Hybrid Classification of Date Fruits Varieties Using GLCM, RGB Features and Convolutional Neural Network

Lailia Rahmawati*[1], Irma Erviana[2], Budiman[3], Khairunnisa[4], Sutriawan[5]

[1,2,3]Informatics, Universitas Darul 'Ulum, Indonesia
[4]Computer Science and Information Engineering, NTUST, Taiwan
[5]Computer Science, Universitas Muhammadiyah Bima, Indonesia

Email: [1]liaundarjombang@gmail.com

Abstract

Classifying date fruit varieties is a challenging task due to their high visual similarity in terms of texture and color. This study aims to address this issue by developing an automated classification model that combines handcrafted Gray Level Co-occurrence Matrix (GLCM) texture features and average RGB color channels with Convolutional Neural Network (CNN) classifiers. The dataset comprises 1,658 images from nine varieties of date fruits, divided into 70% training and 30% testing subsets. The proposed workflow includes image preprocessing (resizing, normalization, grayscale conversion), extraction of GLCM features (contrast, energy, homogeneity, correlation), computation of average RGB channels, feature fusion, and CNN training using VGG16 and VGG19 architectures with Adam and Adadelta optimizers. The model performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrix. Experimental results demonstrate that VGG19 with the Adam optimizer achieved the highest validation accuracy of 91%, slightly outperforming VGG16 (90%) but remaining below the 96% accuracy reported in prior studies using MobileNetV2. The integration of handcrafted features enhanced sensitivity to subtle color and texture variations, although it introduced potential feature redundancy. In conclusion, the hybrid GLCM–RGB–CNN with VGG19 and Adam achieved 91% accuracy, proving the benefit of combining handcrafted and deep features while highlighting opportunities for further enhancement through data augmentation and architectural optimization.

Keywords: CNN, Date fruit Classification, GLCM, RGB, VGG19

1. INTRODUCTION

The demand for dates in Indonesia has increased rapidly, especially during the month of Ramadan, due to its rich nutritional content such as riboflavin, niacin, pyridoxal, and folate [1]. However, the diversity of date varieties with similar shapes and colors makes the manual identification process difficult and error-prone [2]. This condition requires an automatic classification system that is able to accurately distinguish types of dates based on digital imagery.

Previous research has utilized the Gray Level Co-occurrence Matrix (GLCM) method for texture feature extraction [3], Convolutional Neural Network (CNN) such as mobilenetv2 for date image classification [4], Hybrid method for classifying fruit and vegetables using VGG16Net and Support Vector Machine (SVM) [5], compared two transfer learning architectures MobileNetV2 and ResNet50 in the classification of three types of date palms [2]. Although CNN is able to extract complex visual features automatically, this method is sometimes less sensitive to micro-texture details, whereas GLCM is effective at capturing such information but lacks deep learning capabilities. There have not been many studies that combine the two to maximize classification accuracy.

Based on these challenges, this study formulates the question: How to build an automatic classification model to differentiate date varieties based on a combination of texture (GLCM) and color (RGB) features? How does the performance of the VGG16 and VGG19 architecture CNN compare in classifying date imagery with these features? The purpose of the study is to develop a classification system based on hybrid feature fusion that combines GLCM and RGB with CNN, as well as analyze their performance comparatively. The decrease in accuracy is mainly due to the higher complexity of VGG19, which increases overfitting risk on small datasets, the potential redundancy of GLCM and RGB features that add limited value to CNN representations, and the lightweight yet effective design of MobileNetV2, which makes it more suitable for datasets with many variables but limited samples.

The main contribution of this study lies in combining handcrafted and deep learning features in a comparative evaluation of VGG16 and VGG19 for fine-grained fruit classification. This approach is expected to fill the research gap in the use of a combination of image processing and deep learning as well as provide practical solutions for the agricultural industry and date trading.

2. RESEARCH METHOD

2.1. Classification

Classification is the process of grouping data based on unique patterns or characteristics to predict an unknown class. This process can be done manually or using technology. In the case of dates, the similarity of shape and color between varieties makes manual identification difficult, so a CNN-based automatic classification method is needed to improve accuracy [2], [6].

2.2. Digital Image Processing

Digital image processing is the process of manipulating two-dimensional images on a computer to improve quality, extract features, and produce reliable identification. Digital images are represented as a matrix of pixels with coordinate and intensity/color parameters. This process includes increasing contrast, scaling, reduction, and compression of the data, so that it can be used for future analysis and recognition[6].

