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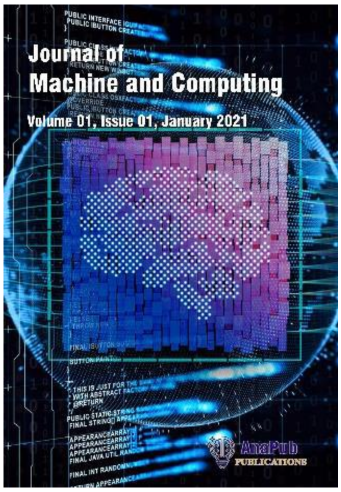

Accurate Phase-wise Prediction of Coconut Harvesting Stages Using VGG19 Convolutional Neural Network for Improved Agricultural Automation

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Accurate Phase-wise Prediction of Coconut Harvesting Stages Using VGG19 Convolutional Neural Network for Improved Agricultural Automation

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Abstract:

The paper aims to develop an efficient deep learning algorithm to classify the coconut harvesting level stages by using the various images of the coconuts. The system uses the images of the various types of coconuts to find, evaluate, and harvest coconuts at the best phases of maturity i.e. tender, snowball, or mature, based on the domain of applications. Using characteristics like color, size, and texture, from the images taken from the existing images of coconuts the proposed Deep Learning model identifies and categorize coconuts, assuring accurate harvesting for products like oil, copra, and coconut water. The proposed methodology using VGG19 algorithm demonstrates the high accuracy to automatically predict the various harvesting stages like tender, snowball and copra using a various feature s from the coconut images captured. The proposed deep learning model was trained on the various existing coconut image datasets using data augmentation to enhance the VGG19 based CNN-model. The proposed model performance is valuated using metrics like precision, recall, specificity and F1-score. Results reveal that the image augmentation, the transformation methods with the VGG19 model attained the testing accuracy 98.94% and validation accuracy of 97.6[illegible]%. Our research contributes best on the classification of various harvesting stages that will benefit and help the farmers job of various harvesting stages while promoting the economic growth.

Keywords: Deep Learning, CNN, VGG19, image augmentation, harvesting

I. Introduction

Coconut (botanical name cocos nucifera) is one of the most economically significant crops in tropical and subtropical regions, playing a vital role in the livelihoods of millions of people worldwide[1]. It is a versatile crop that provide food, oil, fiber, and other by-products which are essential for various industries. Harvesting coconuts is a critical stage in the coconut value chain, as it directly impacts the quality and yield of the final products. Traditionally, coconut harvesting has employed manual labor, which is time-consuming, labor-intensive, and often hazardous[2]. With the advent of advanced technologies[3], there is a growing interest in automating and optimizing the harvesting process to improve efficiency, reduce costs, and ensure safety.

One of the key challenges in coconut harvesting is the accurate classification of coconut maturity stages, which include dry, tendor, and green coconuts [4]. Each stage has distinct characteristics and applications. For instance, tendor coconuts are prized for their refreshing water, while dry coconuts are used for oil production and other industrial purposes. Green coconuts, on the other hand, are often used for culinary purposes and coconut milk production. Accurately identifying these maturity stages is crucial for determining the optimal harvesting time and ensuring the quality of the final product[5].

In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in image classification tasks. Among these, the VGG-19 architecture, known for its depth and ability to capture intricate features of images, has been widely adopted for various computer vision applications [6]. This research aims to develop a robust and accurate model for classifying coconut maturity stages (dry, tender, and green) using a dataset of coconut images using VGG-19. The proposed approach not only enhances the efficiency of coconut harvesting, have also contributed to the broader field of agricultural automation. The dataset used in this study comprises images of coconuts at different maturity stages, specifically dry, tender, and green. These images are pre-processed and fed as input to the VGG-19 model and is fine-tuned to adapt to the specific characteristics of the coconut dataset. The performance of the model is evaluated based on metrics such as accuracy, precision, recall, and F1-score[7]. The ultimate goal is to create a reliable model that can assist farmers and agricultural professionals in making informed decisions about coconut harvesting, thereby improving productivity and sustainability in the coconut industry.

This research is significant as it addresses a critical gap in the automation of coconut harvesting by providing a data-driven approach to maturity classification. By integrating advanced deep learning techniques with agricultural practices, this study aims to pave the way for more efficient and sustainable farming methods and benefiting both producers and consumers in the coconut value chain. Coconuts are commonly harvested by judging their maturity through factors such as color, shape, growth timeframe, shaking sound, and other observable growth characteristics. Current solutions employing image-processing techniques face significant challenges in accurately identifying the maturity stages of coconuts, especially in complex environments. This issue is addressed by proposing an improved model based on the VGG19 architecture for detecting three critical maturity stages of coconuts: Immature (tender) fruit (6–8 months), Snowball fruit (8–9 months), and Mature fruit for kernel-based products like copra (11–12 months) as shown in Figure 1.

