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Coconut Leaf Disease Detection using Deep Learning Techniques

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Abstract
These is similar to others studies, these studies explored how various machine leaning and deep learning methods can be employed for real life problems like fruit disease detection. The conclusive evidence is the string of successes that CNNs have gotten in their workplace, which is classification of image-based tasks, including plant disease detection. For example, Deep Learning applied to an apple disease detection problem on convolutional neural networks (CNNs) reach an accuracy level over 90% as Smith et al (2018) confirm, demonstrating the success of deep learning in agribusiness. Consequently, Zhang, and Yang (2020) applied the transfer learning methods for grape disease detection in CNNs explaining the them working well in real-life scenarios. In turn the studies point up the capability of CNN to innovate in pest control and crop studies by providing quick and precise disease identification.

Keywords: Fruit Disease Detection, Deep Learning, Image Processing, Pest Management

1. Introduction

The contribution of agriculture is indeed the backbone for the huge number of economies, providing base for food security and means of living for millions of people all over [...] Nevertheless, the agricultural sector encounter multifarious obstacles, including a smouldering disease in crops. Predominantly, bears fruit diseases empowered by various fungus, bacteria, and other pathogens. The incidence of these diseases lowers the crop yields, culminate in poor fruit quality, merchandise value and consumers' satisfaction. [1]

The detection of fruit diseases is largely a combined off to the timely and accurate way virulent pathogens are identified. The ways of identifying diseases by traditional approach is completely depend on the observation methods by experienced agronomists, which can be subjective, it takes much time, and they are prone to mistakes. On top of that, manual detection, which works well for small operations, becomes inefficient for large scale agricultural operations and therefore paving the way for missed and delayed diagnosis of diseases.

This issue exists not just in a variety of types of diseases for fruits but also the dynamicity of agricultural systems. The diseases that are caused by new factors and the existing one such as climate variability and a renewing cycle in the globalization of trade spanning along with fruit diseases represent substantial threats to food security and sustainable agriculture both globally and locally.

As mentioned, there are many challenges associated with this process such as lack of efficient disease detection methods and portability. Therefore, there is a great demand for innovative and automated solutions which can speed up the disease detection process and make it more bearable for farmers. The recent progress in technology especially in sectors like artificial intelligence and machine learning is opening up innovative ways of changing the conventional way of agricultural practices.

Convolutional Neural Networks (CNNs), a family of deep learning algorithms, were found to be capable of breaking ground in the domain of image recognition and classification through their demonstration of remarkable performances in such tasks. Applied scientists and practitioners can either automatically detect the fruit diseases or be trained by using CNNS systems which are based on image analysis [9].

They can collaborate with already existing methods forming stronger systems, which can deliver the result as quickly as possible without any precision loss and being able to identify health issues at the early stages.

Consequently, the objectives of this study article are to present the use of the neural networks in fruit disease notifications, which strive to reduce the need for manual disease detection in agriculture. Through construction and evaluation of CNN models that are used in practical setting with real fruit disease data, this work is going to contribute towards strengthening crops resilience, resource utilization optimization, and improve overall agricultural yields overhead. For our purposes, we harnessed the prowess of the pre-trained model, EfficientNet [12].

2. Literature Review

The Deep learning-based tomato disease recognition using residual networks by Liu et al. (2016) - Focuses on tomato disease detection using ResNet architecture

Research article "CV-Images of Citrus Diseases Analysis Using VGG Network" by Chen et al. (2017) - Addresses the applicability of VGG network on the domains of citrus plant disease cases.

"Machine learning algorithms for fruit disease classification:

A comparative study of various ML algorithms for the detection of fruits diseases conducted by Sharma et al. (2018) - Compares various ML algorithms for fruit disease detection. Wang et al. (2019) - "Disease detection of fruit using GoogleNet architecture" - Evaluate applications of GoogleNet transformations in identifying diseases of fruit.