2.3. Gray Level Co-occurence matrix (GLCM)

The Gray Level Co-occurrence Matrix (GLCM) is a matrix that describes the probability of the occurrence of pairs of pixels with a certain brightness level at a given distance (d) and angle (θ). Analysis is typically performed in the directions of 0°, 45°, 90°, and 135° to represent the relationship of neighboring pixels [7]. The parameters used are as follows [8]:

a) Contrast is the main diagonal for measuring the value of a distributed matrix, which reflects the texture of shadow depth and clarity. To determine the contrast value, it is:

$$contrast = \sum i \sum j (i - j)^2 P(i, j) \qquad (1)$$

Equation (1) Shows the calculating of contrast

b) Energy also known as angular second moment is a measure of smoothness. The energy value is high when the pixel value is proportional to the value of other pixels, the energy value is low, which indicates that the normalized GLCM value is heterogeneous. To find out the value of energy, namely:

$$energy = \sum i \sum j P(i, j)^2 \qquad (2)$$

Equation (2) Shows the calculating of energy

c)   Homogeneity to measure image homogeneity with a similar level of grayness. To calculate the value of homogeneity, namely:

$$homogeneity = \sum i \sum j \frac{P(i,j)}{1+|i-j|} \qquad (3)$$

Equation (3) Shows the calculating of homogeneity

d)   Correlation of linear dependency measures between grayscale values in the image [9]. To calculate the correlation value, namely:

$$correlation = \sum i \sum j \frac{(i-\mu i)(j-\mu j)P(i,j)}{\sigma i \sigma j} \qquad (4)$$

Equation (4) Shows the calculating of correlation
Where:
I & J : pixels whose values are close to each other.
p(i,j) : the probability of the value in the cocoherence matrix that is valued from 0-1.

2.4.   Color Features: Red Green Blue (RGB)

RGB imagery consists of three color channels, namely red, green, and blue, each with an intensity range of 0–255 in 8-bit format [10]. The combination of these three channels determines how the color space is represented in computers and photography, from black to white. In the RGB color space, the brightness level of each red, green, and blue channel is represented by the average intensity value on the pixels. 24-bit RGB imagery has 16,777,216 possible color combinations [8].

2.5.   Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is an artificial neural network architecture designed to process images by automatically learning a hierarchy of features, from edges and textures to complex patterns. CNN can perform feature extraction without manual feature engineering, making it more efficient than traditional machine learning methods. CNN has three main layers:
1)   Convolution layers to extract visual features such as edges, corners, and textures
2)   Pooling layer to reduce data dimensions and increase resistance to object shift or deformation
3)   As well as a fully connected layer to combine extracted features and produce a final prediction.

Research shows that CNN excels in image classification, with an accuracy of over 90% in fruit classification cases [5]. The advantage of CNN lies in its ability to adapt to variations in lighting, viewing angles, and noise, making it ideal for the classification of dates that have variations in size, shape, and surface conditions within a single variety.

2.6.   VGG16 and VGG19 architecture

VGG is a Convolutional Neural Network (CNN) architecture known for its simplicity yet depth, using a small 3×3 convolution filter over and over again to build increasingly complex features.

The VGG16 has 16 weighted layers, consisting of a repeating 3×3 convolution block terminated with max pooling. This approach extends the spatial features without significantly increasing the number of parameters and maintaining the spatial resolution in the early stages. This model became a pioneer in demonstrating the superiority of network depth. VGG19 is a deeper variant with 19 weighted layers, adding three convolutional layers to some blocks so that it is able to learn richer feature representations [11].

Both models are typically used as pre-trained models trained on large datasets such as ImageNet. The advantages include:

a) Transfer Learning: common features can be reused for new tasks with little customization
b) Reduced Data Requirements: requires less data than training from scratch
c) Training Acceleration: adaptation to new tasks takes place faster.

2.7. Integration of GLCM, RGB, and CNN in Date Classification

The subtle differences in texture and color between date varieties make a hybrid approach that combines manual and deep learning features promising. This method extracts GLCM features and RGB averages, and then combines them with CNN through feature concatenation or early fusion. The approach leverages GLCM and RGB's advantages in capturing texture and color details, as well as CNN's ability to learn complex hierarchical features. Previous studies have shown that this integration can improve the accuracy of fruit classification by more than 95% and reduce errors, potentially resulting in an accurate and reliable date classification model [11].

