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Rambutan Fruit Sweetness Profiling: Integrating Technology for Enhanced Classification

Sushma M D[1], Anjana Ganapati Bhat[2], Meghashree Kamath[3], Deekshitha[4] and Varshini R Nayak[5]
[1]Research Scholar, Canara Engineering College, Mangalore, Karnataka, India
Email: sushraj11@gmail.com
[2-5]Student, Information Science and Engineering, Canara Engineering College, Mangalore, Karnataka, India
Email: anjanagb801@gmail.com, meghakamath96@gmail.com, deekshithashetty508@gmail.com, rvarshini2152002@gmail.com

***Abstract*— Rambutan fruit (Nephelium Lappaceum), a rare tropical fruit cherished for its unique appearance and flavor, has drawn attention for its limited cultivation. The variable sweetness levels of rambutan fruits, stemming from their limited cultivation, often lead to customer dissatisfaction and economic losses for growers, distributors, and stakeholders in the industry. The need for an automated and dependable system for classification and sweetness prediction is evident. To cope with this problem, the project's goal is to create a consistent deep learning system that uses a variety of features such as color, and size to classify the rambutan fruit into 4 different varieties namely Binjai, E35, N18, and Pulasan and predict the sweetness levels of rambutan fruits into three categories namely sweet, mild sweet and sour accurately. The principal achievement of this study involves the development of a proficient deep-learning model based on the VGG16 architecture. The VGG16 architecture, characterized by its 16-layered Convolutional Neural Network design, demonstrates precision in categorizing rambutan fruits into predetermined varieties and sweetness levels. This model aims to bring about consistency in sweetness levels, ultimately resulting in increased consumer satisfaction and economic benefits for growers and distributors. The implementation included dataset creation of a total of 912 rambutan fruit images, preprocessing, VGG16 model building, training the dataset, and testing them. Hence the results obtained had an accuracy of 88% for classification based on variety and 85% for sweetness classification with 50 epochs of training. This can further be increased with a greater image sample in the dataset and the implementation of diverse preprocessing techniques. In the future, comparative analysis can be done with other deep learning algorithms.**

***Index Terms*— Rambutan classification, Sweetness profiling, Fruit image classification, Fruit variety classification, Rambutan Dataset**

I. INTRODUCTION

In the rapidly evolving landscape of agricultural industries, ensuring product quality and consumer satisfaction remains a critical challenge. The rambutan fruit, known for its distinctive appearance and flavor, has successfully secured a unique position in the global fruit market. However, the limited cultivation of rambutan, coupled with the existence of various varieties and inherent variability in sweetness levels, presents formidable challenges for both growers and consumers alike. The current scenario underscores the increasing demand for solutions that not only streamline cultivation processes but also address the quality and consistency issues associated with rambutan.

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In the context of the fruit industry, traditional methods for classifying rambutan varieties and predicting sweetness levels have proven to be limited in their effectiveness. Conventional approaches depend on manual inspection, which is time-consuming, labor-intensive, and subject to human error. Additionally, these methods struggle to handle the nuances of the diverse rambutan varieties and the fluctuating sweetness levels, hindering accurate and efficient classification.

The limitations of traditional methods highlight the urgent need for innovative approaches to improve the quality control and productivity of the rambutan industry. In response to these challenges, this paper, titled "Rambutan Fruit Sweetness Profiling: Integrating Technology for Enhanced Classification," introduces a pioneering solution. The research leverages advanced deep learning techniques, specifically employing the VGG-16 model, to create a robust classification system. The work intends to address the drawbacks of conventional techniques and offer a more precise, effective, and scalable way of categorizing rambutan varieties and estimating sweetness levels by integrating technology.

The current scenario emphasizes the timeliness and relevance of this research, as the rambutan industry grapples with the need for technological advancements to address its unique challenges. Through a comprehensive exploration of methodology, data analysis, and machine learning model development, this paper aspires to contribute significantly to enhancing the quality standards, economic viability, and consumer appeal of the rambutan industry in the current agricultural landscape.

