InComTech: Jurnal Telekomunikasi dan Komputer
vol.16, no.2, Agustus 2026, 156-170
http://publikasi.mercubuana.ac.id/index.php/Incomtech
P-ISSN: 2085-4811 E-ISSN: 2579-6089

Hybrid Deep Learning–Machine Learning for Bird's Eye Chili Quality Classification

Tri Raharjo Yudantoro*, Zulfa Nurma Novita Sari, Tulus Pramuji, Eko Supriyanto[4], Wahyu Sulistyo, Agus Suwondo, Sindi, Ilham Rizky Harijanto

Computer Engineering Technology Study Program, Department of Electrical Engineering, Semarang State Polytechnic.,
*Email Penulis Koresponden: tryudan@polines.ac.id

Abstract
The manual inspection of dried bird's eye chili (Capsicum frutescens L.) is prevalent yet susceptible to subjectivity, inter-rater variability, and low efficiency. This research introduces a hybrid deep learning and machine learning pipeline for the classification of images into three categories: fresh, medium, and dried. The method encompasses staged image acquisition throughout the drying process, preprocessing (including HEIC to PNG conversion, background elimination, scaling, and normalizing), and real-time augmentation to enhance robustness. Feature embeddings are obtained from MobileNetV2 by transfer learning utilizing a Global Average Pooling head and are evaluated against EfficientNetB0, NASNetMobile, ResNet50, and DenseNet121. The embeddings are categorized using various algorithms: Random Forest (RF), Support Vector Machine, and a shallow Artificial Neural Network, with RF selected for its consistent performance. Evaluation employs an 80/20 split, focusing on accuracy, precision, recall, F1-score, and confusion matrix analysis. Results indicate that MobileNetV2 produces the most distinctive features, whereas RF provides the most reliable downstream predictions: the system achieves 94% validation accuracy during feature extraction and 91% at the final classification stage, alongside high precision-recall and minimal misclassification. The chosen MobileNetV2+RF model is implemented in an Android application for real-time inference from smartphone photos, providing class labels and a moisture-level signal based on mass-loss measurements to aid postharvest decisions. The contributions consist of an objective and efficient quality-assessment pipeline, an empirical model comparison, and a deployable mobile implementation. Future endeavors will focus on extensive datasets, multimodal signals, cross-variety generalization, and more rigorous validation (e.g., cross-validation and external testing) to mitigate generalization risk.

Kata Kunci*:*
Dried Bird's Eye Chili;
Deep Learning;
Random Forest;
Classification;

Riwayat Artikel:
Received 07 November 2025
Revised 24 February 2026
Accepted 27 March 2026

DOI:
10.22441/incomtech.v16i2.36865

This is an open access article under the CC BY-NC license

1. INTRODUCTION

Dried bird's eye chili (Capsicum Frutescens L.) is a valuable horticultural commodity widely utilized in the culinary and spice industries. The drying process is commonly applied to extend shelf life and enhance product distribution. The visual characteristics of dried chili, such as color, wrinkled texture, and consistent size, are essential indicators of its quality. However, in current practice, quality assessment is predominantly performed manually, relying on human observation to evaluate these physical attributes [1], [2].

Manual inspection presents various limitations, including subjectivity, inconsistency among evaluators, and inefficiency, particularly in large-scale production environments. These constraints can lead to misclassification, reduced product quality assurance, and increased operational costs [4][5]. Consequently, there is a growing need for an automatic, accurate, and objective quality assessment method for dried chili [6].

The advancement of artificial intelligence has opened new opportunities for automation in the agricultural sector. Recent applications of machine learning and deep learning models have demonstrated promising results in classifying horticultural products based on image data. Previous studies have employed models such as Support Vector Machine (SVM) using HSV color features to distinguish fresh and rotten green chilies with 100% accuracy [3], [4], [5], [6], [7], [8], [9].