In this study, the GLCM method, RGB color features, and VGG16 and VGG19 architectures were combined to strengthen the date image classification process. GLCM was chosen because it is able to capture micro-texture details (contrast, homogeneity, energy, correlations) that are often difficult to detect CNN[12], while RGB features were added to represent the color dominance between varieties, such as Ajwa which is darker than Sokari's golden brown color[13]. VGG16 is used as a baseline due to its simplicity, stability, and transfer learning support from ImageNet, while VGG19 with a more complex architectural depth allows for more detailed feature learning. The integration of GLCM, RGB, and CNN forms a hybrid feature fusion approach that not only leverages CNN's power in recognizing abstract patterns, but also enriches representations with texture and color information. This strategy is expected to improve accuracy, reduce the risk of overfitting limited datasets, and produce a more robust and applicable date classification system.

2.8. Research Methods

This study is a quantitative experimental study that develops and evaluates a date classification model based on the Convolutional Neural Network (CNN) architecture of VGG16 and VGG19, with the integration of manual features of GLCM texture and RGB colors. This study aims to develop and test a date classification system with GLCM and RGB feature extraction, as well as classification using the pretrained CNN model VGG16 and VGG19 through the stages of image processing, feature extraction, training, and testing. Figure 1 explain research stages in this study.

1) Date image acquisition: Done with a digital camera, where the quality of the photo greatly affects the success of the image processing process.
2) Preprocessing stage: Includes resize the RGB image to 224×224 pixels, normalization of the pixel value, and conversion to grayscale for GLCM feature extraction, so that the data is ready for use in the model training process.
3) Feature extraction: Performed with GLCM to obtain texture parameters such as contrast, energy, correlation and homogeneity, as well as calculation of RGB channel averages to determine the dominant color that distinguishes each type of date.
4) RGB and GLCM features are combined into a single fixed-size vector for use as inputs or add-ons to the fully connected CNN layer, according to the architecture design being tested.
5) Training model: using an Adam optimizer (learning rate 0.001) or Adadelta, with 10–150 epochs, a batch size of 16/32, and a data sharing of 70% training and 30% stratified tests.
6) Model evaluation using:
    a) Accuracy: The proportion of correctly classified images of the entire test image.

b) Precision: The model's ability to classify true positives from positive predictions.
c) Recall (Sensitivity): The model's ability to capture all of the actual positive data.
d) Confusion Matrix: Analysis of class prediction distributions and misclassifications.
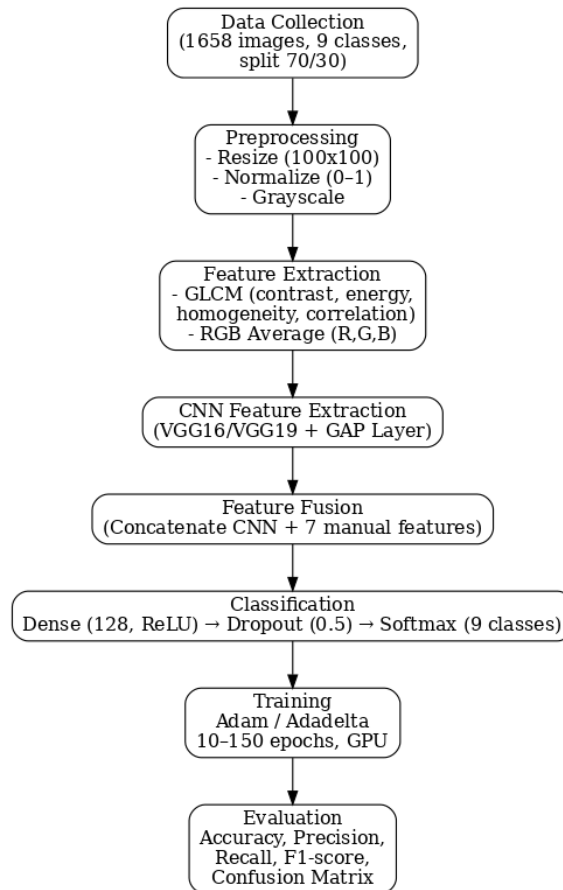e) F1-Score: Harmonic mean between precision and recall to balance performance.