II. LITERATURE SURVEY

In Junhan Wen et al. [1], the study anticipates the sweetness level of strawberry juice, quantified by its total soluble solid (TSS) content or Brix. Various machine learning models, including Convolutional Neural Networks (CNN), Principal Component Analysis (PCA), Multilayer Perceptron (MLP), Variational Autoencoders (VAE), Support Vector Regression (SVR), and Kernelized Ridge Regression (KRR) were employed by the investigators. The findings indicate that a model trained with both environmental and plant data exhibits the highest accuracy in predicting Brix, achieving a notably low Root Mean Square Error (RMSE) of 0.59. Additionally, the integration of image data enhances the prediction of individual fruit Brix, reducing the RMSE from 1.27 to 1.10.

In V. Gautam et al. [2], the study proposes a deep learning framework to categorize diverse varieties of dried fruits, classification is conducted considering attributes such as size, shape, and edge characteristics employing transfer learning techniques. Various pre-trained models, including Xception, Inception, VGG16, VGG19, and SqueezNet, were employed for model training. Classification of dried fruits is achieved by combining the learned weights from these models with features extracted by a fully connected network. The proposed model demonstrates a high classification accuracy of 98.53% when tested on a dataset comprising four distinct types of dried fruits.

In M. N. Y. Ali et al. [3], the research introduces an advanced deep-learning approach for discerning sweet and sour tastes in mangoes through the analysis of mango photos. A dataset comprising 3132 mango images was utilized for training and validation purposes. The methodology incorporates a customized YOLO v3 algorithm. In the evaluation of sour mango data, the system achieved notable performance metrics, including an average precision (AP) of 0.84, precision of 0.75, recall (true positive rate) of 0.94, and an F1-score of 0.83. Similarly, on sweet mango data, the system demonstrated high accuracy with an AP of 0.97, precision of 0.98, recall of 0.97, and an F1-score of 0.98.

In Mohit Kumar et al. [4], The authors of this study aimed to predict apple sweetness and detect diseases by analyzing the fruit's leaf and texture. They developed a novel method called brightness preserving dynamic fuzzy histogram equalization (BPDFHE) for enhancing the quality of apple leaf images for the accurate detection of diseases. The study used a segmentation algorithm, which proved to be highly effective in identifying diseased apple leaves against a live background, with a remarkable 99.8 percent accuracy rate.

In Mustafa Ahmed Jalal et al. [5], study aims to predict the sweetness of oranges using artificial intelligence technologies, specifically by investigating the relationship between sweetness and the RGB (Red, Green, Blue) values associated with the color of the fruit. The researchers hypothesized a link between RGB values and orange sweetness. They used different machine learning algorithms to test this hypothesis, including Support Vector Machines (SVM), KNN, tree-based models, logistic regression, and neural networks. Notably, the study found that the red color component had a stronger correlation with sweetness than the green and blue color components. The researchers used logistic regression as their training model and achieved a 97% accuracy rate.

In A. Alshammari et al. [6], this study introduces an innovative approach to deep learning for categorizing various genetic variants of date fruits. The method involves manipulating photos of date fruit to smooth, normalize, and remove noise. After the processed images are sorted utilizing a U-net transfer encoder learning architecture, significant features are identified using a convolutional radial basis network. After testing on many datasets, the suggested method produced results with 97% accuracy, 93% precision, 83% recall, 89% F-1 score, 63% RMSE, and 83% mean precision.

In J. A. Villaruz et al. [7], in this research paper, the early detection of fruit-bearing rambutan is addressed through the analysis of leaf photographs. To achieve this objective, transfer learning is employed to refine three pre-existing deep learning models: VGG16, GoogLeNet, and AlexNet. All things considered; it is possible to refine deep learning models to accurately identify a plant's sexuality using a new dataset. This is demonstrated by the fact that all models achieve over 95% accuracy even when trained on a limited set of training images, with VGG 16 achieving the greatest accuracy rate at 98.40%.

