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KENDUR REGION COCONUT DISEASE CLASSIFICATION: A COMPARATIVE ANALYSIS WITH DEEP LEARNING AND TRANSFER LEARNING MODELS

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Abstract

Several diseases threaten the coconut sector by impacting the well-being and production of coconut trees. This affects the quality and sustainability of coconut cultivation in India. It is vital to promptly and precisely identify diseases to implement practical management approaches. In this study, we used an unbalanced coconut tree disease dataset from Mendley and applied data augmentation techniques to minimize the imbalance and improve the model's robustness. To classify the diseases accurately, we explored, customized, and trained five deep learning models-VGG19, InceptionV3, DenseNet201, Xception, and ResNet50. Among these, InceptionV3 achieved the highest performance across all metrics, with an accuracy of 99% and a Cohen's Kappa value of 0.96. Furthermore, we compared the performance of our best model against existing methods, demonstrating that our approach outperforms previous works.

Keywords:

Deep Learning, Coconut Disease Detection, Pre-Trained Models, Transfer Learning

1. INTRODUCTION

Coconut palms (Cocos nucifera) support livelihoods and economies worldwide. However, the cultivation of coconuts is threatened by various pathogens, including bacteria, viruses, and fungi, etc. which lead to diseases such as root wilt, bud rot, gray leaf blight, lethal bole rot, cadang-cadang, stem bleeding, and palm lethal yellowing. In addition to these pathogens, pests like the rhinoceros beetle, the Red palm weevil, the black-headed caterpillar, coconut eriophyid Mite², and termites can also cause extensive damage. It is essential to take prompt and deliberate action to address and mitigate these issues that affect coconut cultivation [1].

The traditional method of visually inspecting plants for infections is time-consuming, subjective, and prone to human error. The growing need for accurate and efficient disease detection has prompted researchers and agricultural scientists to explore image processing, machine learning, and deep learning techniques to address the challenges of detecting coconut diseases [2]. Using AI and computer vision capabilities can enhance early disease detection and diagnosis in plants. Overall, cutting-edge technologies are being utilized to modernize conventional farming methods and to improve sustainability.

In the case of the coconut palm, specialized datasets may be limited, and accurate labeling can be difficult to obtain. Transfer learning techniques have revolutionized agricultural diagnostics, especially in detecting plant diseases like coconut diseases. Transfer learning and pre-trained models approach allows for the accurate identification and forecasting of many coconut illnesses. One pre-trained model that can be fine-tuned on various coconut image datasets is a Convolutional Neural Network (CNN) that creates a trustworthy and accurate system for diagnosing illness and predicting [2].

Although advances have been made in the automated detection and classification of coconut tree diseases, the accuracy of current models could be better compared to the other crops, partly due to a lack of comprehensive research and limited access to high-quality datasets. This study seeks to bridge this gap by evaluating five distinct CNN models on one dataset to determine their effectiveness in classifying coconut tree disease images. Based on this comparative analysis, it is possible to identify the strengths and weaknesses of each model and decide the best model for coconut disease detection.

Previous research has examined image processing and deep-learning algorithms. Researchers discovered that the technologies used to identify other crop diseases have an accuracy of 95% to 99%. Coconut disease detection accuracy ranges from 73% to 98.35%. Transfer learning approaches can increase disease identification and prediction accuracy in coconut plantations. This strategy can boost crop productivity and decrease losses by detecting coconut tree diseases early and delivering timely remedial solutions [3]. The study focuses on five major coconut tree diseases: bud root dropping, bud rot, grey leaf rot, and stem bleeding [4].

The paper has the main contributions:

- Comprehensive Evaluation of CNN Models: We thoroughly evaluated five different convolutional neural network (CNN) models to classify images of coconut tree diseases. This comparison provided insights into the strengths and weaknesses of each model, allowing us to determine which architecture is best suited for this task.
- Identification of the Best-Performing Model: Through continuous testing and analysis, we identified the top-performing CNN model that exhibited the highest levels of accuracy and robustness with our data. This finding is crucial for advancing the field of automated coconut tree disease detection.
- Guidance for Future Research and Applications: Our study offers practical guidance on the optimal choice of CNN model for coconut tree disease classification. These insights contribute to developing more effective disease monitoring systems and support future research endeavors in precision agriculture.