Hybrid models that combine the feature extraction capabilities of Convolutional Neural Networks (CNN) with the classification power of Random Forests (RF) have shown superior performance compared to standalone approaches. For example, CNN-RF hybrid model achieved 98% accuracy in plant disease diagnosis. Such approaches offer enhanced accuracy and generalization by integrating the strengths of both deep and conventional learning methods [10].

Motivated by these findings, this study proposes a hybrid deep learning and machine learning model to classify the quality of dried bird's eye chili using digital image characteristics. The model utilizes MobileNetV2 as a lightweight CNN-based feature extractor and Random Forest as the final classifier. The dataset comprises both self-collected images of dried chili and supplementary non-chili images sourced from Kaggle. Furthermore, the proposed model is deployed into a mobile Android application to enable real-time, efficient, and user-friendly chili quality classification.

This study differentiates itself from prior chili-quality research by focusing on quality evaluation during the drying phases (fresh_red, semi-dry_red, dry_red) and by estimating moisture content based on mass loss in accordance with SNI 3389:2023. In contrast to earlier studies that rely primarily on static visual grading, this work contributes (i) a lightweight hybrid pipeline (MobileNetV2 embeddings + Random Forest) designed for small datasets and edge deployment, (ii) a controlled image-acquisition protocol across multiple drying cycles, and (iii) an Android application for on-site inspection. In addition, an empirical comparison of

CNN feature extractors and downstream classifiers is provided to justify the selected configuration.

The main contributions of this study are as follows: (i) A working image pipeline for sorting the drying stages of bird's eye chili, with HEIC-to-PNG conversion and background removal to cut down on noise; (ii) A hybrid model that combines MobileNetV2 transfer learning as a feature extractor with Random Forest as a robust small-data classifier. This model is then compared to a number of CNN architectures and machine learning classifiers; (iii) An Android prototype that can be used in the field that does inference on the device and gives class labels and a moisture level based on mass-loss data to help with postharvest decision-making.

2. METHOD

This research was conducted through several systematic stages designed to develop and evaluate a classification model for the quality of dried bird's eye chilies based on digital images. These stages included data collection, data preprocessing, data augmentation, dataset splitting, model development using a hybrid approach, and model performance evaluation. To provide an overview of the research workflow, Figure 1 presents a flowchart diagram illustrating the proposed research methodology.

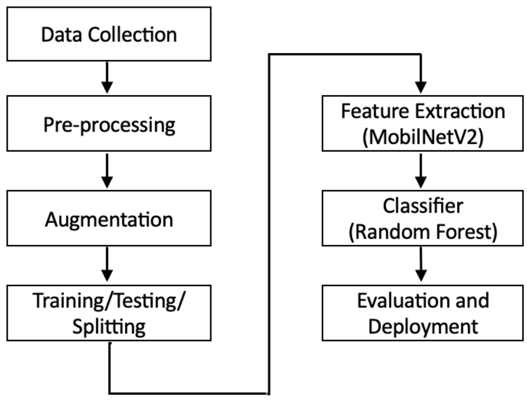

Figure 1. Flowchart of the Research Methodology

2.1 Data Collection

The primary data were collected independently and were solely used for the purposes of this research. The data collection process involved using 30 fresh red bird's eye chilies samples. Each chili was weighed and photographed before the drying process. The chilies were then arranged on an oven tray and labeled with sequential numbers to facilitate data recording and ensure consistency during the drying process.

The images were captured manually using an iPhone camera from a top-down perspective. After the initial image capture, the chilies underwent a drying process using a microwave. The red chilies were dried over 10 cycles. Each drying session lasted for 30 minutes at a temperature of 80° C. In total, 300 chili images were successfully collected. An example of the dataset images is presented in Figure 2.