In Suharjito et al. [8], the study used deep learning models to precisely assess the ripeness stage of oil palm fruit. The researchers collected images of oil palm fruit from plantations, categorizing them into six maturity levels along with preprocessing and data augmenting. They used deep learning techniques for classifying models, specifically Alexnet, MobileNetV1, and MobileNetV2. The models were evaluated using confusion metrics, and the results showed that MobileNetV1 performed the best. This shows that, in comparison to MobileNetV2, preparing the dataset can enhance the MobileNetV1 model's performance.

In M. Kulkarni et al. [9], the presented approach employs Convolutional Neural Networks (CNN) for the precise analysis and identification of variations and patterns, ensuring accurate classification. The methodology advocates for semantic segmentation to distinguish between fresh and spoiled segments within any fruit, relying exclusively on the RGB image information.

In S. Bobde et al. [10], a machine-learning technique has been proposed to automate the sorting of fruits. Using the Fruits 360 dataset, which comprises 131 distinct vegetable and fruit varieties, a fruit categorization model using deep learning was developed using Keras, more precisely a convolutional neural network. Three types of fruits were used in this paper: excellent, raw, and damaged. It had a 95% accuracy rate after 50 epochs of training.

In W. N. S. W. Nazulan et al. [11], this study aims to investigate the sweetness parameter for machine learning algorithms used in fruit recognition and categorization. This work uses the Python platform's K-means clustering algorithm to grade watermelon based on its sweetness level by detecting the skin's color and shape using image processing techniques. The study used 13 watermelon picture samples to evaluate the performance of the suggested detecting technique. Subsequently, the watermelons undergo classification into Grade A, distinguished by a conspicuous sweetness, Grade B, displaying a moderate degree of sweetness, and Grade C, reflective of a reduced level of sweetness. The application of the devised methodology yielded an imprecise prediction for two out of thirteen watermelon samples, indicating an 84.62% accuracy in discerning the sweetness levels of the watermelons.

In P. N. Renjith et al. [12], this research offers a unique architecture for distinguishing between the characteristics of several Durian fruit types which is one of the most exquisite and uncommon fruits cultivated in South Asia. The image processing model plays a crucial role in dividing the classification into two distinct sections: the fruit classification portion and the feature extraction portion. This paper uses the Durian Fruit datasets to evaluate the system. There are two sections to the datasets: training and testing. The durian's features are accurately measured with the application of color extraction and Edge Detection. Also, non-destructive machine learning methods like GNB, SVM, and Random Forest are used to gauge performance. According to the results, the best accuracy of 89.3% was achieved with the SVM approach and 84.3% with the Random Forest method.

In Xiaoyang Liu et al. [13], this research paper aims to detect apples in orchard images using a combination of color and shape analysis. To segment images into super-pixel blocks the researchers use the Simple Linear Iterative Clustering (SLIC) technique, making subsequent analyses more efficient. The Histogram of Gradient (HOG) method is used for shape detection, which provides a detailed representation of the shape characteristics of apples. The reported average recall, precision, and F1 (a measure that balances precision and recall) values of 89.80 indicate a high level of detection accuracy.

In A. Kausar et al. [14], the study introduces a streamlined Pure Convolutional Neural Network (PCNN) characterized by minimal parameters for the accurate identification of diverse fruits. The PCNN comprises seven convolutional layers, some of which are stride-followed, and incorporates a recently developed Global Average Pooling (GAP) layer known for its effectiveness in reducing overfitting by computing the average of entire feature maps. The proposed PCNN model is evaluated on the recently unveiled fruit-360 dataset, consisting of 55,244 color images spanning 81 categories. Experimental results indicate a remarkable 98.88% classification accuracy achieved by the PCNN, showcasing its robust performance in fruit classification.

In T. Ittatirut et al. [15], this research endeavor contains an innovative system that has been devised to assess the sweetness of apples through the analysis of the apple's flesh captured in an image. The system, constructed using MATLAB, comprises four essential modules: i) Image Acquisition, ii) Image Preprocessing, iii) Sweetness Determination, and iv) Result Determination. The evaluation criteria in this study involve two color spaces, namely

RGB and HSV. The primary method employed for sweetness determination is the application of an Artificial Neural Networks (ANN) with the outcome of yielding an average sweetness level of 79.03%.