The rest of the sections follow this outline: Section 2 is a background section. Section 3 and section 4 describe the materials and procedures used, respectively. The results of the experiments are also presented here. Conclusions and future directions are provided in the final section.

2. RELATED WORKS

Yong et al. [4] proposed a deep learning-based recognition model for crop diseases and insect pests in harsh environments. The study developed the Inception-ResNetv2 architecture for the automatic identification of crop diseases. The authors utilized a dataset shared by the AI Challenger Competition 2018. The model has an overall recognition accuracy of 86.11%. Besides, they designed a WeChat applet to deploy the crop disease identification system on smartphones to test in real scenarios. The authors suggested including more variety of samples in the dataset as a future direction. In this regard, the model can achieve higher robustness against various crop diseases [4].

Paymode et al. [5] have designed a transfer learning-based approach for classifying multiple crop leaf diseases. The author's approach employed the VGG16 model, augmented with data augmentation, dataset pre-processing, and intensive training and testing procedures. This resulted in accuracy rates of 95.71% for tomato leaf diseases and 98.40% for grape leaf diseases. Though the results appropriately demonstrated the ability of transfer learning in classifying crop diseases, the authors acknowledged several limitations. The reliance on pre-trained models could perpetuate bias from the original training data and its relation to the system's overall performance in detecting diseases through varied environments or uncommon conditions. In addition, the dataset for this study only covers a small subset of the actual conditions applicable in agriculture, so its model cannot be very well generalized to other crops or environments [5].

Regarding coconut disease detection in previous studies, Kavithamani et al. [6] developed a deep-learning model to predict and classify white fly diseases. They used images from the Kaggle data repository to train the model. For crown identification, they employed the VGG16 model to classify the images as healthy or unhealthy, and for other purposes, they used a custom model called DCNN. The model achieved an impressive accuracy of 98.35%, surpassing the 96.12% obtained using GLCM [6].

Maray et al. [7] proposed an AI-enabled model for detecting and classifying coconut tree diseases. First, the AIE-CTDDC model employs a median filtering-based noise removal. After that, a Bayesian fuzzy clustering-based segmentation approach is employed. Furthermore, the capsule network (CapsNet) approach is a feature extractor. This work uses the Harris Hawks Optimisation and Gated Recurrent Unit model to identify disease in coconut palms. They have a good accuracy of 97.75% with this model [7].

In a comparative assessment of Pest damage identification of coconut plants using damage texture and color analysis, Berman et al. present precise results for identifying pest damage on coconuts through color and texture analysis. A color and texture-based damage analysis is presented to classify the five pest attacks on coconuts. The images of the coconut pest attacks were taken for this study using a digital camera in a stable environment [5]. The features extracted using the Gray Level Run Length Matrix (GLRLM) and Gray Level Co-occurrence Matrix (GLCM) methods were effective for pest damage identification, suggesting that these fused features serve as reliable texture-based techniques for this task. The study reports the performance of various classifier models, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), and Naive Bayes (NB). Among these, ANN and SVM achieved the highest accuracy, with results nearing 100% [8].

Singh et al. [9] proposed a web application using Deep learning algorithms to identify diseases and pests in coconut trees, namely stem bleeding disease, leaf blight disease, and Red palm weevil infection. Image segmentation techniques such as thresholding, watershed, and k-means clustering were used to prepare images for classification. The study found that k-means clustering segmentation outperformed other approaches and achieved good classification accuracy using CNN models such as InceptionResNetV2 and MobileNet. They got an accuracy between 73.5% and 82% with tuning, and also Cohen's kappa value ranges from .60 to.77 [9]. By applying these techniques in coconut disease detection, the models showed a range of accuracy from 73% to 98.5%. These results signify the potential for improvement in accuracy, loss value, and Cohen's kappa values by exploring new pre-trained models. This paper analyzes identifying the optimum model and perform comparative assessments. Employing these approaches could facilitate the identification of the most suitable model for our dataset. Previous studies mainly focused on coconut disease caused by pests. but this paper comprehensively addresses five coconut diseases: Bud rot, grey leaf, leaf rot, bud root dropping, and stem bleeding.

