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Deep Learning for Arecanut Maturity Assessment: A Comparative Analysis of Fine-Tuned CNN Models in RGB, Saturation, and Grayscale Domains

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Abstract: The classification of arecanut maturity is essential for agricultural practices, enabling precise harvesting and optimizing yield. This research explores a deep learning-based approach using transfer learning to classify arecanut maturity levels from images captured in field conditions. Leveraging four pre-trained convolutional neural network (CNN) models—MobileNetV2, InceptionV3, DenseNet-121, and VGG-16—the study analyses model performance across three distinct color spaces (RGB, Saturation, and Grayscale). Due to the limited dataset, data augmentation techniques such as rotations and flips were incorporated to expand the sample size and reduce overfitting. Fine-tuning was applied to the final layers of each model, adapting the networks to the task of arecanut classification. Results demonstrate that MobileNetV2 achieved the highest classification accuracy of 86.07% on RGB images, with accuracy metrics for each model showing that RGB space consistently outperformed Saturation and Grayscale spaces in this application. The findings suggest that combining fine-tuning and data augmentation optimizes model performance, providing a feasible solution for arecanut maturity classification in resource-limited agricultural settings.

Keywords: *Arecanut, MobileNetV2, Classification, Convolution Neural Network, data-augmentation, fine-tuning and Transfer learning.*

1. INTRODUCTION

Agriculture plays a pivotal role in driving the GDP of many developing nations, including India, where commercial crops greatly support economic growth and farmer livelihoods. One such valuable crop, arecanut (Areca catechu), widely known as betel nut, is heavily cultivated in India [1]. Arecanut serves various purposes in products like medicines, tea powder, and soaps, making it a vital commercial crop for the Indian economy [2].

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A key step in arecanut farming is accurately assessing the maturity level of the arecanut bunches to classify them as either "Mature," which are ripened and ready for harvest, or "Immature," indicating they are unsuitable for immediate harvesting. Precise maturity identification is essential to ensure product quality and avoid premature harvesting, which can cause significant economic losses for farmers [3]. Traditionally, maturity assessment is conducted through visual inspection, which can be challenging due to the height of areca trees, as well as variations in maturity indicators such as color, shape, and texture that differ based on soil and environmental conditions. Additionally, skilled labour for this task is often scarce.

In the view of helping the farmers, few works has been done on arecanut maturity level identification using image processing techniques. Segmentation and classification method for raw arecanuts using three-sigma control limits has proposed in [4]. The method utilized color features of raw arecanuts, focusing on segmentation accuracy to assess the maturity and quality of the arecanuts. This approach demonstrated how statistical modeling can aid agricultural classification by capturing variations within acceptable ranges, enhancing the consistency of arecanut quality assessment processe. Texture-based classification techniques for unharvested arecanuts have been proposed in [5]. Using texture features, the study applied pattern recognition methods to categorize arecanuts, emphasizing the importance of texture in identifying maturity levels. HSV color model for segmenting arecanut bunches, focusing on color attributes to distinguish maturity levels is presented in [6]. The HSV model allowed for effective separation of arecanut bunches from the background based on hue and saturation components, improving segmentation accuracy for further classification tasks. From this work, it is concluded that segmented images give better result for further analysis. To remove the unwanted background in the unharvested arecanut bunch image using YCgCr color model which helps to find the crop's maturity effectively has been done by [7]. A four class classification of harvested raw arecanuts into four groups: Minne, Ape, Bette and Gorabalu based on different color attributes using a K-NN classifier has been done in [8].

Current literature on arecanut classification primarily focuses on traditional segmentation and classification methods, relying on features like color and texture in post-harvest images. This post-harvest approach, however, doesn't address the difficulties faced by farmers in assessing arecanut maturity at the time of harvest. An automated method for in-field maturity classification could greatly benefit farmers by facilitating real-time decisions. Recent advances in computer vision and image classification offer promising solutions, with many image classification models and algorithms delivering high accuracy in various applications [9-10].