III. Methodology

This research initiative introduces an extensive approach for devising a machine learning and deep learning model designed to categorize diverse types of rambutan fruit and assess their respective sweetness levels. The foundational step involves creating the dataset, specifically curated for rambutan fruit images, which is subsequently pre-processed for uniformity. The dataset is categorized into 2; train and test, where each folder has 4 different varieties of Rambutan fruits namely Binjai, E35, N18, and Pulasan. Every subsequent variety is subcategorized into 3 sweetness levels namely Sweet, Mild Sweet, and Sour. The VGG16 deep learning architecture is selected due to its proven efficacy in image classification tasks and is adapted by modifying its output layers for both variety classification and sweetness levels. The model is trained using a meticulously labelled dataset, incorporating data augmentation techniques to enhance robustness. Rigorous evaluation is conducted on validation and test sets, employing performance metrics such as confusion matrices for variety and sweetness classification. The results are thoroughly analysed, and the final model is deployed, accompanied by a user-friendly interface for real-time image classification and sweetness level estimation. This methodology strives to contribute a comprehensive framework for the successful implementation of a sophisticated rambutan fruit quality assessment system, fostering advancements in both agricultural technology and artificial intelligence applications. Fig. 1. shows the methodology diagram for the proposed classification system.

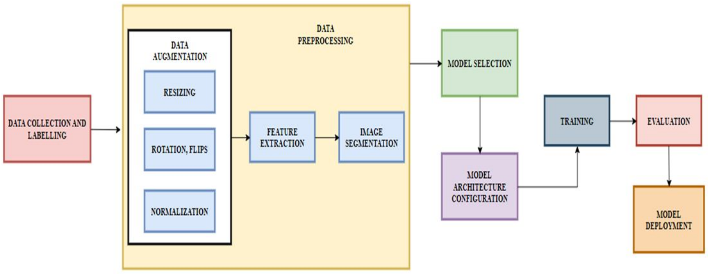

Fig. 1. Methodology diagram for Rambutan Variety and Sweetness level classification

Pre-processing

By applying various transformations to the data at hand, such as resizing (224*224), scaling, rotation, flipping, and normalization, common methods of pre-processing like data augmentation are employed to increase the diversity of the dataset; feature extraction is used to select relevant traits or features from raw data, like the hairy textures of the fruit image. To simplify the image's representation, additional image segmentation is carried out to split the image into relevant segments or areas.

Algorithm: VGG16

Prominent for its effectiveness in classifying images, the VGG16 model has a deep Convolutional Neural Network (CNN) architecture. VGG16 stands out for having a simple and uniform design with an overall total of 16 weighted layers, comprising 3 fully linked layers and 13 convolutional layers. As seen in Fig. 2, the layers of convolution are organized in consecutive blocks.

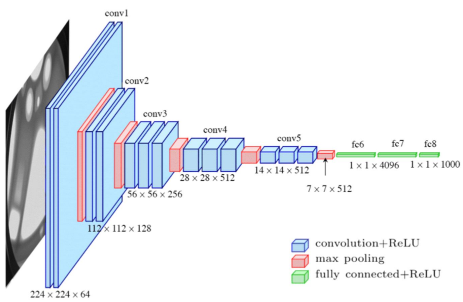

Fig. 2. 16 layers of the VGG16 model

In every layer, there are blocks comprising numerous 3x3 convolutional layers, succeeded by max-pooling layers for spatial down-sampling. The utilization of these compact convolutional filters enables the model to discern intricate patterns and features within the input images. Leveraging the features that were previously retrieved, fully connected layers at the end of the network help to facilitate high-level reasoning and decision-making. Fig. 3 provides a detailed depiction of the 16 layers comprising the VGG16 model.