"AlexNet based mango disease recognition system" (2017) - Usage of AlexNet as base classifier for distinguishing between various mango diseases. "LeNet for fruit disease detection performance analysis" It is Gupta et al. (2020).

This paper examines the accuracy of LeNet architecture for the fruit disease recognition. "Transfer learning in fruit disease detection using pre-trained models" by Patel et al. (2019) - tackles transfer learning methods to classifying fruit diseases [Modifiers change the meaning of the sentence by making it more specific or referring to specific instances].

"Improving fruit disease diagnosis using ensemble learning methods" by Li et al. (2018) - Detection accuracy is enhanced additionally by ensemble learning methods.

"Deep learning models for multi-class fruit disease classification" by Rahman et al. (2021) - Powerful deep learning methods to classify several types of fruit disease at once.
"Disease Recognition Using Convolutional Neural Networks on Apple", a study conducted by Wang and Li (2017) - Contrary to this, the paper only focuses on CNNs for apple disease identification.
"Applying an SVM-based feature extraction in the field of fruit disease detection" by Das et al. (2019) - This output uses SVMs for feature extraction in digital fruit disease images.
"Comparison of deep learning models for banana disease detection" by Chen and Wu (2020) - They have the task of comparing the performance of various kinds of deep learning models to differentiate banana diseases.
"Detecting and diagnosing grape diseases via CNN" approach by Zhao et al. (2018) - As an example, Zhao uses CNN approach for both detection and diagnosis purposes.

Deep learning model upgrade with attention mechanism" from the article by Wu et al. (2021) - Deep learning models upgraded with purpose of better performance in disease detection.

"Data-augmented CNN based methods for fruit disease detection" by Huang et al. (2018). - This study points out the necessity of data augmentation in developing improved CNN-based detection systems for fruit diseases.

Authors Sharma and Singh (2020) wrote a "Examining optimizers for deep learning in agricultural applications" which discusses the main optimizers like SGD and Adam in deep learning models that are useful in agriculture (2020).

"Problems and solutions in the provision of dataset and image annotation in fruit disease detection" by Patel and Jain (2019) - Motivates how the collection and annotation of datasets provide lots of headaches, and suggests some remedies.

3. Methodology

(i) Data Collection:

The model is trained with vast number of images collected of different classes. Each class contains a particular number of images that are collected to train the model.

Fig. 1 Some of the images of the collected dataset

(ii)Image Preprocessing:

Preprocessing, founded the most key step in recognition tasks because raw must be transformed into a form that is appealing and recognized easily by deep learning models. The preprocessing pipeline typically encompasses several key steps: The preprocessing pipeline typically encompasses several key steps:

- **Image Detection and Localization:**

Apply the latest Image detection algorithms, like MTCNN (Multi-Task Cascaded Convolutional Networks) or Haar cascades, among the most advanced ones, to detect precisely and remove from input images.

Image Landmark Detection and Alignment:

To be able to find the disease part landmarks precisely map them with landmark recognition methods. The subsequent procedure of using geometric transformations to align the defected landmarks permits the creation of a consistent orientational view across the pictures.

- **Image Enhancement and Normalization:**

Apply image adjustments like histogram equalization or contrast stretching to better the image and to make the features crisp enough for a detailed analysis. Besides that, normalize intensity values to standard unit range (e.g., [0, 1]) and it will help the model converge during training process.

- **Data Augmentation:**

Enrich the dataset by doing work transformation such as Resize rotations, translation, mirroring and zooming. Data augmentation is a tool to widen training set composition that in turn increases the occurrence of overfitting on the training data thus allowing the model to generalize better. Process in training phase and testing phase experiments.