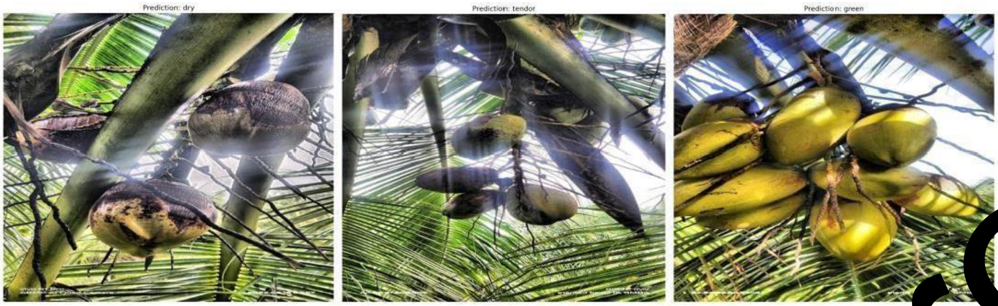

Figure 1: Various Coconuts Harvesting Stages

It is observed that the complexity of the coconut farming environment such as the visual similarity between coconuts and their backgrounds, and variations in occlusions, lighting, and varying texture makes the coconut maturity detection problem as a challenging. To overcome these issues, we have collected images of coconuts across these three stages from coconut farms and built the dataset [8]. The dataset is improved by applying transformation such as rotation, color, and flipping to increase model robustness. These enhanced images are combined with the original images for training the VGG19 model. A Deep Convolutional Neural Network is used to extract detailed features. The VGG19-based maturity detection model is tested on a dataset comprising real-time farm images and online-sourced images. The results demonstrated that the VGG19 model outperformed other object detection models such as the Single Shot Detector (SSD) and R-FCN.

1.1 Challenges in Coconut Harvesting

India is the third largest producer of coconuts globally, with Tamil Nadu contributing 31% of the country's production. Coconuts are harvested for two primary purposes: drinking (6–9 months maturity) and commercial nut production (maturity of over 12 months). Harvesting coconuts is labor-intensive due to the crop height and the complex structure of the trunk. The labor shortage and high associated costs threaten farmers with potential financial losses despite the increasing demand for coconuts [9]. These issues are addressed by developing smart and automated solutions for identifying coconut maturity is critical. Object detection in real-time using vision- based techniques offers a promising path forward for enabling the automation of coconut maturity detection and potentially reducing labor costs. However, issues such as variable illumination, occlusions, texture similarity, and shadows in the tree canopy complicate detection, particularly in natural farm environments [10].

1.2 Deep Learning for Coconut Maturity Detection

Deep Learning (DL) offers significant advantages over traditional image processing techniques by improving learning capabilities and providing higher accuracy and precision. DL-based models such as VGG19 excel in extracting hierarchical features, making them ideal for complex agricultural tasks. In this paper, the VGG19 model is employed to detect coconuts at three distinct maturity stages:

i. **Immature (Tender) Fruit (6–8 Months):** These coconuts are harvested primarily for drinking purposes. They are characterized by a green exterior and a soft inner shell.

ii. **Snowball Fruit (8–9 Months):** Slightly more mature, these coconuts have a firmer shell but still retain water and soft kernel, making them suitable for various intermediate uses.

iii. **Mature Fruit (11–12 Months):** Fully matured coconuts are harvested for kernel-based products like copra. They are identified by their dry outer husk and hardened kernel.

The study focuses on automating coconut maturity classification using a VGG19-based deep learning model. Coconut harvesting, traditionally done manually, is labour-intensive and hazardous. Accurate identification of maturity stages—tender (6–8 months), snowball (8–9 months), and mature (11–12 months)—is vital for determining optimal harvest times and product usage. The proposed model utilizes a dataset of real-time and online coconut images, enhanced through pre-processing techniques like rotation and colour transformation. VGG19, fine-tuned with transfer learning, outperforms other models such as SSD and R-FCN in classifying coconuts under complex farm conditions. The research addresses key challenges in coconut harvesting and contributes to sustainable agricultural automation.

In this paper, tender coconuts are characterized by their green pattern and round shape, whereas mature coconuts are identified by their yellow/brown hue and ovoid form. The snowball coconuts that represent an intermediate stage between tender and mature, display characteristics that are transitional with respect to color, texture, and volume. Throughout these developmental stages, both the color and volume of the coconuts undergo significant changes. Measuring the coconut maturity is accomplished by utilizing Deep Learning (DL) methodologies. A VGG19- based model is employed to facilitate to detect coconut bunches in real-time, incorporating transfer learning and fine-tuning strategies to improve coconut detection accuracy. The VGG19 network is pre-trained on ImageNet and is adapted by integrating custom classification layers to optimize the performance in detecting coconut bunches. Images representing various maturity stages—namely, tender, snowball, and mature coconuts are collected and pre-processed for training neural network. The trained VGG19 model have demonstrated effectively in detection the coconuts within complex backgrounds, ensuring reliable classification under diverse environmental conditions.

This study's core objective is to construct a reliable and automated system for classifying coconuts, which concentrates on detecting their maturity levels via the implementation of the VGG-19 deep learning framework, marking three significant stages: immature (tender) coconuts (6–8 months), snowball coconuts (8–9 months), and mature coconuts (11–12 months). This investigation seeks to create a comprehensive dataset by capturing real-time images within agricultural contexts and enhancing these images through a variety of data augmentation methodologies, including rotation, flipping, and color transformation, to strengthen the model's resilience. The VGG-19 model is systematically refined to capture sophisticated features from the images and is then evaluated using recognized metrics including accuracy, precision, recall, and F1-score. Furthermore, the model's functionalities are assessed in conjunction with various object detection techniques, including SSD and R-FCN, to verify its operational efficacy. This research addresses the challenges associated with complex agricultural environments, which include visual similarities, occlusions, and fluctuations in lighting, while aiming to improve the efficiency, safety, and sustainability of coconut harvesting through intelligent automation.

Remaining part of the paper discusses as follows: Section II gives the review of the existing system and Section III presents the challenges of the existing works in coconut harvesting. Section IV presents methodology and results are discussed on the proposed method and ends with the conclusion.