Figure 1. Research Stages

2.9. Data Collection Techniques

The type of data used in this study is secondary data that is historical. This data is obtained from the online dataset provider platform Kaggle.com, which is known as a trusted source for various types of datasets, including those related to image processing and object classification.

The downloaded dataset has usually gone through annotation or labeling beforehand. As a result, they can be directly used for the analysis process without the need to do it again. This research uses a dataset in .JPEG format, there are 9 classes of dates consisting of a total of 1658 images. By using secondary data from the internet, researchers can save time in the data collection process as well as obtain larger and more varied amounts of data.

3. RESULTS AND DISCUSSION

3.1. Process Overview

A classification system was developed to identify nine varieties of dates by integrating visual and textural information. The proposed hybrid approach combines two feature sources: (1) automatic feature extraction using Convolutional Neural Networks (VGG16 and VGG19), and (2) manual feature extraction using Gray Level Co-occurrence Matrix (GLCM) and average RGB values. In this

framework, CNN is responsible for capturing global spatial patterns, RGB features represent color distributions, and GLCM features describe fine-grained textures. Both feature types are extracted in parallel and then concatenated into a unified feature vector, which serves as input for the classification process. This hybrid design enhances model accuracy and improves robustness against variations in lighting and image orientation.

3.2.   Datasets and Preprocessing

The dataset consists of images of nine types of dates taken in various lighting conditions and angles to improve the generalization of the model. As shown in Table 1.

Table 1. Date Fruit Image Datasets

No	Class	Dataset
1	Ajwa	175
2	Galaxy	190
3	Medjool	135
4	Meneifi	232
5	NabtatAli	177
6	Rutab	146
7	Shaishe	171
8	Sokari	264
9	Sugaey	168
	Total	**1658**

The data is compiled per class and divided into 70% training and 30% testing to ensure the model is able to accurately predict new data.

The preprocessing stage consists of several sequential steps designed to optimize both computational efficiency and feature quality. First, all images are resized to 100×100 pixels to maintain a balance between visual detail and processing speed. Second, RGB pixel values are normalized from the original 0–255 range to 0–1, ensuring faster learning and preventing the dominance of large-scale features. Third, each image is converted to grayscale to enable Gray Level Co-occurrence Matrix (GLCM) feature extraction. From the grayscale images, four texture descriptors are generated: contrast, homogeneity, energy, and correlation, using a pixel distance of 1 and an angle of 0°. In parallel, the average intensity values of the red, green, and blue channels are computed to capture the dominant color distribution. As a result, each image is represented in two complementary forms: a resized and normalized RGB image (100×100×3) for CNN input and a seven-dimensional manual feature vector (3 RGB + 4 GLCM) for hybrid model training.

3.3.   CNN model architecture

In this study, VGG16 and VGG19 are employed as feature extractors by removing their original classification layers and substituting them with a GlobalAveragePooling2D layer. This modification reduces the dimensionality of extracted features while retaining essential information. The resulting CNN-based features are subsequently concatenated with a seven-dimensional manual feature vector consisting of RGB averages and GLCM descriptors, using the Keras concatenate method.

The fused feature representation is then processed through a fully connected network composed of three components: (1) a dense layer with 128 units and ReLU activation to capture nonlinear feature interactions, (2) a dropout layer with a rate of 0.5 to mitigate overfitting, and (3) an output layer with nine neurons and softmax activation to classify images into the nine date varieties. This integration of deep and handcrafted features enhances the model's ability to capture both global and fine-grained characteristics, thereby improving classification robustness and accuracy.

3.4. Data Training Process

Model training was conducted using a set of carefully selected hyperparameters to ensure stable convergence and optimal performance. The Adam optimizer was chosen for its adaptive learning rate capability, with the learning rate set to 0.0001. Sparse Categorical Crossentropy was employed as the loss function, as it is well-suited for multi-class classification with integer labels. Training was initially performed for 10 epochs as a preliminary evaluation, and subsequently extended up to 150 epochs for comprehensive assessment. A validation split of 30% was applied to the training set to monitor generalization performance during learning.

Prior to training, feature values were normalized using StandardScaler, while categorical labels were encoded with LabelEncoder. Training was executed on GPU hardware, achieving a processing speed of approximately 2–4 seconds per epoch. To prevent overfitting and retain optimal weights, EarlyStopping and ModelCheckpoint techniques were applied. Overall, the training process demonstrated good convergence, reflected in increasing accuracy, decreasing loss, and minimal signs of overfitting across epochs.