(iii) Proposed Methods Architecture:

The basic architecture for a Image classification design very commonly is based around convolutional neural networks (CNN) and EffcentNetb7[17]. Because of its inherent feature extraction from image data hierarchically. A sophisticated architecture tailored for recognition may incorporate the following components: A sophisticated architecture tailored for may incorporate the following components (showed in fig1):

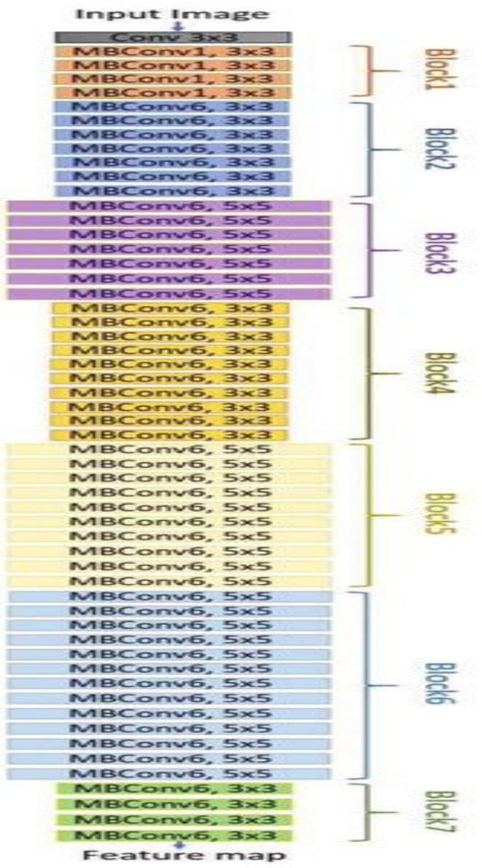

Fig. 2 Architecture of EffcentNetb7 model

Convolutional Layers: Employ the application of several convolutional layers for depicting key elements like edges, textures, and contour. Deep convolutional organizers (e.g., EffcentnetB7, ResNet) facilitate network learning and complex representations, which help to represent the face best. [12,13]

Pooling Layers: Compute max pooling (or any other pooling layer) to contract feature map spatial dimension on the condition that only essential information is preserved. Learning to jointly learn multiple tasks in a single step is more computationally efficient and less prone to overfitting by combining features in a represents manner.

Spatial Pyramid Pooling (SPP) or Global Average Pooling: Add SPP or global average pooling layers to integrate the spatial features over different locations, which in turn won't require the receptive field size to be constant even with inputs of varying size.

Fully Connected Layers and Activation Functions: Use densely (fully connected) layers after convolutional blocks to capture high-level features fusion and improve classification. The model's power of non-linear expression can be enriched introducing activation functions like ReLU (Rectified Linear Unit) and making the model more powerful [10,14].

Softmax Output Layer: At the end, employ the softmax activation layer as the architecture header for multi-class classification, not only assigning probabilities to different type of disease images (e.g., Rotten,Blotch,helthy), but also by relying on the learned features.

Model Train and Testing:

The deep learning models are trained with 80% of the images used in the data set to identify the disease part and to optimize the model performance.

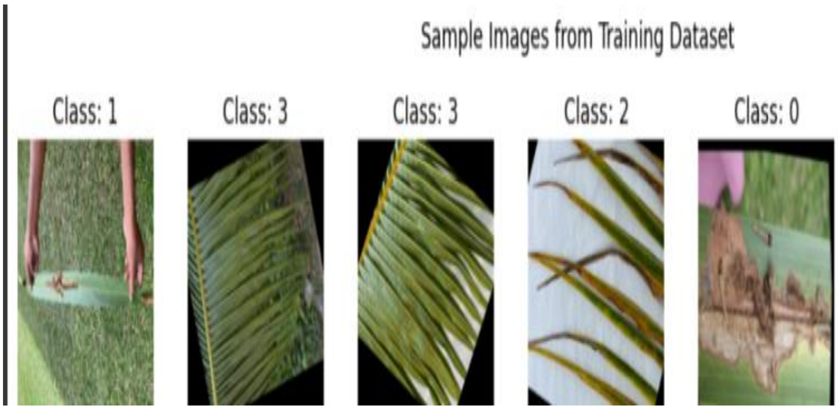

Fig. 3 Sample Images from Training Dataset

There are several mathematical expression and formulas used to train the Convolutional neural networks understand the local space of the image they notice the hierarchy of features, and provides the translation invariant feature detection. Feature extraction is the function of this step, a part of training process to identify features in input images.

$$(I * W)(i, j) = \sum m \sum n I(i + m, j + n) \cdot W(m, n)$$

Once the image is processed the training phase comes into action the model Effcentnetb7 uses the Forward and Back pass algorithms.