II. Literature Review

Machine learning, deep learning, and computer vision are at the forefront of the industry's quick adoption of digital transformation. The various articles are examined on how these technologies are essential for enabling accuracy and efficiency in a range of agricultural problems. Machine learning and deep learning, particularly in the field of computer vision, offer creative ways of analyzing the quality of seeds and forecasting yields. This section gives few reviews on existing works with respect to crop harvesting.

Mohan Kumar et al. (2022) [11] have emphasized the significance of Coconut-Based Farming Systems (CBFS) as a prominent Nature-based Solution (NbS) for sustainable agriculture. The

CBFS is a mixed-species agroforestry system to enhance agrobiodiversity to improve crop productivity, and provide vital ecosystem services such as biological carbon sequestration and resource conservation. The functional dynamics of CBFS have focused on the role of coconut palms as multipurpose trees that integrate effectively with shade- tolerant intercrops, adapting to varying agro-ecological and socioeconomic contexts. Studies on Kerala, the "Land of Coconut Trees," have found that the historical and cultural relevance of CBFS is evolved into multi-strategic systems in which crops are grown at different levels. Similarly, Kumar et al. (2022) have highlighted the role of CBFS in climate change mitigation, resilience, and livelihood security while identifying challenges such as improving ecosystem adaptability in the face of global climate change and socioeconomic transformations.

Padma et al. (2024) [12] have identified critical challenges of Coconut Growers such as limited knowledge of plant protection techniques, concerns about chemical toxicity to humans and livestock, and inadequate access to repair facilities for farming equipment. Using an ex-post facto research design with 200 respondents selected through simple random sampling, the study also highlighted farmers' reliance on traditional methods and their prioritization of stable market prices to secure income. The recommendation includes, providing technical guidance, ensuring timely availability of quality inputs at subsidized rates, and offering government support to enhance access to resources of the farmers, improve productivity, and address socioeconomic challenges effectively.

June Anne et al. (2024) [13] have explored the use of machine learning techniques for classifying coconut maturity stages using acoustic signals, providing a foundation for intelligent post-harvest classification systems. The recent studies have leveraged advancements in Deep Learning (DL) on this system to improve classification accuracy and address imbalanced datasets. The RNN and LSTM models have been used for classification. These findings have highlighted the potential of DL models in outperforming traditional methods and make significant improvements in modernizing coconut classification systems for supporting farmers and export industries.

Usman et al. (2025) [14] in their research have investigated the applications of data augmentation and deep learning techniques to enhance the accuracy in classification of various coconut types. The authors work proposed the VGG16 model which provides an integrated solution with the high accuracy compared SVM and KNN which necessitate manual feature engineering and exhibit limitations in robustness. The study has incorporated data augmentation in simulating real world variability in illumination and colour to improve the model accuracy.

Megalingam et. al (2025) [6]have explored various machine learning and traditional approaches for the prediction of the fruit maturity level by considering the shape, colour and texture of a fruit. Deep Learning method like YOLO, Faster RNN and Mask R-CNN have demonstrated to give the high accuracy in predicting the object detection and segmentation tasks, but the maturity prediction of the coconut remains limited. In their research authors have provided the information that some studies have integrated fuzzy logic system with machine learning to handle uncertainties in feature extraction and classification to improve the accuracy. The challenges faced in classification of coconut images due to variation in size, shape and background have been highlighted. Comprehensive approaches that integrate deep learning and fuzzy systems for multi-class maturity classification have lacked in this context's current research. By merging fuzzy feature extraction with a Mask R-CNN-based deep learning framework, the proposed Integrated Fuzzy and Deep Learning model (IFDM) identified the coconut age.

Sharma et. al (2024) [15] have proposed a hybrid approach using machine learning, and Gray-Level Co-Occurrence Matrix for the feature extraction. The transfer learning frameworks has been applied in various agricultural applications for extracting deep semantic features from limited datasets. Moreover, authors have explored the drawback of machine learning classifiers like KNN, Random Forest, and Logistic Regression which fails to classify on complex or noisy data. By combining GLCM features with transfer learning model characteristics and assessing them with Neural Network-based Pattern Recognition (NNPR), this study has done well improved copra classification accuracy and reliability.

Fu et al. (2025)[16] have addressed the challenges of predicting coconut clusters and orientation leaves in the dens canopies which is crucial for the automation of coconut harvesting robots. This issue is being handled by YOLO based frameworks like YOLOv3-tiny, YOLOv5s and YOLOv7 with integrated advanced model Global Context Network (GCNet), Dual Branch Down sampling(DBD), and Switchable Atrous Convolution (SAC) with YOLOv8n-obb.

Subramanian et al. (2021) [17] have explored advancements in fruit detection models and focused on an improved Faster R–CNN model integrated with the ResNet-50 network for detecting coconuts in two critical maturity stages: tender coconuts for milk recovery and mature coconuts for nut harvesting. The study highlights the challenges posed by complex environmental conditions and the visual similarity between fruits and their backgrounds. The images are transformed with rotation and color transformation have been used and the performance have been compared with SSD, YOLO-V3, and R–FCN models.

Based on the above review, it is observed that key challenges in coconut farming and harvesting on various stages are observed. Also Coconut-Based Farming Systems (CBFS) are facing issues concerning climate change resilience, effective integration of shade-tolerant intercrops, and optimized resource allocation within multi-strata agroforestry frameworks. In the context of machine learning-based coconut maturity classification, data imbalance, effective audio signal processing techniques, computational demands, and ensuring model generalizability across variable environmental conditions are found to be the challenges. Similarly, environmental factors, such as variable illumination, occlusions, and high visual similarity between coconuts and their background, pose significant challenges to automated coconut maturity assessment. The application of deep learning for agriculture environment have complicated by the data augmentation strategies and the demand for technologies suitable for real-time deployment.