Transfer learning has become a prominent technique in image classification, especially when applied to agricultural datasets where large labeled datasets are limited. By leveraging pre-trained models from extensive datasets like ImageNet[11], researchers can achieve high accuracy with less labeled data, making it ideal for tasks like crop maturity assessment. Studies have shown that transfer learning improves the classification of crops and plants by allowing pre-trained models to adapt to specific tasks through fine-tuning [12-14]. In arecanut maturity classification, transfer learning with models like MobileNetV2, DenseNet-121, and InceptionV3 allows the models to apply learned visual patterns to identify mature and immature arecanut bunches accurately.

MobileNetV2 is valued for its efficient design, utilizing inverted residuals and depthwise separable convolutions to achieve lightweight, low-power processing, making it ideal for real-time, field-based applications in agriculture, like disease detection and crop classification [15-16]. This model's efficiency makes it suitable for assessing arecanut maturity in resource-limited settings. DenseNet-121, recognized for its dense connectivity that reuses features across layers, excels in fine-detail tasks, such as identifying texture and color changes, which are key indicators in crop maturity detection [17]. In agriculture, DenseNet-121 has been effective in distinguishing subtle texture differences, which is directly relevant to assessing arecanut maturity [18].

InceptionV3 is known for its multi-scale feature extraction, employing parallel convolutional layers to capture different spatial resolutions within an image. This model performs well in complex recognition tasks where both large and small visual cues matter, making it suitable for tasks requiring subtle feature recognition, such as arecanut maturity identification [19]. It has been applied to tasks requiring multi-scale processing, such as plant disease detection, where its ability to focus on various spatial features aids in recognizing nuanced visual indicators [20]. Lastly, VGGNet-19's deep architecture and small convolutional filters enable robust spatial feature extraction, yielding high accuracy in complex classification tasks, though it is computationally demanding. This network is effective in environments with adequate resources and is useful for precise maturity classification tasks in agriculture [21].

This paper presents an automated approach for assessing arecanut maturity by categorizing bunches into "Mature" and "Immature." Key contributions include utilizing transfer learning for unharvested arecanut classification and analyzing performance across different color spaces (RGB, HSV, and Grayscale) using four pre-trained models: MobileNetV2, DenseNet-121, InceptionV3, and VGGNet-19.

In section 2, the materials and procedures used in this work are detailed, in section 3, the conducted experiments are detailed. Results of the study are explained in section 4, finally in section 5, the conclusion is drawn and several recommendations for future work are indicated.

2. METHODOLOGY

The proposed method involves collecting arecanut images from fields and pre-processing them for model compatibility. Once pre-processed, the images are fed into deep learning models to classify the maturity level of the arecanuts. The complete methodology is outlined below.

2.1 Dataset Description

This study utilizes a dataset from [22] to evaluate the proposed method. The dataset comprises 1,017 images of arecanut bunches, with 629 immature and 388 mature bunches, providing a balanced set for training and validation. The images were captured using an OPPO F3 smartphone with a 16-megapixel camera, mounted on a selfie stick at an angle of 45 degrees, approximately 50 cm from the bunches. This setup was used to capture images of 7–9-year-old areca palms, typically 12–14 feet tall, between 9 AM and 1 PM, aligning with standard harvesting hours. To ensure consistent resolution, all images were resized to 256 × 256 pixels and saved in JPEG format.

2.2 Image Pre-processing

The original high-resolution images were resized to 224 × 224 pixels for optimal memory use and efficient processing. Given that the color of the arecanut fruit indicates maturity, we transformed the RGB images to grayscale and HSV saturation images, facilitating analysis across multiple color spaces.

2.2.1 RGB Color Space

The RGB color space, widely used in digital imaging, represents colours by combining red, green, and blue channels, making it ideal when color details are crucial [23-24]. This dataset originally stores arecanut images in RGB format, capturing all color information needed for classification tasks.