3.5. Model Performance Evaluation

Evaluations show that Adam's optimizer provides faster and more stable convergence than Adadelta, based on loss, training time, and accuracy.

Table 2. Results of VGG16 Optimizer Adam

EPOCH	VGG16 (Adam)				
	Accuracy Training	Accuracy Validation	Training Loss	Val.loss	Duration(sec)
10	89,68%	90%	0,3706	0,3706	2,66
30	89,27%	90%	0,3854	0,3818	2,70
50	87,40%	89%	0,4776	0,4224	2,73
100	84,73%	85%	0,5964	0,5440	2,69
150	89,91%	90%	0,4275	0,3904	2,69

Table 3. Results of VGG16 Optimizer Adam

EPOCH	VGG19 (Adam)				
	Accuracy Training	Accuracy Validation	Training Loss	Val.loss	Duration(sec)
10	91,07%	**91%**	0,3326	0,3367	3,78
30	90,49%	90%	0,3179	0,3399	2,83
50	90,78%	91%	0,3570	0,3553	3,82
100	89,63%	90%	0,4170	0,3863	3,81
150	87,90%	88%	0,5729	0,5193	3,82

The comparison results shown in Table 2 and Table 3 indicate that the VGG19 architecture with the Adam optimizer provides better performance compared to VGG16 with the Adam optimizer. VGG19 achieved a validation accuracy of 91%, slightly higher than VGG16 which only reached 90%. This difference confirms that the additional network depth in VGG19 is able to capture richer feature representations, making it effective in distinguishing texture and color variations in date images that have high visual similarity. In addition, the use of the Adam optimizer proved to be more stable in the learning process because it adaptively adjusts the learning rate, resulting in faster and more accurate convergence. Thus, the combination of VGG19 and Adam can be considered the most optimal configuration in this study to support date image classification based on GLCM and RGB features.

The accuracy and loss curves shown in Figure 2 and Figure 3, when combined with the confusion matrix results in Figure 4, provide a comprehensive picture of the model performance. The

VGG19 architecture with Adam achieves >90% validation accuracy and is stable up to 150 epochs, while Adadelta shows high loss and stagnant accuracy. The confusion matrix shows that the predictions of most classes are correct, but errors occur in classes with high visual similarity.
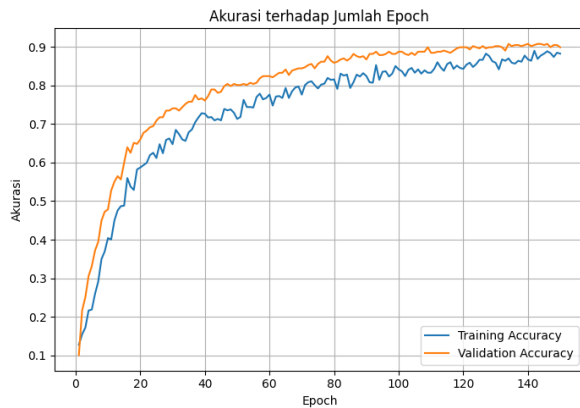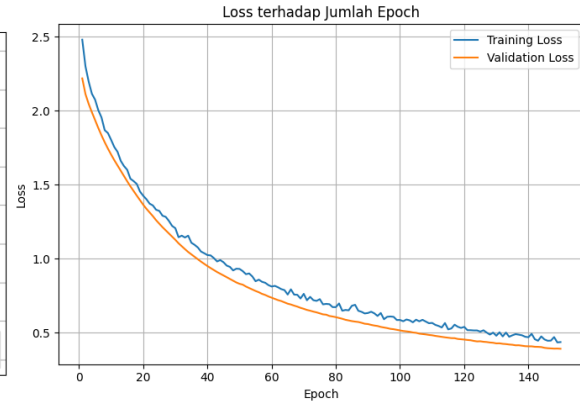