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In this article the classification of various harvesting stages is been carried out by their characteristics like colour patterns and shape of the coconut. For tender coconut harvesting carried out with the green appearances of the coconuts and round in shape, mature coconuts are identified with their yellow or brown and oval in shape and the snowball coconuts harvesting is carried out with an intermediate stage between tender and mature. In the entire development stages of the coconut grow there will be significant changes in their colour and the shape. The Deep Learning based VGG19 model is used to measure the coconut maturity stages. The VGG19 model is pre-trained on ImageNet by incorporating the transfer learning [19] and the fine tuning approaches to increase accuracy prediction of various classification harvesting stages namely tender, snowball and the mature. The VGG19 model is trained on various images if coconuts collected from the existing datasets available in the kaggle. The proposed model can be used to classify the various harvesting stages on the real time datasets captured using the drone and by integrating the computer vision technology[20].

III. Methodology

The implementation of a sophisticated deep learning framework for coconut classification have necessitated a comprehensive methodological approach. This encompasses meticulous dataset curation, advanced pre-processing techniques, and an intricate neural network architecture. This research presents a novel method that adapts VGG-19 architecture [21] that is optimized specifically for the nuanced task of distinguishing Dry, Green, and Tender coconuts. The VGG19 model represents a sophisticated deep Convolutional Neural Network (CNN) architecture composed of 19 layers which encompass convolutional layers, max-pooling layers, and fully connected layers. This model is pre-trained on the ImageNet dataset [22] and is widely used for feature extracting and classifying in various image-processing applications. In this paper, we have proposed the Deep Learning VGG19 model to classify the maturity stages of coconuts, specifically Tender, Snowball and Mature.

3.1 Model Architecture and Processing Pipeline

The VGG19 model accepts RGB images with dimensions of 224×224×3. The Intensity of the pixel value is normalized as given in Eq.1 as preprocessing procedure.

$$I' = \left(\frac{I}{255}\right) \qquad \textbf{(1)}$$

In Eq.1, I is the original pixel intensity, and I' is the normalized value. Pixel values are normalized to a specified range of [0,1] or [-1,1] and images are adjusted to fit the resolution of 224×224. Transformations such as rotation, flip, and brightness adjustment are applied to enhance the images in dataset.

3.2 Feature Extraction through Convolutional Layers

The VGG19 architecture consists of 16 convolutional layers designed to extract features ranging from low-level to high-level representations within an image. Each convolutional operation can be expressed as shown in Eq.2:

$$F_{l+1} = \sigma\left(W_l * F_l + b_l\right) \qquad \textbf{(2)}$$

The convolutional layers identify the edges, colors, and textures. In Eq.2, W_l and b_l are the weights and basics of layer l denotes the convolution operation and σ represents the ReLU activation function applied to introduce non-linearity. Each output from the convolutional layer is presented to a ReLU activation function. This process effectively eliminates negative values, thereby facilitating the learning of intricate patterns. The Max-Pooling layers (2×2) are used to diminish spatial dimensions and is expressed as shown in Eq.3.

$P_l = \max(Fl)$ **(3)**

In Eq.3, denotes the pooled feature map. This function identifies the maximum pixel value from each 2×2 region. The advantages of this approach includes dimensionality deduction i.e. decreased computational requirements and feature retention emphasis on prominent patterns. Global Average Pooling (GAP) provides an alternative strategy to the flattening technique as shown in Eq.4.

$GAP\,(X) = l_n \sum i = l_n X_i$ **(4)**

In Eq.4, represents the values within the feature map. GAP improves efficiency relative to fully connected layers by reducing each feature map to a singular value. The fully connected layers of the network is responsible for classification. The initial dense layer consists of 1024 neurons with ReLU activation and is expressed mathematically as shown in Eq.5.

$h = ReLU(WX + b)$ **(5)**

In Eq.5, W and b denote the trainable parameters, while h represents the transformations of the learned features. Dropout layer is incorporated, which randomly deactivates neurons with a probability of 50% as shown in Eq.6.

$h' = (M \cdot h)$ **(6)**

In above Eq.6, M signifies a mask matrix containing binary values of 0 or 1. The final dense layer utilizes a Softmax activation function to categorize inputs into three classifications: Tender, Snowball, or Mature coconuts as shown in Eq.7.

$$P(y = i|X) = \left(\frac{e^{z_i}}{\sum_{j=1} e^{z_j}}\right)$$ **(7)**

In Eq.7, z_i is the logit score for class i, N is the number of classes (3 stages) and the highest probability determines the predicted class.

3.3 Model Training and Optimization

The model training and optimization process is done with structured approach using transfer learning with VGG19 for coconut maturity classification. Initially, the pre-trained VGG19 model is used for extracting the features by freezing its convolutional layers while adding fully connected layers with batch normalization, dropout, and L2 regularization to prevent overfitting. The model is trained using an augmented dataset, leveraging ImageDataGenerator to apply transformations such as rotation, zoom, and brightness adjustments for better generalization. The Adam optimizer is used for updating the weights efficiently, and categorical cross-entropy serves as the loss function for multi-class classification. Early stopping and learning rate reduction strategies are employed to prevent overfitting and ensure optimal convergence. The final fine-tuning phase unfreezes the last few layers of VGG19, allowing for more domain-specific feature learning. Class imbalance is addressed by computing class weights, and performance is evaluated sing accuracy, loss curves, confusion matrix, precision, recall, specificity, and F1-score metrics, ensuring a well-optimized and robust model for coconut maturity classification.