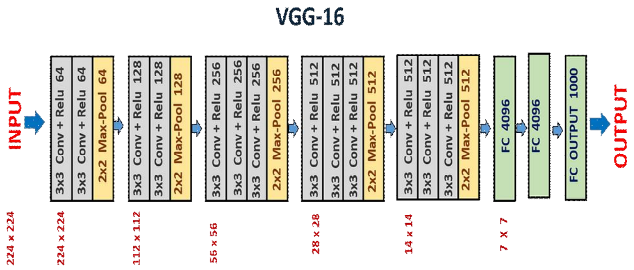

Fig. 3. Detailed 16 layers of the VGG16 model

The choice of the VGG16 architecture is substantiated by its superior performance when compared to alternative models like AlexNet and GoogLeNet, as highlighted in reference [7], where VGG16 demonstrated the highest accuracy of 98.40%. Moreover, VGG16 is renowned for its simplicity and uniform architecture, making it an optimal choice for image classification tasks.

The pre-training of VGG16 on large datasets, most notably ImageNet, is one of its main advantages. Through this pre-training, the model is endowed with a wealth of attributes that it has acquired from a wide variety of images, some of which are unrelated to the particular task at hand. This feature improves the model's capacity to generalize and recognize complex patterns across a range of datasets.

Furthermore, the transfer learning capability of VGG16 is of paramount importance in our context. In scenarios where labeled data for a specific task is limited, VGG16's pre-trained knowledge allows for effective adaptation. The model can leverage the learned features from ImageNet and fine-tune its parameters on our rambutan dataset, thereby overcoming the challenge of insufficient labeled data. This adaptability is crucial for achieving accurate and robust results in our unique domain.

Hence, these attributes collectively make VGG16 a compelling choice for our research on variety and sweetness level classification of Rambutan fruits based on their images, ensuring not only high precision but also adaptability to the challenges posed by limited labeled data in our specific task.

Training and Testing

The dataset is split into training and validation (75%- 25% of the total dataset respectively) sets. Hyperparameters are adjusted and fine-tuning is done based on generalization performance and evaluation results.

IV. Implementation

A. Dataset Creation and Data Labelling

The dataset of rambutan fruit images was created by leveraging the ‘google_images_download’ library in Python. Specific keywords representing different rambutan varieties were employed such as Binjai, E35, N18, and Pulasan, and images were sourced from the internet. Configuration parameters, including the maximum number of images to download, the output directory path, and the executable chrome driver path, were specified. Additionally, certain images were sourced from the Kaggle website to enrich the dataset [16].

The process of data labeling entailed the classification of images into specific categories, accompanied by renaming. Following this, the annotated dataset was partitioned into distinct training and testing subsets (75% and 25% respectively), enabling the seamless training and evaluation of the model. Each category was further subdivided into three sweetness levels, specifically identified as Sweet, Mild Sweet, and Sour.

A total of 912 rambutan fruit images were downloaded, out of which each variety contained 228 images respectively. 171 images (75%) of the specific variety were put in the train folder and 57 images (25%) were put in the test folder of the dataset. Each variety was sub-categorized into 3 sweetness levels namely sweet, mild sweet, and sour in which each classification comprised 57 training images and 19 images for testing purposes. The splitting of the images for train and testing was done randomly without any specific pattern. Fig. 4 shows the splitting of the dataset into varieties and sweetness levels.

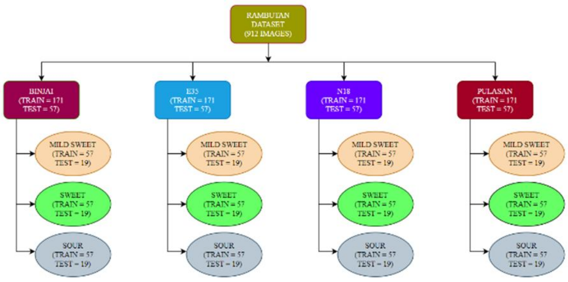

Fig. 4. Dataset Splitting into Varieties and Sweetness Levels

B. Image Pre-Processing and Augmentation

Cleaning the dataset is an essential part of preprocessing. Python script was employed to apply essential transformations to the acquired rambutan fruit dataset. The images underwent preprocessing steps such as resizing to a consistent dimension (here, 224*224), and normalization.