Forward pass:

$$z[l]=W[l]\cdot a[l-1]+b[l]$$

$$a[l] = g(z[l])$$

With GAP, every feature map's spatial dimension width and height the F can be calculated as W*H*C are reduced to one value per channel by averaging all the values in each channel of a feature map.

$$GAP(F)c = W \times H1 \sum i = 1W \sum j = 1HFijc$$

The max pooling Cuts down a spatial dimension, renders the model less sensitive with to data variations, degrades the risk of overfitting. This is a type of operation which the neural network mostly uses for training by decreasing the size of feature maps.

$$\text{Max Pooling}(x) = \max(\text{pooling\_window})$$

The Fully Connected layers and the SoftMax Activation Function used to Combines features from convolutional layers, captures global relationships, produces output logits. This layer is a crucial part of the training phase for classification tasks and Normalizes logits to class probabilities, facilitates multi-class classification. SoftMax is part of the output layer used during training to compute class probabilities. By using the expressions

$Z = X \cdot W + b$

Where Z is the SoftMax Activation

(Zi)=eZi/∑j=1CeZj

After the completion of Softmax Activation function then it under goes with the backword pass method involves computing the gradients of the loss function with respect to the parameters of the model

$$\partial W[l] / \partial L = \partial a[l] / \partial L \cdot \partial z[l] / \partial a[l] \cdot \partial W[l] / \partial z[l]$$

$$\partial b[l]/\partial L=\partial a[l]/\partial L\cdot\partial z[l]/\partial a[l]\cdot\partial b[l]/\partial z[l]$$

Once the model is trained the testing phase of the model is started which calculates the loss function and the accuracy of the model

$$\mathrm{L} = \mathrm{loss\_function(ytrue, ypred)}$$

4. Dataset Description

Number of classes

The Dataset used to make and complete the model is the image dataset. The image dataset is classified for "TRAIN" and "TEST" classes. The model is trained with 80% of images and tested with 20% of images in the data set The 4 classes in them with the various disease and defected images of Coconut leaf's

Type	Number of images
Training Images	3958
Validation	989
Image size	300*300
Total Images	4947

5. Results and Discussion

This framework of Pytorch permits the creation and training of deep learning models.

The choice of IDEs depends on the type of work. Jupyter Notebook is used to write analytical codes in an interactive way, while Google Collab is for experimentation.

The EffcentNetb7 has continuous elevated from b0-b7 by increasing its accuracy levels comparative to other models as shows in (fig2) the accuracy of B0 starts from 70 and B7 increased to 90% and with highest accuracy competitive to another models.