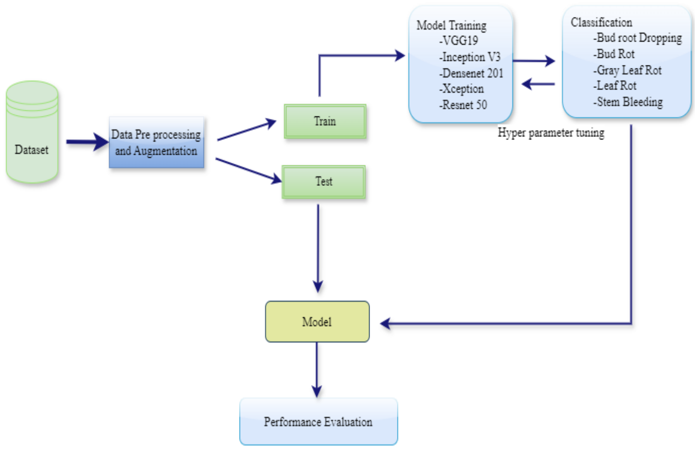


Fig.1. Methodological Framework

(a) Bud root Dropping (b) Gray leaf (c) Leaf rot

(d) Stem bleeding (e) Bud rot

Fig.2. Sample images of various classes of the coconut tree disease dataset

3. MATERIALS AND METHODS

An overview of the techniques and methodology used for the model is explained in this section. The subsections include dataset description, pre-processing, augmentation technique, and a detailed view of the methodological schema. A workflow diagram of the overall methodology is illustrated in Fig.1.

3.1 DATASET

This study employed the "Coconut Tree Disease Dataset (Mendeley)", which contains images from various coconut plantations with different growth stages, environmental conditions, and disease manifestations in the Kendur region, located in Shirur Taluka, Pune district, Maharashtra, India [1]. The images are in high-resolution, each measuring 768 pixels in width and 1024 pixels in height [1]. The dataset consists of images grouped into five different types and focuses on diseases affecting coconut trees. The diseases listed in these classes are common to coconut trees and include bud rot dropping, bud rot, grey leaf rot, leaf rot, and stem bleeding [1], [10]. With this varied dataset, important diseases affecting coconut trees are comprehensively represented. Sample images from the dataset are mentioned in Fig.2, and details of the dataset are shown in Table.1.

3.2 PRE-PROCESSING

Resizing and Augmentation: the original 256×256-pixel pictures were resized to different dimensions depending on the model. Since the dataset is not balanced and does not have the same amount of images for each class [2], we used several augmentation procedures on preprocessed images, such as rotation, horizontal and vertical flipping [11], zoom adjustments, shearing, and rescaling [12].

3.3 DATASET SPLIT

We used an 80:20 data split to our dataset to facilitate accurate classification. We carefully developed five separate Convolutional Neural Network (CNN) Pre-defined models, each perfectly adjusted to differentiate among the five distinct classes in our dataset [13].

Table.1. Dataset Description [1]

Class	Disease Name	Total Images
1	Bud Root Dropping	514
2	Bud Rot	470
3	Gray Leaf Spot	2135
4	Leaf Rot	1673
5	Stem Bleeding	1006
	Total	**5798**

3.4 DISEASE CLASSIFICATION WITH PREDEFINED MODELS

For classification, we have used five different predefined models. In this work, we customized the pre-defined architectures by adding/removing some layers for better performance. During training, we implemented various techniques to enhance the resilience and versatility of our classification models. We trained across ten epochs, using *early stopping* criteria to avoid overfitting and assure optimal model performance. In addition, we used *dropout* layers to reduce the risk of overfitting by randomly deactivating a subset of neurons during training. Each batch of data performed *batch normalization* for stabilizing and accelerating the training process.