2.2.2 Grayscale Color Space

Grayscale conversion reduces images to shades of gray, with each pixel represented by an intensity value from black (0) to white (maximum intensity). This reduction simplifies computations and highlights intensity-based features, which are valuable for texture and edge analysis [23-24]. A common formula for this conversion is given in Eq.1.

$$Gray = (0.2989 \times R) + (0.5870 \times G) + (B \times 0.1140)$$

This formula reflects human color sensitivity, enhancing green, red, and blue channels according to perceptual importance. Grayscale images derived from RGB are stored separately for further analysis.

2.2.3 Saturation Component in HSV Color Space

The HSV color space, often more intuitive for image processing than RGB, represents colors through Hue, Saturation, and Value components. Saturation measures color intensity, with high saturation indicating vivid colors and low saturation indicating faded, grayish tones. This attribute is useful for distinguishing between mature and immature arecanut bunches [25]. Saturation component can be computed from RGB image using Eq-2 ,

$$\text{Saturation} = 1 - \frac{3}{(R+G+B)}[\min(R, G, B)] \quad (2)$$

Where R, G, B, are primary color components blue, red and green respectively.

2.3 Dataset Partitioning

The images are partitioned into training (70%), validation (20%), and testing (10%) datasets for each color space (RGB, grayscale, and saturation). This partitioning strategy ensures adequate data for model training, validation, and evaluation. Table 2 summarizes the distribution across the color spaces, providing a balanced dataset for comprehensive model assessment. The sample images in Figure 1 illustrate the variations in RGB, grayscale, and saturation datasets, showcasing the diversity of color spaces used in this study. This methodology, utilizing different color spaces, enables a robust evaluation of the proposed approach in distinguishing maturity levels in arecanut bunches.

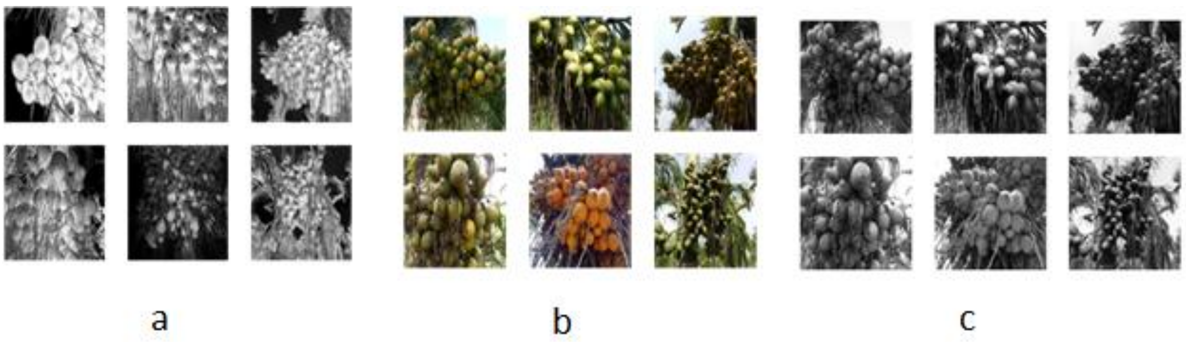

Fig 1: Sample images in the used dataset.

(a) Saturation component images b) RGB images (c) Grayscale images

Table 1. Description of d a t a s e t used in the proposed work datasets.

Color space	Training dataset	Validation dataset	Test dataset	Total
RGB Images	712	203	102	1017
Saturation Images	712	203	102	1017
Gray Scale	712	203	102	1017

2.4. *Classification:* Transfer Learning Technique.

In this research, we employ transfer learning techniques to classify arecanut bunch images into maturity categories. Building and training a deep neural network (DNN) from scratch can be time-intensive and resource-demanding, requiring significant expertise and computational power [26]. To overcome these challenges, transfer learning is utilized; allowing us to leverage pre-trained models developed for large datasets and adapts them to our smaller dataset.

Transfer learning involves taking a pre-trained model, originally trained on a large dataset (e.g., ImageNet), and modifying it to suit a new, related task, such as arecanut maturity classification. This approach provides several advantages, including faster training and reduced need for extensive data, making it particularly valuable for agricultural datasets where labeled images are often limited. In this study, we use pre-trained models such as MobileNetV2, InceptionV3, DenseNet-121, and VGG-16, fine-tuning each model to optimize classification accuracy for arecanut images.