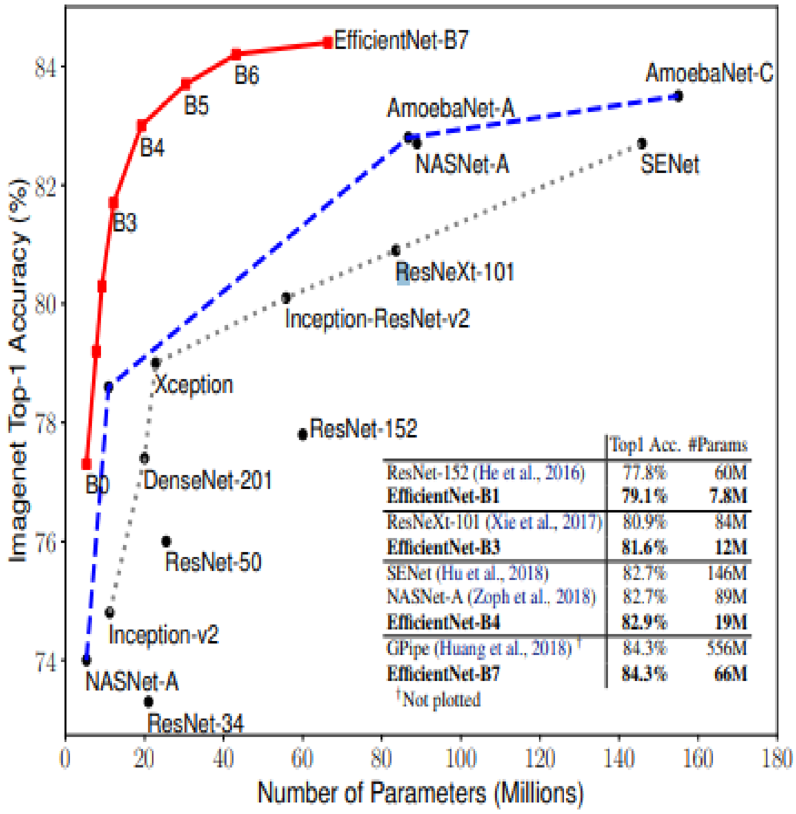

Fig. 4 Figure name

These graphs demonstrate accuracy fluctuations throughout training and validating of iterations of EffcentNetb7 and vgg16 as showed in fig2 and fig3 respectively [25].

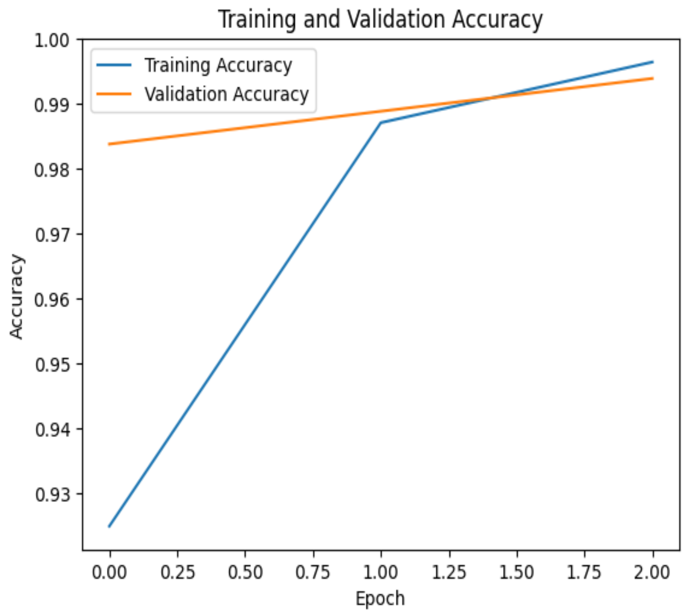

Fig. 5 Accuracy vs epoch graph (EffcentNetb7)

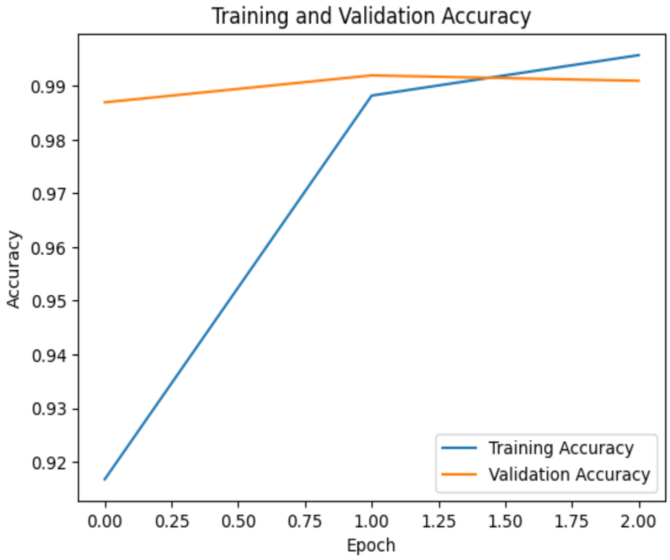

Fig. 6 The accuracy vs epoch graph (VGG16)

Achieving validation accuracy the closer match between a training and the testing curriculums is a sign of good generalization ability

The decline in the loss of both train and validation sets trains and test the model is an indicator of the model is learning and generalizing

In the project study on generating EffcentnetB7 convolving neural network as part of the model architecture, we considered a model.