3.4.1 VGG19:

It is an expansion of the VGG16 architecture developed by the University of Oxford's Visual Geometry Group (VGG). It is known for its simplicity and efficiency and has 19 layers, including 16 convolutional layers and three fully connected layers. This more complex design enables the model to extract higher features from the input images. Despite its enhanced depth, VGG19 maintains the fundamental features of the VGG architecture [2], including compact 3x3 convolutional filters and max-pooling layers [14].

3.4.2 Inception V3:

Inception V3 is a deep convolutional neural network architecture commonly used for image categorization and object identification. InceptionV3 introduces the "Inception module," which contains parallel convolutional layers with varying filter sizes. This enables the network to gather local and global information at various sizes, improving its capacity to detect complex picture patterns and objects [2]. InceptionV3's architecture has 48 layers, including convolutional, pooling, fully connected, and auxiliary classifiers [15].

3.4.3 Densenet 201:

As the name suggests, DenseNet is distinguished by dense connections, each receiving direct input from all preceding layers. This architecture varies from ordinary feed-forward networks, where each layer communicates only with the preceding layer. DenseNet overcomes the vanishing-gradient problem typical in deep networks, allows for robust feature propagation between layers, supports feature reuse, and significantly decreases the overall number of parameters [2]. This unique architecture, developed by Gao Huang, Zhuang Liu, and Laurens van der Maaten, has received attention for its potential to improve gradient flow, promote feature reusability, and achieve cutting-edge performance in various deep learning applications [16].

3.4.4 Resnet 50:

ResNet is a brand-new residual network that He et al. and colleagues suggested. This paradigm addresses the problem of network deterioration and simplifies network training. On the ImageNet dataset, their 152-layer residual network produced a fantastic 3.57% error rate. The complete 3 x 3 convolutional layer of the VGG model serves as the foundation for the standard ResNet50 model, with two identical 1×1 convolution layers in each residual block. After every convolutional layer, there is a batch normalization layer and a ReLU activation function. Finally, normalization is achieved by applying the softmax function [17].

3.4.5 Xception:

Xception, "Extreme Inception," is a convolutional neural network (CNN) architecture created by François Chollet, the genius behind the Keras deep learning framework. This revolutionary design reimagines the standard convolutional layer by substantially using depth-wise separable convolutions. Unlike traditional convolutions, which operate on all input channels simultaneously, depth-wise separable convolutions break the process into two stages: depthwise convolution and pointwise convolution. This precise separation considerably decreases computing complexity while retaining representational capacity, making Xception computationally efficient [18] [19]. All the model's performances were measured using accuracy, precision, and recall and systematically compared their findings to determine which performed best with our dataset. Through this comprehensive study, we could effectively select the best model to classify plant diseases from our dataset.