Rescaling, shifting, shearing, and zooming were specified. Further, to enhance the model's robustness and generalization, data augmentation techniques were implemented including random rotations, horizontal flips, and changes in brightness. Fig. 5 shows the images of the different varieties of rambutan fruits that are considered for the implementation.

a. Variety 1: Binjai

b. Variety 2: E 35

c. Variety 3:N18

d. Variety4: Pulasan

Fig. 5. Rambutan fruit varieties (a.) Binjai variety (b.) E35 variety (c.) N18 variety (d.) Pulasan variety

C. Training and Testing using VGG16

Our approach leveraged deep learning with VGG16, fine-tuning the model for specific rambutan fruit classification tasks.

The model's architecture was expanded through the incorporation of global average pooling, a dense layer utilizing ReLU activation, and the inclusion of a dropout layer. Two distinct output layers were specified: one dedicated to variety prediction and another for predicting sweetness levels.

The model was compiled with a reduced learning rate for fine-tuning. Categorical cross-entropy loss functions were specified for both variety and sweetness predictions.

The model underwent 50 training epochs utilizing training data, and validation was conducted on separate testing data. The training objective was to enhance the model's proficiency in categorizing rambutan varieties and determining sweetness levels.

D. Performance Matrix

Various performance metrics were employed to comprehensively evaluate the model's effectiveness with varying epochs. The formulas used for Variety and Sweetness Level Prediction Metrics are given below.

a) Accuracy: It is determined by dividing the total number of samples by the number of accurate predictions, and it serves as a gauge for a model's overall correctness.

Accuracy rate = Number of Correct Predictions / Total Number of Samples (1)

b) Precision: It is an evaluation of the model's accuracy in identifying positive examples among all the positive instances it predicts.

Precision rate = True Positives *100 / (True Positives + False Positives) (2)

c) Recall: The model's recall, also known as sensitivity or true positive rate, is a metric of its capacity to find all pertinent positive examples.

Recall rate = True Positives * 100 / (True Positives + False Negatives) (3)

d) F1 Score: It is the harmonic mean of precision and recall.

F1 Score = 2 * (Precision * Recall) / (Precision + Recall) (4)

V. RESULTS

The result of the deep learning models' performance is conducted through the analysis of achieved accuracy. The classification of rambutan fruit based on variety and sweetness level is subsequently determined. Employing the VGG16 algorithm yields an accuracy rate of approximately 88% for variety classification and 85% for sweetness classification with 50 epochs. This algorithm enhances the precision of categorizing rambutan fruit into Binjai, E35, N18, and Pulasan varieties, further distinguishing between three sweetness levels: Sweet, Mild Sweet, and Sour, based on attributes such as color, hair length, and hair thickness.

Following the earlier delineation of variety and sweetness level classification for rambutan fruits, four performance metrics are computed and examined within the performance matrix. The subsequent calculation of parameters with the limited number of images in the dataset and varying epochs yields the following results.

TABLE I. PERFORMANCE MATRIX RESULTS FOR VARIETY CLASSIFICATION

No. of Epochs	Accuracy	Precision	Recall	F1 Score
10	0.28	0.36	0.37	0.37
30	0.73	0.72	0.76	0.74
50	0.88	0.89	0.87	0.88

TABLE II. PERFORMANCE MATRIX RESULTS FOR SWEETNESS CLASSIFICATION

No. of Epochs	Accuracy	Precision	Recall	F1 Score
10	0.28	0.35	0.37	0.36
30	0.50	0.52	0.51	0.52
50	0.85	0.85	0.86	0.85

VI. CONCLUSION

The findings derived from the application of the VGG16 algorithm led to the conclusion that rambutan fruits can be effectively categorized into different varieties and sweetness levels by considering their size and color attributes. The accuracy thus obtained was 88% for variety classification and 85% for sweetness classification with a total of 912 images in the dataset and 50 epochs. However, by more preprocessing and with a larger amount of rambutan fruit images in the dataset, the model can be further trained efficiently to increase the accuracy.

In the future, more rambutan fruit samples with wider variations of varieties at different sweetness levels will be needed for better classification. Further preprocessing can be implied to obtain more accuracy. Employing various machine learning algorithms for comparative analysis can also contribute to refining the classification system.

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