2.4.1 Fine-Tuning and data augmentation in Transfer Learning

Fine-tuning is a crucial part of transfer learning, where adjustments are made to specific layers of a pre-trained network to better align with a new classification task [27]. In this work, fine-tuning involved attaching a fully connected layer to the pre-trained base models, set to classify images into two categories: "Mature" and "Immature." During the training process, this fully connected layer, along with select layers in the deeper sections of the base model, is trained on our dataset. This approach allows the model to "learn" task-specific features while retaining the general, robust patterns learned from the original large dataset.

To address potential overfitting due to the small size of the training set, several data augmentation techniques [28], such as rotation and flipping, are applied. This expands the effective dataset size and introduces more variety, helping the model generalize better to unseen images. Additionally, fine-tuning reduces overfitting by refining the model on arecanut-specific features while maintaining the benefits of transfer learning.

3. EXPERIMENTAL SETUP

The experimental setup for this study was conducted on Google Colab[29] using Python, TensorFlow [30] , and Keras[31] , enabling the implementation and fine-tuning of deep learning models for classifying arecanut maturity. Four pre-trained models—MobileNetV2, InceptionV3, DenseNet-121, and VGG-16—were trained across three color spaces (RGB, Saturation, and Grayscale) to assess classification performance under varying conditions, focusing on data augmentation, fine-tuning, and dropout regularization. To optimize training, the Adam optimizer [32] was used with a learning rate of 0.0001, while a dropout rate of 0.5 was implemented to reduce model variance by randomly deactivating neurons, thus enhancing model generalization. Each model was trained for 20 epochs to stabilize and refine the learning process.

The experiment analyzed three configurations, each assessing the impact of fine-tuning and data augmentation on classification accuracy using the MobileNetV2 model as a baseline:

1. **Baseline Model without Fine-Tuning or Data Augmentation**: Initially, MobileNetV2 was trained on the dataset without applying fine-tuning or data augmentation, resulting in a modest classification accuracy of around 62%, highlighting the model's limited adaptability due to insufficient data.
2. **Model with Fine-Tuning Only**: In this configuration, MobileNetV2 was fine-tuned on the arecanut dataset without any data augmentation. This led to a marked improvement in accuracy, achieving a validation accuracy of 94.33%, but signs of overfitting were evident, as training accuracy surpassed validation accuracy. This overfitting effect is common in transfer learning with small datasets when fine-tuning alone is applied without additional augmentation.
3. **Model with Fine-Tuning and Data Augmentation**: The final configuration combined both data augmentation and fine-tuning, resulting in enhanced accuracy without overfitting, as MobileNetV2 demonstrated robust classification performance. This finding aligns with studies that show combining fine-tuning with data augmentation helps improve model generalizability, especially in deep learning applications with limited training data.

Table 2 and Figure 2 provide a comparison of results across these configurations, indicating that the third configuration—combining fine-tuning with data augmentation—achieved the best classification accuracy and generalizability. Due to these advantages, this third method was adopted to train all four models in this study, enhancing performance across RGB, Saturation, and Grayscale color spaces.

Table 2: Comparison of the effect of fine-tuning and data augmentation technique for the MobileNetV2 model on classification of RGB images.

	Baseline Model without Fine-Tuning or Data Augmentation	Model with Fine-Tuning Only	Model with Fine-Tuning and data agumentation
Training Accuracy	61.66%	99.92%	96.33%
Validation Accuracy	62.37%	94.33%	94.85%