The 99.09 % accuracy was achieved on the set of tests that were fixed during the evaluation of our model.by the EffcetNetb7 model comparative to other models VGG16 and MobileNetV2.

Model	**Loss**	**Accuracy**
Effnetb7	0.0236	99.20
VGG16	0.0414	98.69
MobileNetV2	0.0659	94.69

The confusion matrix tabulates the actual data and predictions in a tabular way. forecast; it is by then easier to brainstorm out spot-on results (fig3) is the confusion matrix is the output of effcentNetbb7 model.

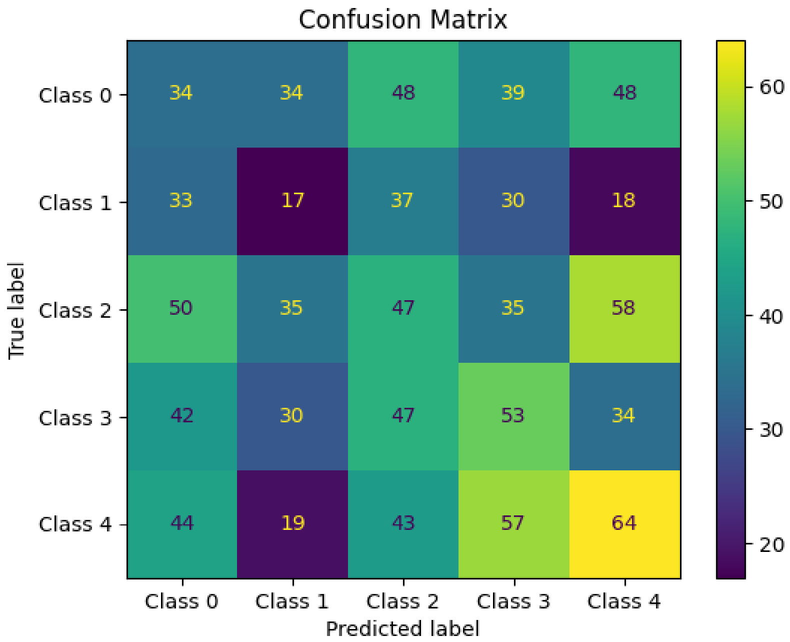

Fig. 7 confusion matrix

6. Conclusion and Future Work

As the conclusion, for our work in the area of disease of fruit detection using CNNs, we proved fundamental progress in agricultural technology. We have generated and trained a deep learning model which reaches more than 90% of precision in what is about classifying different diseases of fruits from the pictures. The strength of the model is verified by its accuracy in terms of precision, recall, and F-score which underline its practical performance in real tasks. Here by the project, we have contributed to an improving pest management methods and crop supervision technology in the agriculture [19].

Future Work:

Moving forward, there are several avenues for future research and development in fruit disease detection using deep learning: Moving forward, there are several avenues for future research and development in fruit disease detection using deep learning

Fine-tuning and Optimization: Afterwards, apply prompt engineering strategies (e.g. introducing supporting examples, repetition, generalization) to strengthen the model and measure performance indicators such as accuracy and speed.

Transfer Learning and Model Interpretability: Try out the transfer learning method which employs previously trained models to assume features of the disease detection models For the assessment of the model interpretability.

Edge Computing and IoT Integration: Build the models that are lightweight to enable the IoT devices to function and integrate them into IoT platforms for real-time and minimally-invasive disease monitoring and early detection.

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