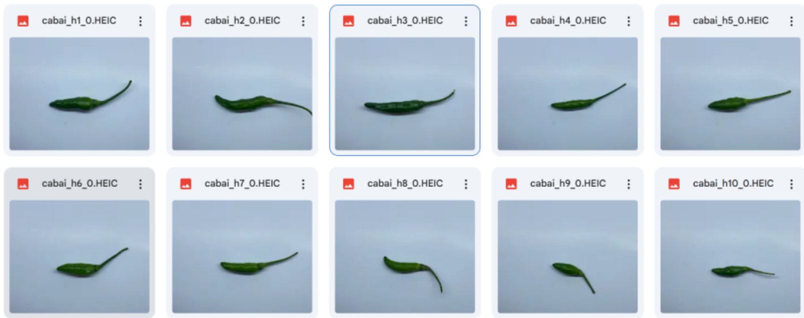

Figure 2. Dataset of Chili Images

In addition to the visual data, the author also recorded physical attributes such as chili weight and moisture content. After each drying cycle, the chilies were reweighed using a digital scale to monitor weight reduction. The moisture content of each chili was calculated using the following formula [12] (1):

$$water\ content\ (\%) = \frac{W_{first} - W_{last}}{W_{first}} \times 100\% \tag{1}$$

Description:
W_{first} = Weight of the chili before the drying process
W_{last} = Weight of the chili after the drying process

The calculated moisture content percentage reflects the amount of water present in the chili samples. This information is utilized to classify chilies into several categories: fresh_red, semi-dry_red, and dry_red. Fresh chilies typically exhibit a high moisture content, with a maximum level of approximately 90%. In contrast, according to the Indonesian national quality standard for dried chili (SNI 3389:2023), the maximum allowable moisture content for dried chilies is 11%.

2.2 Preprocessing Data

After the chili image data were collected, the next stage involved data preprocessing, a series of preprocessing steps were carried out as part of the data preprocessing pipeline, which included data augmentation, format conversion, and resizing. The first step in this process was converting the image format from .heic to .png, since all chili images were captured using an iPhone camera, which by default stores images in the .heic format. The .png format was selected due to its support for transparency, which facilitates background removal without altering the main object [11].

Following the format conversion, the original background of each image was removed to ensure that the model focuses solely on the primary object the chili. This step was crucial to minimize noise and improve the effectiveness of the feature extraction process during model development [12].

2.3 Data Augmentation

One of the challenges encountered during the training of the chili image classification model is the limited amount of available training data. To address this issue and effectively expand the dataset, data augmentation techniques were applied using the ImageDataGenerator library provided by the Keras framework. Data augmentation is a technique used to generate new variations of existing images by applying a range of transformations, thereby increasing the diversity of the dataset without the need for manual data collection. This approach enhances the diversity of training data and helps reduce the risk of overfitting [13], [14].

Several augmentation techniques were implemented in this study, including pixel normalization to standardize the image data scale, as well as visual transformations such as zooming and brightness adjustments. These transformations were applied randomly during the training process, allowing the model to receive different input variations at each iteration. The augmentation process does not alter the data labels but only modifies the visual aspects of the images, such as scale and lighting intensity. An example of the augmented data results can be seen in Figure 3, which illustrates the visual variations of chili images after the augmentation process was applied.

Figure 3. Sample of Chili Dataset After Augmentation

2.4 Dataset Splitting

The image dataset used in this study was divided into two main subsets: training data and testing data, with a split ratio of 80% for training and 20% for testing as it is a common practice, retaining a representative portion for evaluation. As shown in Table 1, each class category contains 192 images for training and 48 images for testing, resulting in a total of 576 training images and 144 testing images [15].

Table 1. Distribution of Train and Test Images per Class

Class	Train	Test
fresh_red	192	48
semi-dry_red	192	48
dry_red	192	48
Total	**576**	**144**

2.5 Models

The proposed model adopts a hybrid pipeline that combines MobileNetV2 for feature extraction and Random Forest (RF) for final classification. Prior to inference, each chili image is resized to 224×224 pixels and normalized to the [0, 1] range to match the input requirements of the feature extractor. MobileNetV2 is employed via transfer learning and used without its original fully connected classification head. Instead, the Global Average Pooling (GAP) output is retained to generate compact feature embeddings, providing a computationally efficient representation while preserving discriminative visual cues.

