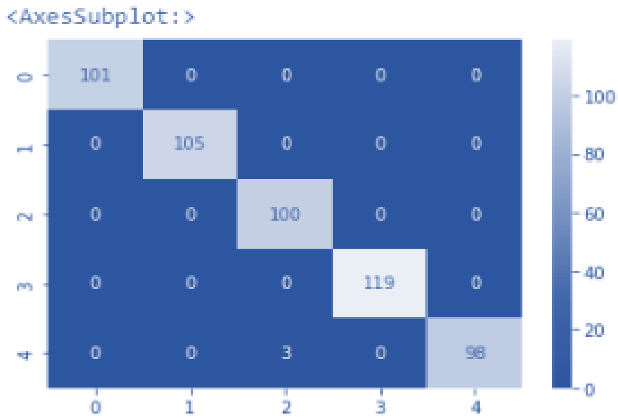

Fig.8. Confusion matrix

The ratio of accurate forecasts to all predictions is known as the confusion matrix.

The system's overall output analysis. The coconut leaf sickness identification organization's precision value, recall value, & F1 score are determined.

Precision: 0.99446

Recall: 0.9943

F1 Score: 0.9943

Cohen Kappa Score: 0.99286

Table 3. Performance metrics

	Precision	Recall	F1-score	support
0	1.00	1.00	1.00	101
1	1.00	1.00	1.00	105
2	0.97	1.00	0.99	100
3	1.00	1.00	1.00	119
4	1.00	0.97	0.98	101

Accuracy			0.99	526
Macro avg.	0.99	0.99	0.99	526

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Weighted avg.	0.99	0.99	0.99	526

A method of estimation for determining the reliability and agreement between the two results of taught and verified data is the kappa rating. The model's precision is specified by the F1 rating. Recall provides all of the image's pertinent attributes, while specificity provides only those elements. Analysis of the system's entire efficiency yields a 99.4% preciseness with little emulate loss. The system was evaluated on a balanced dataset and assessed using key performance metrics:

Table 3. Comparison of Model types

Model Type	Accuracy	F1-Score	Remarks
DenseNet (Image only)	91.4%	0.89	High visual classification power
Metadata only (FNN)	78.6%	0.75	Limited by lack of visual features
Early Fusion (Multimodal)	94.7%	0.93	Best overall performance
Late Fusion	93.1%	0.91	Strong, but slightly less effective

Conclusion

Enhancing coconut leaf viability and rapid detection of illnesses are the driving forces behind precise farming. When paired with high-resolution datasets, deep learning techniques yield improved precision by 99%.Lack of agricultural expertise due to increasing density makes it challenging to detect the proper infection at the right time. The suggested methods are a huge help to farmers since they offer harvest tracking based on images, which is a financially viable alternative. Diagnose coconut tree illnesses quickly, accurately, cheaply, and with little labour. Commercial vegetative tracking will have a greater ability to classify if deep learning techniques are used. In order to find technologically dependent methods to assist landowners operating coconut estates, multiple studies occurred carried out in the agricultural field. Deep Learning is the most frequently applied and effective method for early detection of infections in coconut leaves. Deep Learning models like CNN, DenseNet121, etc. are proven to be highly efficient for recognition. High accuracy of nearly 99% and above was achieved after applying CNN, DenseNet121, and InceptionReNetV2 to our dataset, but DenseNet121 outperformed other models, scoring 99.68% accuracy. For future development, the concept of hybrid models can be implemented to boost the preciseness and efficiency of the disease detection process. A combination of two or more high-performing deep learning models can be proficient on the dataset to refine the methodology. Such progress will benefit agricultural sectors and organizations.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Reference