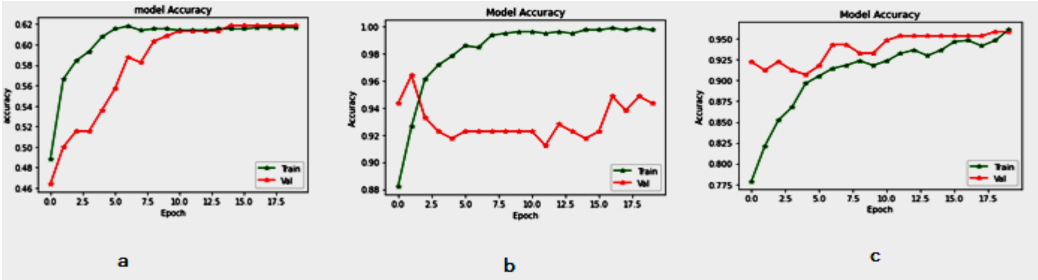

Figure 2. Accuracy versus epoch graph for the MobileNetV2 model on classification of RGB images. (a) : Baseline Model without Fine-Tuning or Data Augmentation , (b): Model with Fine-Tuning Only and (c): Model with Fine-Tuning and data augmentation

4. RESULTS AND DISCUSSION

The experimental results from this study reveal the performance of four fine-tuned deep learning models—MobileNetV2, InceptionV3, DenseNet-121, and VGG-16—across three color spaces (RGB, Saturation, and Grayscale) for classifying arecanut maturity. Table 3 provides a comparison of classification accuracies for each model on the three test datasets, highlighting the efficiency and limitations of each model under different color representations.

4.1 Performance Analysis

The MobileNetV2 model achieved the highest classification accuracy at 86.07% when tested on RGB images, indicating a strong capability to differentiate between mature and immature arecanut bunches in this color space. Figure 3 illustrates MobileNetV2's classification performance, showing its ability to correctly label images with associated confidence percentages. The bar graph alongside each image displays the prediction probabilities for the two classes (Mature and Immature), which further highlights the model's confidence in its predictions. The results indicate that MobileNetV2's lightweight architecture, combined with data augmentation and fine-tuning, allows it to deliver accurate and efficient classification.

For the Saturation image dataset, MobileNetV2 again performed best with an accuracy of 85.25%, slightly lower than its RGB performance, while VGG-16 performed similarly (84.43%). The saturation component in HSV images helps distinguish color intensity, which can aid in maturity detection. However, its performance, while robust, generally lagged behind RGB images, suggesting that full color information provided by RGB might offer richer feature representation for this classification task.

4.2 Color Space Impact on Classification

The grayscale dataset yielded the lowest classification accuracies across all models, with DenseNet-121 reaching the highest at 66.67% accuracy, while MobileNetV2 performed at 60.78%. Grayscale's limited intensity-based representation may be insufficient for capturing color-based maturity features essential in arecanut classification. These findings align with other studies, which report that RGB and saturation channels often perform better than grayscale in tasks that rely heavily on color cues.

Table 3. Performance comparison of fine-tuned CNN models across different color spaces for arecanut maturity classification

Dataset name	Mobile NetV2	Inception-V3	DenseNet-121	VGG-16
RGB-Images	**86.07**	80.39	85.25	84.43
Saturation Images	85.25	80.33	82.79	84.43
Grayscale-Images	60.78	64.71	66.67	58.62

5. CONCLUSION

This study successfully applied fine-tuned CNN models to classify arecanut maturity levels, achieving promising results on a small, field-captured dataset. Among the tested models, MobileNetV2 demonstrated the best accuracy on RGB images, indicating that RGB color space captures critical maturity-related features more effectively than Saturation and Grayscale spaces for arecanut classification. Through careful experimentation, it was observed that combining fine-tuning and data augmentation effectively reduces overfitting, improving model generalization. The study underscores the effectiveness of transfer learning and data augmentation techniques for agricultural image classification tasks, especially when datasets are limited. Future work could explore further refinements such as hyperparameter tuning, additional data augmentation techniques, or the integration of multi-spectral data to enhance classification accuracy further. This research contributes valuable insights to the development of automated arecanut maturity classification tools, potentially aiding farmers in optimizing harvest timing and improving crop quality.