The resulting embeddings are subsequently fed into an RF classifier, which serves as the final decision-making component. This design leverages MobileNetV2's representational capacity for image data and RF's robustness to limited data and feature noise, resulting in stable classification performance.

The system assigns each image to one of three classes—fresh_red, semi-dry_red, and dry_red—using a two-stage architecture (Figure 4). Although end-to-end CNN classifiers can capture richer spatial relationships, the relatively small dataset (300 original chili images) increases the risk of overfitting when training or fine-tuning a full CNN classifier. Therefore, MobileNetV2 is used to extract transferable representations, and GAP produces compact embeddings that are classified by RF. RF is well suited for small-sample settings due to bagging-based ensembling, stable decision boundaries, and minimal hyperparameter requirements. Moreover, RF supports fast training and lightweight deployment as an ensemble of decision trees, which is practical for mobile/edge scenarios and facilitates future integration of additional features without redesigning the full CNN.

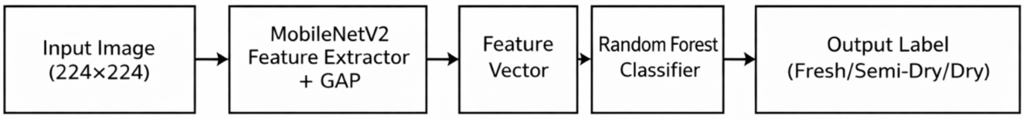

Figure 4. Chili image classification flowchart

The end-to-end pipeline—from image input to embedding generation and RF-based decision making—is summarized in Figure 5, which presents the block scheme of the hybrid model implemented in this study.