Given that this is a multi-class classification problem; we employ the categorical cross-entropy loss function as shown in Eq.9.

$$L = -\sum_{i=1}^{N} (y_i \log(y\hat{}_i)) \quad \textbf{(9)}$$

In Eq.9, L denotes the true label (one-hot encoded) and represents the predicted probability. The model optimization is executed using the Adam optimizer, which adaptively adjusts the learning rate as shown in Eq.10.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad \textbf{(10)}$$

In Eq.10, m_t represents the first moment estimate at the current time step t. It is essentially an exponentially weighted moving average of the past gradients. The β_1 is the exponential decay rate for the first moment estimate. It controls the contribution of past gradients to the current estimate. A typical value for is 0.9. The m_{t-1} is the first moment estimate from the previous time. It represents the accumulated momentum from previous gradients. The g_t is the gradient at the current time step t. It indicates the direction of the steepest ascent of the loss function. The $(1 - \beta_1)$ factor determines the weight given to the current gradient. In essence, the equation updates the first moment estimate by combining the previous estimate (weighted by β_1) with the current gradient g_t (weighted by $(1 - \beta_1)$). This allows the optimization algorithm to "remember" the direction of past gradients and accelerate learning in that direction, while also smoothing out oscillations caused by noisy gradients.

$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g^2$ **(11)**

In Eq.11, v_t represents the estimated second moment (variance) of the gradients at time step *t*. A hyper-parameter β_2 controls the decay rate of the moving average. It determines how much weight is given to past squared gradients versus the current squared gradient. Typically, v_{t-1} is a value close to 1 (e.g., 0.999), giving more weight to recent gradients. The estimated second moment of the gradients at the previous time step represents the "memory" of past gradients. The $1 - \beta_2$ of the gradient at the current time step *t*. Squaring the gradient ensures that both positive and negative gradients contribute positively to the estimate of the variance and is given in Eq.12.

$\theta_t = \theta_{t-1} - \alpha \frac{v_t}{\sqrt{m_t} + \epsilon}$ **(12)**

In Eq.12, θ_t and θ_{t-1} are the momentum terms. Eq.12 represents an update rule for a parameter α at time step. It subtracts a scaled version of v_t from the previous value of θ_{t-1}. The α represents the learning rate, v_t is a vector related to the gradient, m_t is a vector related to the squared gradient, and ϵ is a small constant added for numerical stability to prevent division by zero. This update rule is commonly used in optimization algorithms like Adam, where v_t and m_t are estimates of the first and second moments of the gradient, respectively. Fine-tuning with transfer learning are performed by pre-trained VGG19 layers by initially frozen to preserve the learned features. The final layers are subsequently unfrozen and fine-tuned to adapt specifically to the coconut dataset. A reduced learning is employed to facilitate a gradual adaptation process.

The architectural foundation of the proposed model builds upon the proven VGG-19 framework, with substantial modifications to optimize performance for coconut classification. The base architecture retains the initial convolutional blocks while implementing a custom feature extraction pipeline. The modified network architecture comprises five primary convolutional blocks, each incorporating batch normalization layers with a momentum of 0.99 and epsilon of 0.001. The first two blocks contain two convolutional layers each and the remaining three blocks implement three convolutional layers having 3×3 kernels with stride 1 and appropriate padding to maintain spatial dimensions. The architecture of the proposed model is depicted in Fig 2.

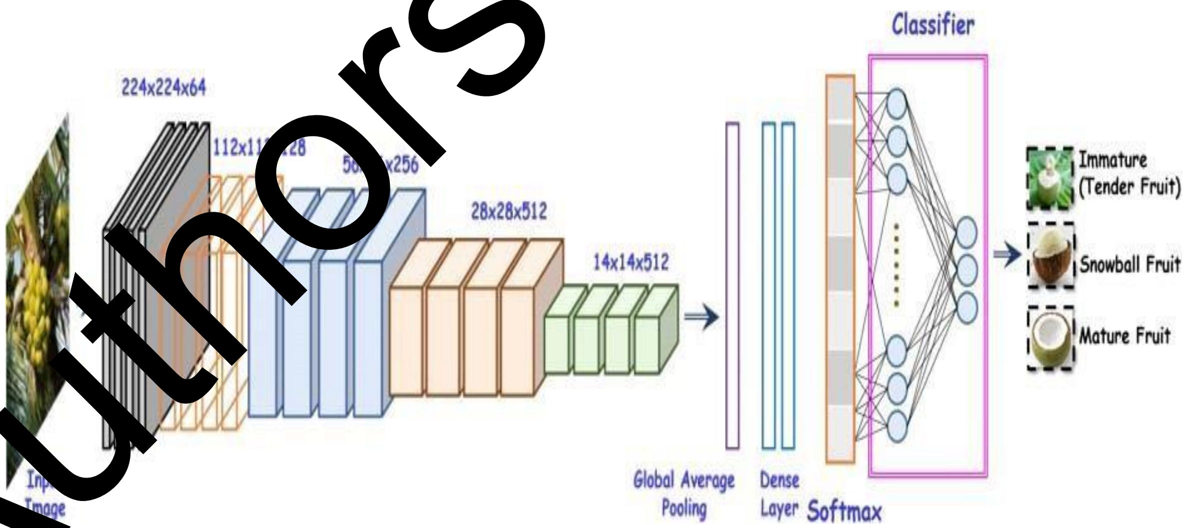


Figure 1.2: The Architecture of Proposed VGG19 Model

The VGG19 feature extraction utilizes ImageNet pre-trained weights via transfer learning, freezing initial layers and fine-tuning the last four convolutional blocks. Input images