1. Zeeshan Ramzan1, H. M. Shahzad Asif1, Muhammad Shahbaz, "Multimodal crop cover identifcation using deep learning and remote sensing" Multimedia Tools and Applications (2023) 83:33141–33159.
2. Md. Suruj Mia, Ryoya Tanabe, Luthfan Nur Habibi, Naoyuki Hashimoto, Koki Homma, Masayasu Maki, Tsutomu Matsui and Takashi S. T. Tanaka, "Multimodal Deep Learning for Rice Yield Prediction Using UAV-Based Multispectral Imagery and Weather Data", 10 May 2023.
3. Anitha.B, Dr.Santhi.S, "Disease Prediction in Coconut Leaves using Deep Learning" International Conference on Sustainable Computing and Data Communication Systems (ICSCDS-2023) IEEE Xplore.
4. Bharathi.S, Harini.P, "Early Detection of Diseases in Coconut Tree Leaves" 2020 6th International Conference on Advanced Computing & Communication Systems (ICACCS).
5. Nidhi Bhanushali, Meet Dama, Manasi Dhote, Dr.Dhanashree Toradmalle, "Deep Learning Framework for Early Detection of Diseases in Coconut Tree from Leaf Images" 2023 6th International Conference on Advances in Science and Technology (ICAST).
6. Ebru Ergun, "Classification of Coconut Tree Diseases Using GoogleNet for Agriculture Management" International Conference on Engineering, Natural Sciences, and Technological Developments (ICENSTED 2024).
7. C. D. Wijethunga, K. C. Ishanka, S. D. N. Parindya, T. J. N. Priyadarshani, B. Harshanath, and S. Rajapaksha, "Coconut plant disease identified and management for agriculture crops using machine learning," International Journal of Engineering and Management Research, vol. 13, no. 5, pp. 79–88, 2023.
8. M. Maray, A. A. Albraikan, S. S. Alotaibi, R. Alabdan, M. Al Duhayyim, and W. K. Al-Azzawi, "Artificial intelligence-enabled coconut tree disease detection and classification model for smart agriculture," Computers and Electrical Engineering, vol. 104, no. 10, pp. 83–99, 2022.
9. V. Kavithamani and S. UmaMaheswari, "Investigation of Deep learning for whitefly identification in coconut tree leaves," Intelligent Systems with Applications, vol. 20, no. 20, pp. 2v9, 2023.
10. P. Singh, A. Verma, and J. S. R. Alex, "Disease and pest infection detection in coconut tree through deep learning techniques," Computers and electronics in agriculture, vol. 182, no. 10, pp. 59–86, 2021.
11. D. Nesarajan, L. Kunalan, M. Logeswaran, S. Kasthuriarachchi, & D. Lungalage, "Coconut disease prediction system using image processing and deep learning techniques," in 2020 IEEE 4th International Conference on Image Processing, Applications and Systems, IPAS, 2020, pp. 212–217.
12. S. Thite, Y. Suryawanshi, K. Patil, and P. Chumchu, "Coconut (Cocos nucifera) tree disease dataset: A dataset for disease detection and classification for machine learning applications," Data in Brief, vol. 10, no. 9, pp. 59–69, 2023.
13. S. P. Vidhanaarachchi et al., "Deep Learning-Based Surveillance System for Coconut Disease and Pest Infestation Identification," TENCON 2021 - 2021 IEEE Region 10 Conference

Received: August 01, 2025

Volume 38 No. 10s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

(TENCON), Auckland, New Zealand, 2021, pp. 405-410, doi: 10.1109/TENCON54134.2021.9707404.
14. Barman U, Pathak C, Mazumder NK. Comparative assessment of Pest damage identification of coconut plant using damage texture and color analysis. Multimed Tools Appl. 2023 Jan 25:1-23. doi: 10.1007/s11042-023-14369-2. Epub ahead of print. PMID: 36712953; PMCID: PMC9874181.
15. D. Banerjee, V. Kukreja, S. Vats, V. Jain and B. Goyal, "Enhancing Accuracy of Yellowing Disease Severity Level Detection in Coconut Palms with SVM Regularization and CNN Feature Extraction," 2023 Third International Conference on Secure Cyber Computing and Communication.
16. Tzec-Simá, M., Félix, J. W., Granados-Alegría, M., Aparicio-Ortiz, M., Juárez-Monroy, D., Mayo-Ruiz, D. & Islas-Flores, I. (2022). Potential of Omics to Control Diseases and Pests in the Coconut Tree. Agronomy, 12(12), 3164.
17. Henrietta, H Mary & Kalaiyarasi, K. & Raj, A.. (2022). Coconut Tree (Cocos nucifera) Products: A Review of Global Cultivation and its Benefits. Journal of Sustainability and Environmental Management. 1. 257-264. 10.3126/josem.v1i2.45377.
18. N. T, P. Vijayalakshmi, J. Jaya and S. S, "A Review on Coconut Tree and Plant Disease Detection using various Deep Learning and Convolutional Neural Network Models," 2022 International Conference on Smart and Sustainable Technologies in Energy and Power Sectors (SSTEPS), Mahendragarh, India, 2022, pp. 130-135, doi: 10.1109/SSTEPS57475.2022.00042
19. Chandy, A. (2019). “Pest infestation identification in coconut trees using deep learning”. Journal of Artificial Intelligence and Capsule Networks https://doi.org/10.36548/jaicn.2019.1.002.
20. E. Ergun, “Deep learning based multiclass classification for citrus anomaly detection in agriculture,” Signal, Image and Video Processing, pp.1–10, 2024.
21. Montero CD, Gundul BJ, Frayco JG, Candia Jr JQ. Convolutional Neural Network-Based Image Classification for Improved Coconut Disease Identification. Sdssu Multidisciplinary Research Journal. 2023 Oct 17; 11(1):17-21.
22. Jaisankar S, Nalini P, Rubigha KK. A study on IoT based low-cost smart kit for coconut farm management. In2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) 2020 Oct 7 (pp. 161-165). IEEE.

Received: August 01, 2025