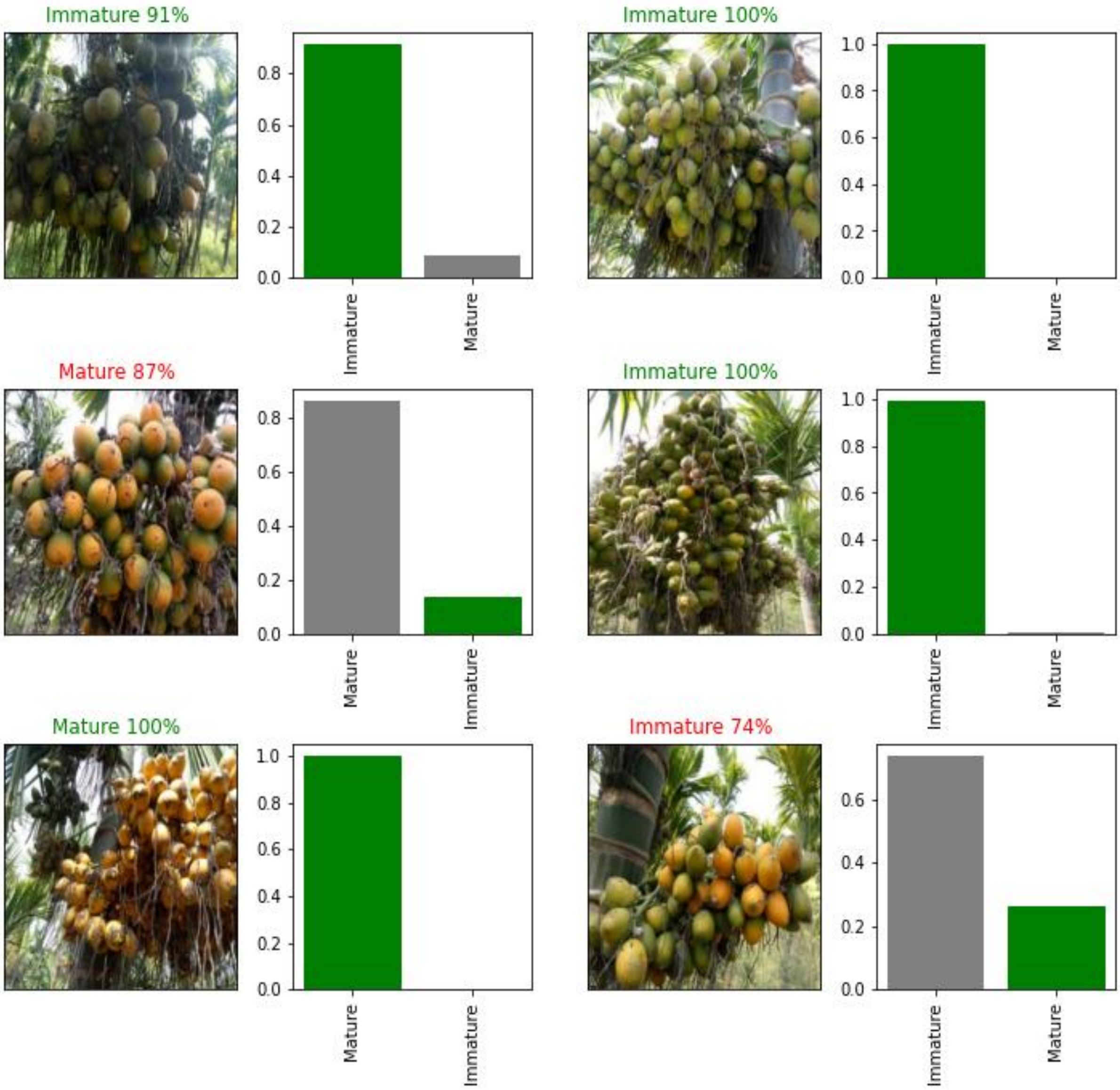

Figure 6: Prediction of MobileNetV2 model on *RGB* test dataset.

6. STATEMENTS AND DECLARATIONS

Funding: No funds have been taken for this work from any organization.

Conflict of Interest: Authors have no conflict of interest.

Availability of data and materials:

Dataset used in this work is available in http://davangereuniversity.ac.in/arecanut-database/

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