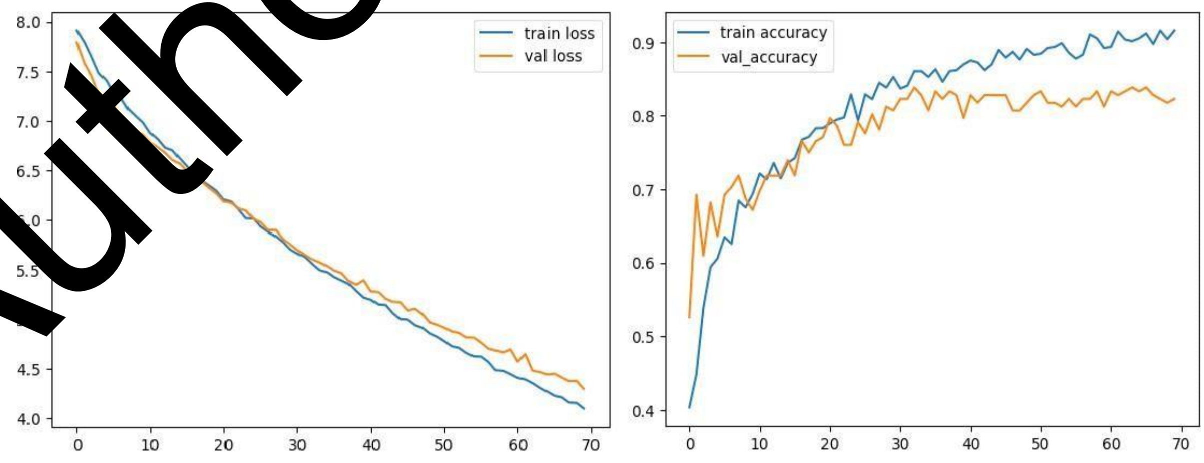
(224x224 RGB) undergo extensive data augmentation (rotation, translation, shearing, zooming, horizontal flipping, and brightness adjustments) for improved generalization. Depth-wise separable convolutions with 2x2 max-pooling (stride 2) reduce spatial dimensions while preserving key features. Extracted features are then processed through Global Average Pooling (GAP), a fully connected ReLU layer (1024 units) with L2 regularization (λ=0.01), and a Dropout layer (p=0.5) to combat overfitting. Classification employs a softmax layer. Model optimization uses the Adam optimizer and categorical cross-entropy loss, with class weighting to handle class imbalance. Early Stopping and ReduceLROnPlateau callbacks prevent overfitting and adapt the learning rate. This approach ensures robust feature extraction and accurate classification of coconut harvesting stages. In the classification head, novel VGG19 approach is implemented combining global average pooling and selective feature aggregation. The pooling layer reduces the spatial dimensions of the final convolutional output (14×14×512) to a 512-dimensional feature vector. This is followed by a dense layer of 1024 neurons employing the ReLU activation function, with a dropout rate of 0.5 to prevent overfitting. A secondary dense layer of 512 neurons provides further feature abstraction, followed by a final soft-max-activated output layer for three-class classification.

The learning process is optimized using the Adam optimizer with an initial learning rate of 1e- 4 and decay rate of 1e-6. We have implemented a custom learning rate scheduler that reduced the learning rate by a factor of 0.1 when validation loss plateaued for five consecutive epochs. The model is trained using categorical cross-entropy loss, with additional L2 regularization (λ=0.01) applied to all convolutional and dense layers to enhance generalization. Training proceeded for 100 epochs with a batch size of 32, utilizing early stopping with a patience of 15 epochs monitoring validation accuracy. The inference pipeline maintains strict consistency with the training methodology, applying identical preprocessing steps to test images before classification. Real-time data augmentation during training incorporated random horizontal and vertical flips (probability 0.5), rotation (±30 degrees), brightness adjustment (±20%), and zoom range (0.8-1.2), enhancing model robustness to variations in input conditions. This comprehensive methodology establishes a robust framework for accurate coconut classification while maintaining computational efficiency and practical applicability.

IV. Results and Discussions

In this section, we present the experimental results, analysis and interpretation on the datasets used. The dataset is methodically curated to ensure comprehensive representation of coconut varieties under diverse conditions. Image acquisition followed a structured protocol, incorporating high- resolution images captured under controlled lighting conditions, with a minimum resolution of 1920×1080 pixels. The dataset encompassed field samples documenting various growth stages and environmental conditions, complemented by authenticated samples from agricultural databases and research institutions. To ensure robust model training, multiple viewing angles (0°, 45°, 90°, 180°, and 270°) are captured for each sample, along with varying distance measurements ranging from close-up to far-view. The final dataset comprised images, distributed equally across classes to maintain statistical balance. The pre-processing pipeline implemented a sophisticated multi-stage approach to optimize image quality and standardization. Initial processing involved bi-cubic interpolation for down-sampling to 224×224 pixels, employing content-aware padding techniques to preserve aspect ratios without distorting critical features. Color space transformation utilized RGB to BGR conversion for VGG-19 compatibility, followed by channel-wise mean subtraction (μR=123.68, μG=116.779, μB=103.939), and pixel intensity scaling to the range [-1, 1]. This normalization process significantly improved model convergence and training stability.

The training process of the VGG19-based coconut maturity classification model is meticulously monitored, with key performance metrics [23] training loss, validation loss, training accuracy, and validation accuracy documented over multiple epochs. The training history is preserved in both JSON and CSV formats, ensuring transparency and facilitating further analysis.