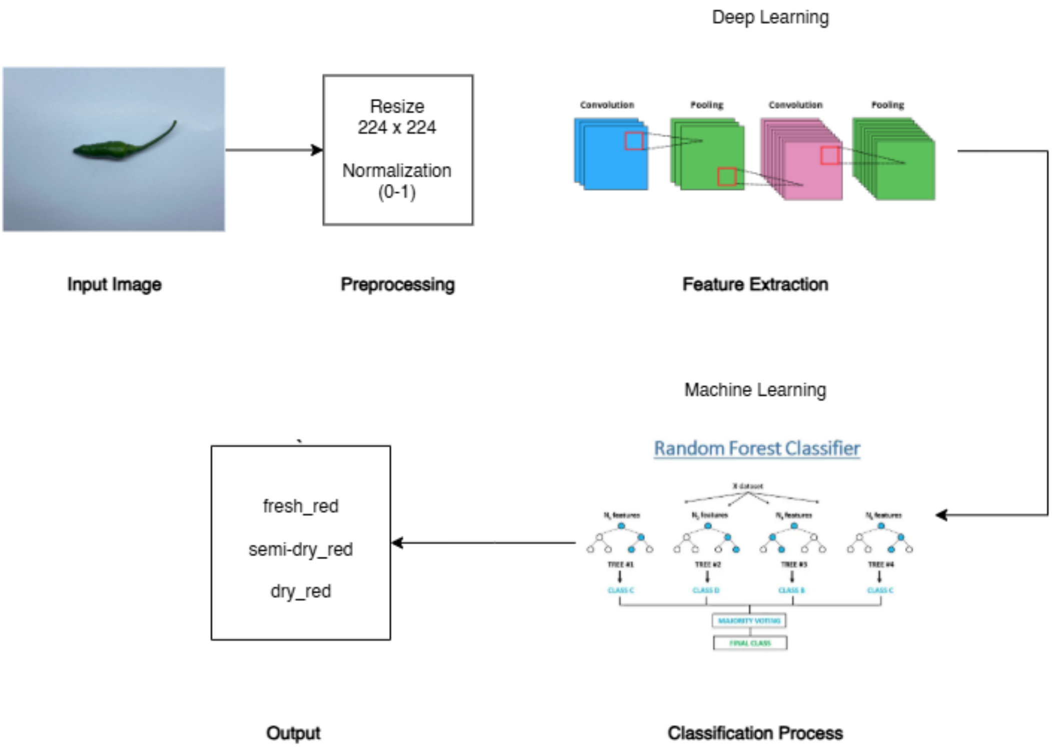

Figure 5. Block Scheme of the Hybrid Model

2.6 Evaluation

The performance evaluation of the model is conducted by assessing its accuracy for each classification outcome. To determine the optimal model, additional performance metrics are computed. The evaluation was carried out using visualizations such as performance graphs and a confusion matrix to analyze the model's effectiveness including Precision, Recall, and F1-Score [18]. The formulas used for these metrics are as follows, the Accuracy is calculated using Equation (2), Precision is shown in Equation (3), Recall in Equation (4), and F1-Score in Equation (5).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F1 - Score = 2 \times \frac{precision \ \times recall}{precision \ \times recall} \tag{5}$$

The Confusion Matrix is used to analyze the model's ability to predict the correct class label of an object. It consists of four components which is, True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). As shown in Figure 6, TP refers to the number of correctly predicted positive cases, TN indicates correctly predicted negative cases, FP represents incorrect positive predictions, and FN refers to missed positive predictions.

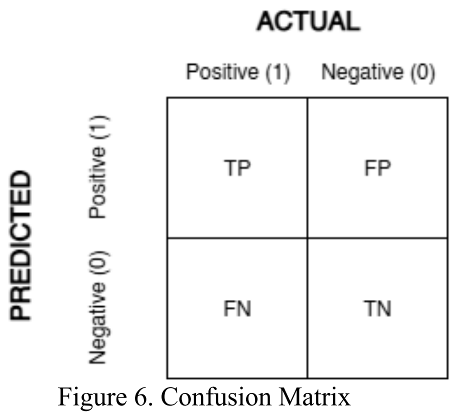

Figure 6. Confusion Matrix

2.7 Android Deployment

The selected MobileNetV2+RF pipeline was integrated into an Android application to enable field-ready quality inspection using smartphone photos. On-device inference follows these steps: (1) capture or select an image (camera/gallery); (2) apply the same preprocessing used during training (resize to

224×224, normalization, and optional background removal); (3) run MobileNetV2 to generate a feature embedding via Global Average Pooling; and (4) classify the embedding using the RF model to obtain one of three labels (fresh_red, semi-dry_red, dry_red). The application is designed to operate offline after installation, enabling use in production areas with limited connectivity. For deployment efficiency, the feature extractor can be exported to TensorFlow Lite, while the RF parameters (tree structures) can be packaged as an embedded model file for local evaluation. Future work will report device-specific latency (ms/image) on representative mid-range and low-end Android hardware and evaluate optional compression (e.g., quantization for the CNN and pruning or tree-size reduction for RF) to reduce storage and improve runtime. The on-device inference workflow is summarized in Figure 7 [16].

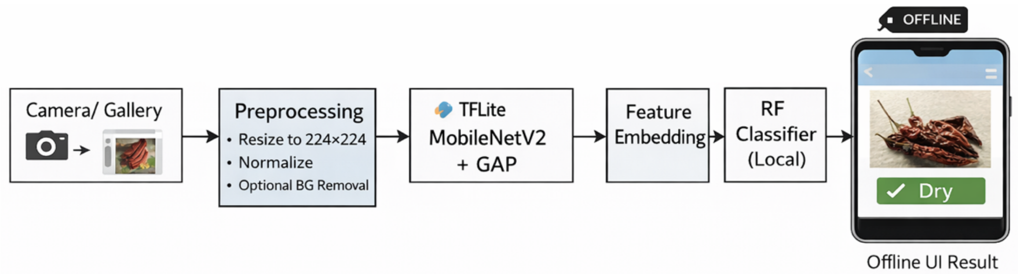

Figure 7. Mobile inference workflow diagram

3. RESULT AND DISCUSSION

This section outlines the outcomes of the research and the experiments carried out. It also provides a discussion of the findings and an analysis of the test results.