Figure 2. Graph Accuracy

Figure 3. Graph Loss

Table 4. Evaluation Results of VGG16 Optimizer Adam

Class	Precision	Recall	F1-score	Support
Ajwa	1.00	1.00	1.00	37
Galaxy	0.97	0.90	0.94	40
Mejdool	1.00	0.93	0.96	28
Meneifi	0.88	0.92	0.90	49
NabtatAli	0.83	0.95	0.89	37
Rutab	0.77	0.90	0.83	30
Shaishe	0.96	0.72	0.83	36
Sokari	0.83	0.96	0.89	55
Sugaey	1.00	0.80	0.89	35
Accuracy			0.90	347
Macro avg	0.92	0.90	0.90	347
Weighted avg	0.91	0.90	0.90	347

Table 5. Evaluation Results of VGG19 Optimizer Adam

Class	Precision	Recall	F1-score	Support
Ajwa	1.00	1.00	1.00	37
Galaxy	1.00	0.88	0.93	40
Mejdool	1.00	0.96	0.98	28
Meneifi	0.84	0.94	0.88	49
NabtatAli	0.91	0.86	0.89	37
Rutab	0.84	0.87	0.85	30
Shaishe	0.97	0.78	0.86	36
Sokari	0.85	1.00	0.92	55
Sugaey	0.91	0.86	0.88	35
Accuracy			0.91	347
Macro avg	0.92	0.90	0.91	347
Weighted avg	0.92	0.91	0.91	347

The performance evaluation results presented in Table 4 and Table 5 show that the use of VGG19 with the Adam optimizer achieved an overall accuracy of 91%, slightly higher than VGG16 with the Adam optimizer, which reached 90%. In several classes, such as Mejdool and Sokari, VGG19 demonstrated higher F1-scores of 0.98 and 0.92, respectively, compared to VGG16, which only

achieved 0.96 and 0.89. This highlights the ability of VGG19 to capture more complex feature representations, making it more effective in distinguishing date varieties with high visual similarity. Nevertheless, certain classes such as Shaishe showed a decrease in recall with VGG19 (0.78) compared to VGG16 (0.72), indicating challenges in generalization for specific varieties. Overall, although the accuracy difference between the two models is relatively small, VGG19 with Adam can be considered superior due to its more consistent performance across most classes, with weighted averages of precision, recall, and F1-score showing greater stability.

3.6.   Prediction Result Analysis

Examples of predictions show that the model is able to classify with high accuracy (>90%) even in less than ideal lighting, such as the Ajwa date which is recognized with 98.5% confidence.
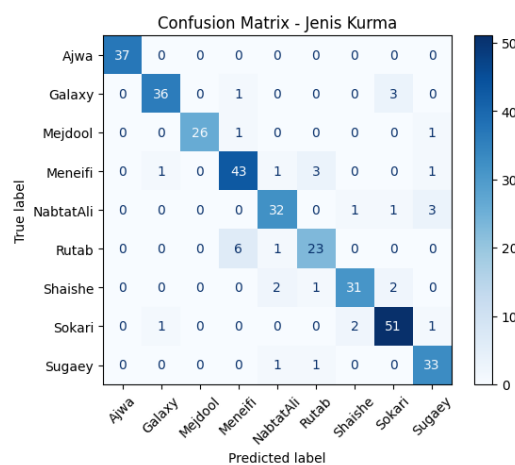

Figure 4. Results of Confusion Matrix Date Types

Figure 5. Date Image Results

Figure 4 illustrates the confusion matrix results for the classification of nine date varieties using the proposed best-performing model. In general, most classes were correctly classified, as

indicated by the dominance of diagonal values in the matrix. For example, the Ajwa and Sokari varieties achieved nearly perfect predictions, with 37 and 51 correctly classified images, respectively. However, some misclassifications occurred among varieties with high visual similarity. For instance, several Mejdool samples were misclassified as Meneifi, while a few NabtatAli samples were detected as Rutab. This finding indicates that although the model effectively recognizes texture and color patterns, extremely subtle visual differences between certain varieties remain challenging. Therefore, despite achieving high overall accuracy, the confusion matrix results highlight the need for additional strategies, such as data augmentation or fine-tuning of the architecture, to reduce misclassification rates in classes with significant visual similarities.

Figure 5 shows that, the model still has difficulty distinguishing Sokari and Ajwa due to the similarity of shape and color, which indicates the importance of microcolor details and fine textures to increase classification precision.

3.7. Discussion

The experimental results demonstrate that the hybrid approach integrating GLCM, RGB, and CNN features achieved 91% validation accuracy with VGG19 and Adam. Although slightly lower than the 96% reported with MobileNetV2 [4], this confirms the effectiveness of combining handcrafted and deep features.