4. RESULTS AND ANALYSIS

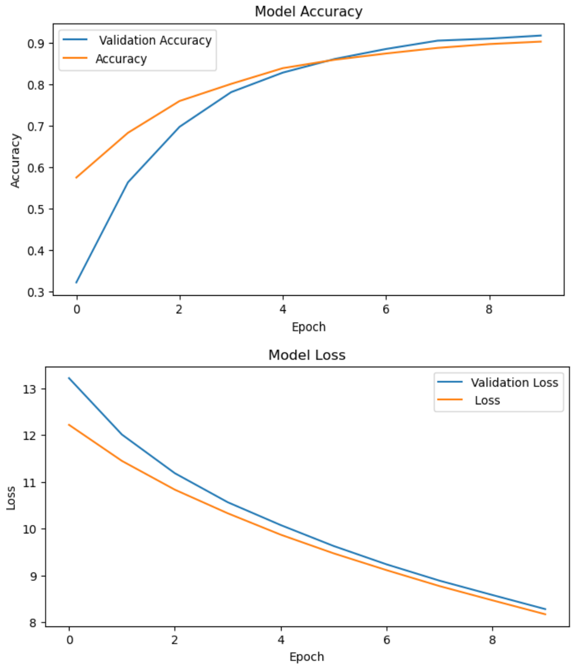
The models are implemented using Python through tensor flow and Kerals with Jupyter Notebook. The performance of the models is carefully investigated and presented in this section. This work comprehensively assessed the model's effectiveness by considering essential performance indicators, including precision, Recall, Cohen's kappa coefficient [20], and accuracy. Hyperparameter tuning details are mentioned in Table.2. Examining the data in Table.3 shows that classifying model classes 1 and 5 was more manageable than the other classes. The data's quality posed challenges to the task, particularly in assessing the model's effectiveness for Class 4 visualizations in Fig.3 that the Inception V3 model indicates that its however, performs the best. In addition, it has a high Cohen's Kappa score, and the model demonstrated good accuracy. It is evident from the results that predictions closely match the results. These visualizations and metrics clearly show that Inception V3 is very good at classifying coconut tree diseases, making it a reliable choice for this task. In addition, the VGG19 model also yields good visual results when compared to the other models.

It should be noted that while VGG19 can identify features well, it is, however, that despite VGG19's good visualization performance, Cohen's Kappa score should be higher. These lower score predictions must align more closely with the actual results than Inception V3. As datasets are scarce in this field, our test was necessarily limited to the "Coconut Leaf Dataset for Pest Identification" provided through Kaggle. By analyzing Table.3, we understood that the custom-made inception v3 stood high in accuracy. which means the top model can generalize the unseen data.

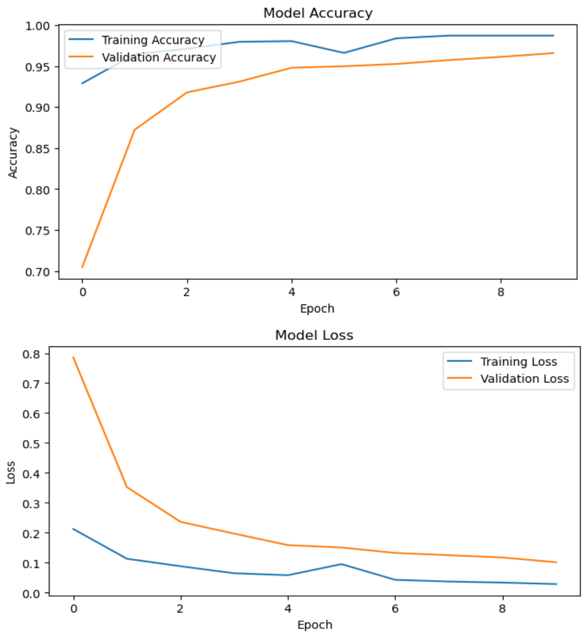
We plotted the accuracy vs. loss and ROC-AUC curves for each model, as shown in Fig.3(a)-Fig.3(d) and Fig.4(a)-Fig.4(d). It is pretty complex to thoroughly validate the generalization of our models across conditions and types of diseases. A comparison is made from related works mentioned in Table.4. Due to the unavailability of existing literature reviews in this field, the work was limited to comparing only two works. In those papers, a different dataset was used, but still, some of the diseases were the same also. We have tried our model with a benchmarking dataset [13] to generalize the model capacity.