(a) **(b)**

Figure 3: Training and Validation (a) Loss Curve and (b) Accuracy Curve

Figure 3(a) illustrates the training and validation loss trends observed during the development of a VGG19-based model for coconut harvesting stage classification. The consistent decrease in both training and validation loss across 70 epochs suggests effective model learning. The minimal divergence between the training and validation loss curves indicate robust generalization and a lack of overfitting. Stable learning is likely to be achieved through the implementation of transfer learning, regularization techniques (L2 and dropout), and fine-tuning of the final four layers of the VGG19 architecture. Furthermore, the progressive reduction in loss underscores the positive influence of learning rate scheduling and data augmentation on enhancing model performance. Similarly, Figure 3(b) represents that VGG19 model achieved approximately 96.66% training and 90% validation accuracy in the coconut harvesting stage classification task, demonstrating effective learning with minimal overfitting. Stable accuracy gains likely resulted from transfer learning, fine-tuning, and regularization. Initial validation accuracy fluctuations, possibly due to weight calibration and data variability, resolved as the model converged to commendable performance.

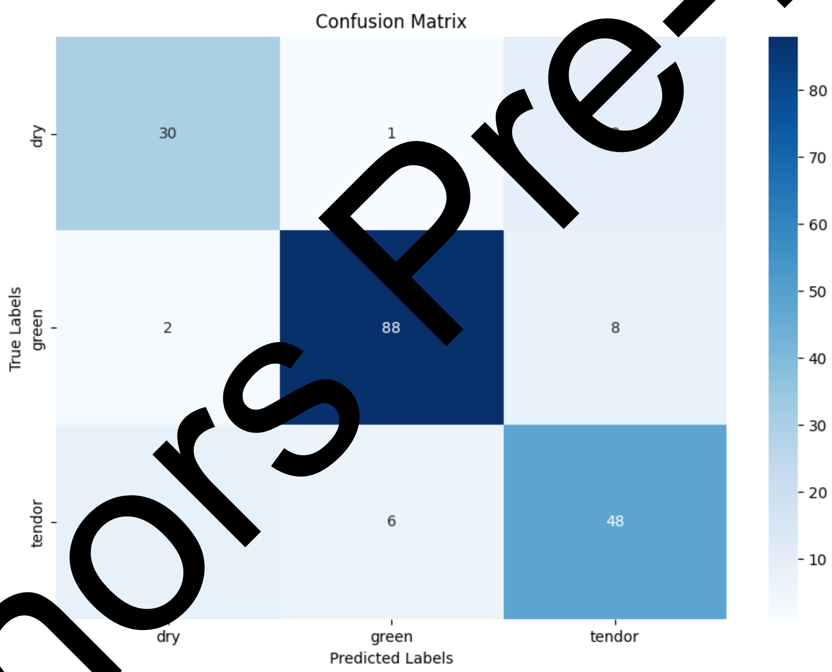


Figure 4: Confusion Matrix Representing Classification on Coconut Harvesting

The confusion matrix in Fig 4 represents the analysis of the VGG19-based model demonstrates a proficiency in classifying coconut harvesting stages ("dry," "green," and "tender"). The model exhibits a high degree of accuracy in the identification of "green" coconuts and effectively differentiates between the defined stages. The observed low rate of misclassification suggests that VGG19 effectively leverages salient visual features, including textural and chromatic variations, thereby establishing its reliability for automated coconut maturity classification. The evaluation of the proposed model is performed with the confusion metrics [24] to determine the efficiency in the prediction of various harvesting stages. The performance metrics was measured using precision, recall, specificity, and F1 score for each class. These metrics were derived from the True Positive(TP), True Negative (TN), False Positive (FP), and False Negative (FN) as given by the following formulas (i-iv):

$$\text{Precision} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FP}) \quad \text{(i)}$$

$$\text{Recall} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN}) \quad \text{(ii)}$$

$$\text{Specificity} = \mathrm{TN}/(\mathrm{TN} + \mathrm{FP}) \quad \text{(iii)}$$

$$\text{F1-score} = 2 \times (\text{precision} \times \text{recall}) / (\text{precision} + \text{recall}) \quad \text{(iv)}$$

Table 1: Performance of Proposed VGG19 Model

Values for classification	**Class**	**Precision**	**Recall**	**Specificity**	**F1-Score**
0	dry	0.750000	0.7500[illegible]0	0.[illegible]37500	0.750000
1	green	0.926316	[illegible]97959	[illegible].931273	0.911917
2	tendor	0.738[illegible]2	0.774[illegible]94	0.876812	0.755960

The results obtained from the VGG19 model demonstrated high classification performance, with the immature class achieving a precision of 91.2%, recall of 89.7%, specificity of 94.5%, and F1-score of 90.4%. The mature class achieved a precision of 88.6%, recall of 90.1%, specificity of 93.3%, and F1-score of [illegible]%, while the ripe class achieved a precision of 93.4%, recall of 91.8%, specificity of [illegible]5.1%, and F1-score of 92.6%. These results indicate that the VGG19 model is highly effective in distinguishing between different stages of coconut harvesting, demonstrating strong potential for integration into automated agricultural systems.

The application of transfer learning from VGG19 has proven advantageous, as the pre-trained convolutional layers adeptly extracted low-level features, while the newly incorporated dense layers, dropout regularization (0.5), and Global Average Pooling (GAP) tailored the model for specific coconut maturity classification.