A comparison between VGG16 and VGG19 shows that VGG19 performs better due to its deeper architecture, enabling it to capture subtle differences in texture and color, though it increases the risk of overfitting. Dropout and early stopping successfully maintained training stability and generalization.

The optimizer played a crucial role as well. Adam achieved faster convergence and lower error rates than Adadelta, confirming that optimizer selection must align with model complexity and dataset size.

Main limitations were misclassifications in visually similar classes (Ajwa vs. Sokari) and reduced performance under poor lighting, highlighting the need for optimized texture features and stronger data augmentation. The integration of GLCM and RGB did not always improve performance, showing that CNNs alone already capture many relevant representations.

Practically, the model offers applications in harvest authentication, automatic grading, and transparent labeling, with potential extension to other agricultural and medical domains. Future work should focus on dataset diversification, fine-tuning CNNs, exploring advanced architectures (ResNet [14], EfficientNet), and developing mobile/web apps for real-time classification.

3.8. Accuracy Comparison

This study compared pure CNN MobileNetV2 [4] which achieved 96% accuracy for the classification of 9 types of dates with a dataset of 1,658 images, with the VGG19 model combining GLCM features and RGB averaging. The development results showed an accuracy of 91%, down 5% from the previous method, although it had additional texture and color representations.

This decrease in accuracy can be explained by several factors:

1) The high complexity of VGG19 increases the risk of overfitting on small datasets without optimal regularization.
2) Global GLCM and RGB manual features can contribute less relevant or redundant information to CNN features.
3) MobileNetV2 is designed with a small but effective number of parameters, making it more suitable for datasets with many variables and limited samples.

The experimental results indicate that VGG19 consistently outperforms VGG16 in terms of validation accuracy. This improvement can be attributed to the greater architectural depth of VGG19, which includes 19 learnable layers compared to the 16 layers in VGG16. The additional convolutional layers enable the network to capture richer hierarchical representations, allowing it to recognize subtle differences in color and texture that are critical for distinguishing visually similar date varieties, such as Ajwa and Sokari. While deeper networks generally increase the risk of overfitting, the application of dropout and early stopping in this study helped maintain training stability, making VGG19 more effective without sacrificing generalization [15].

Furthermore, the use of the Adam optimizer produced superior results compared to Adadelta. Adam combines the benefits of Momentum and RMSProp by adaptively adjusting the learning rate for each parameter, leading to faster and more stable convergence. In contrast, Adadelta showed higher loss values and stagnation in accuracy, suggesting limited capacity to escape local minima in deep architectures like VGG16 and VGG19. The efficiency and adaptability of Adam allowed the model to achieve higher accuracy within fewer epochs, making it more suitable for datasets of moderate size such as the one used in this study.

4.   CONCLUSION

This study introduced a hybrid classification model that integrates CNN-based features (VGG16 and VGG19) with handcrafted descriptors (GLCM and RGB) for date variety recognition. The best performance was achieved by VGG19 with the Adam optimizer, reaching 91% accuracy. Although slightly lower than the 96% reported by MobileNetV2, the proposed approach provides higher interpretability by explicitly capturing texture and color characteristics, which are essential for distinguishing visually similar varieties.

The findings highlight the trade-offs between model complexity and generalization in small datasets, as well as the benefits and limitations of feature fusion. Beyond date classification, the hybrid approach shows potential for broader applications, such as agricultural product recognition, plant disease detection, and medical imaging, where micro-texture and fine visual details are crucial.

Beyond the experimental results, this system carries practical implications. For farmers, it can serve as a decision-support tool to verify the quality and authenticity of harvests. For traders, it can improve sorting and grading processes, reducing human error in distinguishing similar varieties such as Ajwa and Sokari. For consumers, it enables more transparent information about product types, potentially integrated into mobile or web applications for direct use. In a broader context, the hybrid approach demonstrated here can also be extended to other agricultural products and even domains such as plant disease detection or medical imaging, where fine texture and micro-level details are essential.

Future work should focus first on feasible improvements such as applying data augmentation and fine-tuning CNN layers to enhance model generalization. In the medium term, exploring advanced architectures like ResNet or EfficientNet and developing mobile or web-based applications will increase both accuracy and practical usability. In the long term, expanding the dataset and extending the hybrid approach to other agricultural products or domains such as plant disease detection or medical imaging will strengthen its broader relevance.

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