Table.2. Hyperparameter details

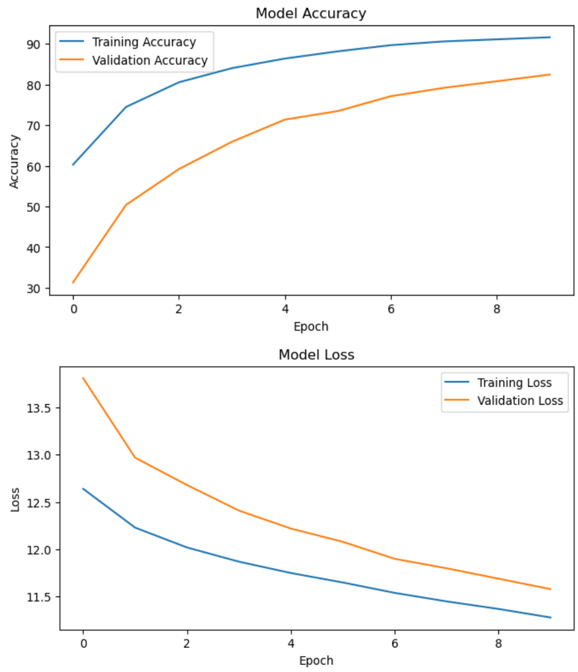
Hyperparameters	Tuning rate
Epoch	10
Dropout rate	0.5
Activation Function	Relu
Learning Rate	0.001
Batch size	32