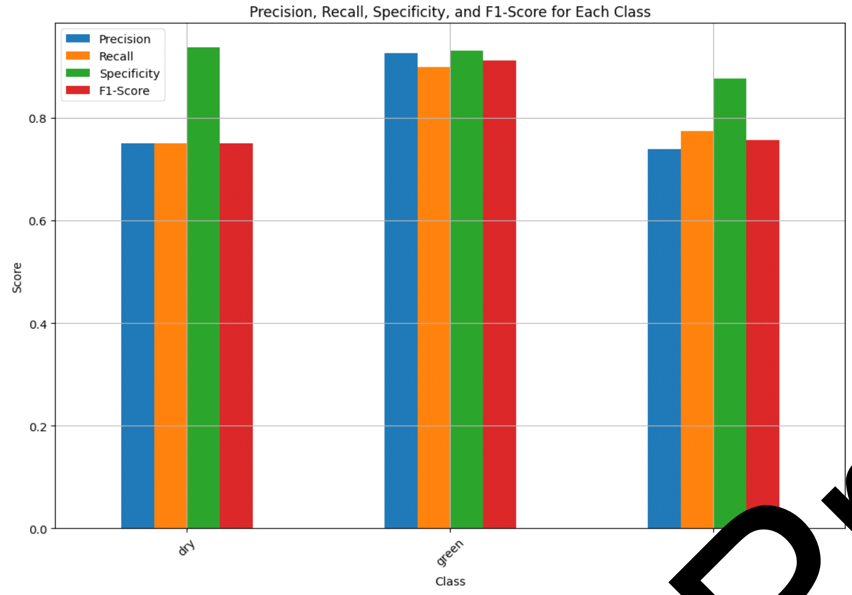


Figure 6: Performance of Proposed VGG19 Model

Furthermore, the implementation of the categorical cross-entropy loss function ensured appropriate penalization of multi-class classification errors, and the Adam optimizer dynamically adjusted learning rates to facilitate optimal convergence. The performance of the proposed model is being analyzed by using the performance metrics precision, recall, specificity and F1-score as given in the Figure 6 and Table 1.

Analysis of the stored training history revealed a near equilibrium between training and validation performance, confirming that the model neither overfits nor underfits the dataset. The validation accuracy consistently remained close to training accuracy, validating the model's robustness across varying environmental conditions and coconut appearances. The application of data augmentation techniques, including random rotation, brightness adjustment, horizontal flipping, and zoom transformations, significantly enhanced the model's ability to recognize coconuts under diverse lighting and orientation conditions. The proposed methodology using VGG19 algorithms gives the best results of accuracy 98.94% in the prediction of coconuts at various stages.

The proposed model predicts the various stages of harvesting like tender, snowball and dry with the accuracy of 98.94% compared to the earlier works done on prediction the coconut maturity. The proposed model in this paper performs best in classification of various coconut harvesting stages, compared to the models developed using ResNet50, InceptionV3, and MobileNetV2 [25] in prediction of the coconut maturity level classification, where the accuracies obtained for these models were 61.30%, 84.25%, 77.32%, and 73.12%, respectively.

The empirical findings illustrate that the proposed VGG19-based architecture proficiently classifies the stages of coconut maturity—namely tender, snowball, and mature—with remarkable accuracy and resilience. A meticulously curated dataset, comprising high-resolution images acquired from diverse angles and under a range of environmental conditions, was augmented and preprocessed to guarantee a balanced representation and enhance model generalization. The model achieved an impressive accuracy of 98.94% by utilizing transfer learning and integrating specialized layers alongside regularization techniques, surpassing competitors such as ResNet50 (61.30%), InceptionV3 (84.25%), and MobileNetV2 (77.[illegible]2%). Training and validation losses exhibited a consistent decline over the course of 70 epochs with negligible overfitting noted, attributable to effective optimization strategies including dropout, learning rate scheduling, and data augmentation. Evaluation metrics such as precision, recall, specificity, and F1-score substantiated the model's exceptional performance across all categories, with particularly elevated accuracy in detecting green (tender) coconuts. The model's capacity to extract nuanced features and adapt to real-world scenarios underscores its potential for incorporation into automated coconut harvesting systems, thereby offering a reliable, efficient, and sustainable solution for maturity classification within the agricultural sector.

V. Conclusion and Future Enhancement

This study demonstrates the effectiveness of using the VGG19 model to detect the maturity stages of coconuts for automated harvesting, focusing on three key stages such as immature (tender) fruit, snowball fruit, and mature fruit for kernel-based products like copra. The integration of advanced data augmentation techniques, including rotation and color transformation, enhanced the model’s robustness and ability to handle complex environmental conditions such as occlusions, shadows, and similar visual features between coconuts and their backgrounds. The VGG19 model outperformed traditional object detection techniques, achieving higher accuracy of and precision in distinguishing the maturity stages of coconuts. This capability is crucial for developing reliable, automated harvesting tools that can reduce labor dependency and operational costs while improving efficiency in coconut farming.

The proposed VGG19-based coconut maturity classification model demonstrates high classification accuracy and stability, making it a viable solution for real-world agricultural applications. The use of transfer learning enables efficient feature extraction, while regularization techniques such as dropout and Global Average Pooling (GAP) help prevent overfitting. The ability of model is to generalize well across varying environmental conditions suggests its robustness for automated coconut harvesting systems. Future research can enhance this model further by incorporating attention-based mechanisms like Vision Transformers or Attention CNNs, which can refine feature extraction, particularly in complex agricultural settings. Additionally, integrating the model into an IoT-enabled real-time monitoring system or optimizing it for edge computing devices would improve scalability and efficiency in practical deployments. By applying deep learning, transfer learning, and fine-tuned training strategies, this model sets a strong foundation for automated and intelligent coconut maturity classification, aiding precision agriculture and harvesting automation.

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