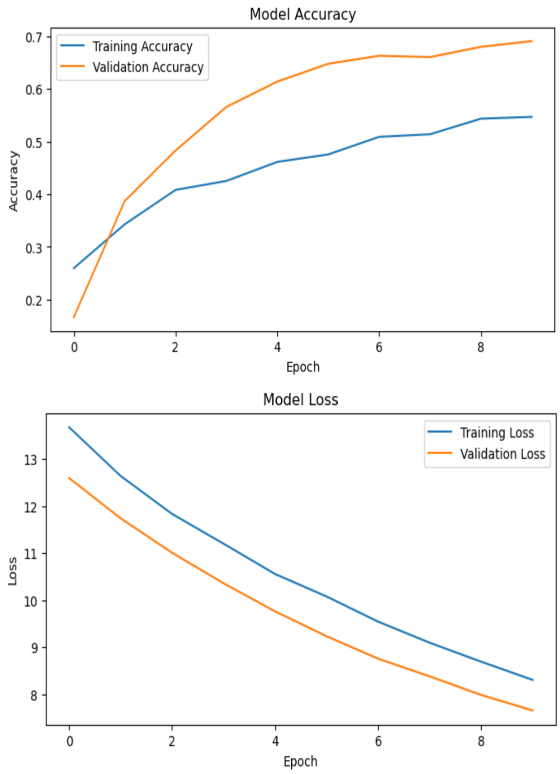
(a) VGG19: Accuracy and Loss



(b) Inception v3: Accuracy and Loss

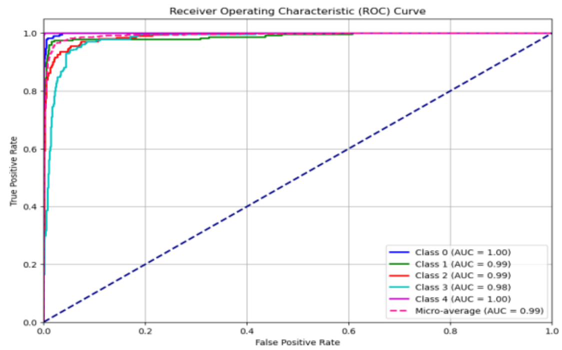


(c) DenseNet 201: Accuracy and Loss

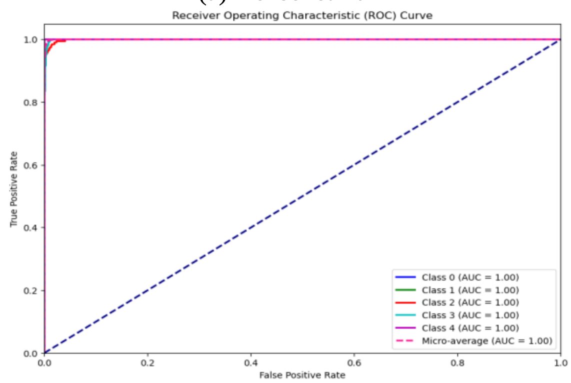


(d) Resnet 50: Accuracy and Loss

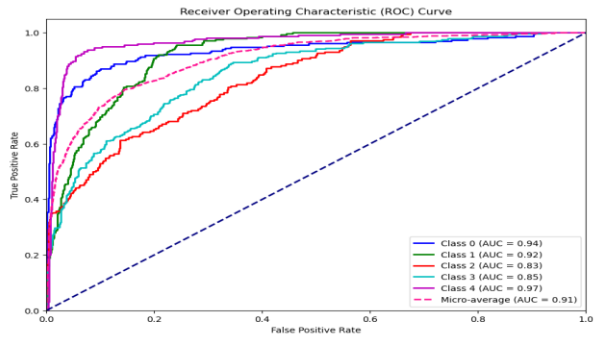
Fig.3. Accuracy and loss for the custom models



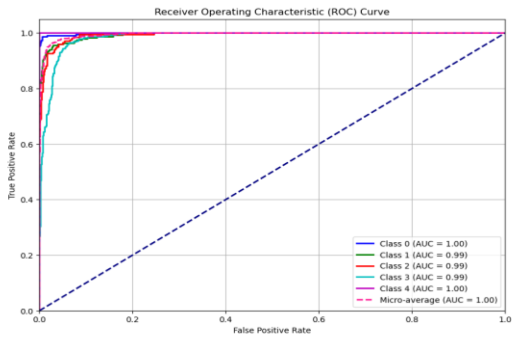
(a) Densenet 201



(b) Inception v3



(c) Resnet 50



(d) VGG19

Fig.4. ROC curve for the proposed model

Table.3. Performance Comparison of Different Models

	Precision					**Recall**					**Cohen's Kappa**	**Accuracy (%)**
	Class					Class						
Model name	1	2	3	4	5	1	2	3	4	5		
Densenet 201	1	.962	.952	.9893	1	1	.92	.975	.945	1	.94	93.75
VGG19	.946	.956	.923	.88	1	.977	.96	.882	.886	.991	.952	96.92
Inception v3	.96	.92	.963	.92	.99	.978	.963	.92	.94	.98	.96	**99 %**
Xception	93.3	.94	.953	.90	.996	.96	.974	.95	.921	.98	.943	94.1
Resnet 50	.9051	.9143	.8983	.8776	.995	.967	.94	.8235	.8413	1	.90	91.67

Table.4. Comparison with another dataset

Sl. No.	**Model Name**	**Dataset**	**Methodology**	**Accuracy**
1	Inception v3 [15]	Coconut leaf data set for pest identification (*Kaggle*)	Transfer learning	94.85%
2	Inception Resnetv2	Coconut disease and pest infection dataset (private)	Transfer learning Custom made CNN	81.48% 96.94%
3	ResNet 50	Coconut tree dataset (*Mendeley*) [1]	Transfer learning	94%
4	Inception v3 (*Proposed*)	Coconut leaf data set for pest identification (*Kaggle*) [21]	Transfer learning	**95.2%**
5	Inception v3 (*Proposed*)	Coconut tree dataset (*Mendeley*) [1]	Transfer learning	**99%**

5. CONCLUSION

This study aimed to evaluate five different CNN models for coconut illness detection to determine the most appropriate. As a result, the model was also applied to a new dataset that included disease data discovered recently and performed well. We conducted a careful analysis using multiple custom models such as VGG19, dense net 201, inception V3, exception, and resnet50 and achieved good accuracy and loss. Additionally, we utilized other matrices to determine the best model and calculated precision, recall, and Cohen's Kappa for the model. Following this, we plotted the ROC-AUC curve for visualization and included the AUC for each class in the graph. This enabled us to identify the best model and the area under the curve for each class. In all scenarios, we found Inception V3 the best classifier regarding accuracy and cohen's kappa.

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