3.1 Model Selection

The model selection process in this study was conducted through two primary stages, the image feature extraction stage and the classification stage based on the extracted features.

In the feature extraction stage, a transfer learning approach was employed by comparing several popular deep learning architectures, including MobileNetV2, EfficientNetB0, NASNetMobile, ResNet50, and DenseNet121. All models were configured without the top classification layer (include_top=False) and fine-tuned on the last 50 layers. The top of each network was customized with additional layers consisting of a GlobalAveragePooling2D layer, a dense layer with 256 neurons, and a Dropout layer with a rate of 0.5 to mitigate overfitting risks. Model training was conducted using the Adam optimizer with a learning rate of 0.00001, and the EarlyStopping callback was applied to halt training when no significant improvement in validation loss was observed.

The comparison of feature-extraction performance across different models is summarized in Table 2. Although ResNet50 and DenseNet121 were also evaluated as feature extractors, their validation accuracy and/or inference cost were inferior to the models reported; therefore, they are omitted here for brevity.

Table 2. Comparison of Feature Extraction Models

Model	Total Parameter	Accuracy	Inference speed	Model size
MobileNetV2	2.586.691	96%	50.26 ms/pic	26.98 MB
NASNetMobile	4.544.079	74%	198.93 ms/pic	26.83 MB
EfficientNet	4.378.78	33%	87.40 ms/pic	39.12 MB

Based on the training results, MobileNetV2 demonstrated the most optimal performance among all the models, achieving the highest and most stable validation accuracy, as illustrated in Figure . MobileNetV2 maintained a validation accuracy approaching 0.9, indicating superior performance.

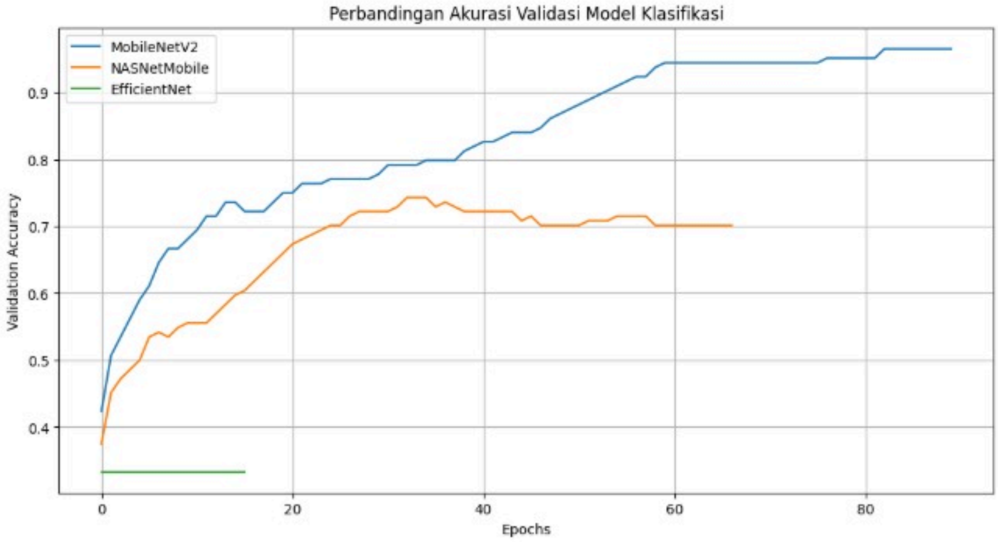

Figure 8. Combined Validation Accuracy Graph of Various Feature Extractors

In addition, MobileNetV2 also exhibited the lowest validation loss during training, as shown in Figure . Accordingly, MobileNetV2 was selected as the primary model for feature extraction in this system.

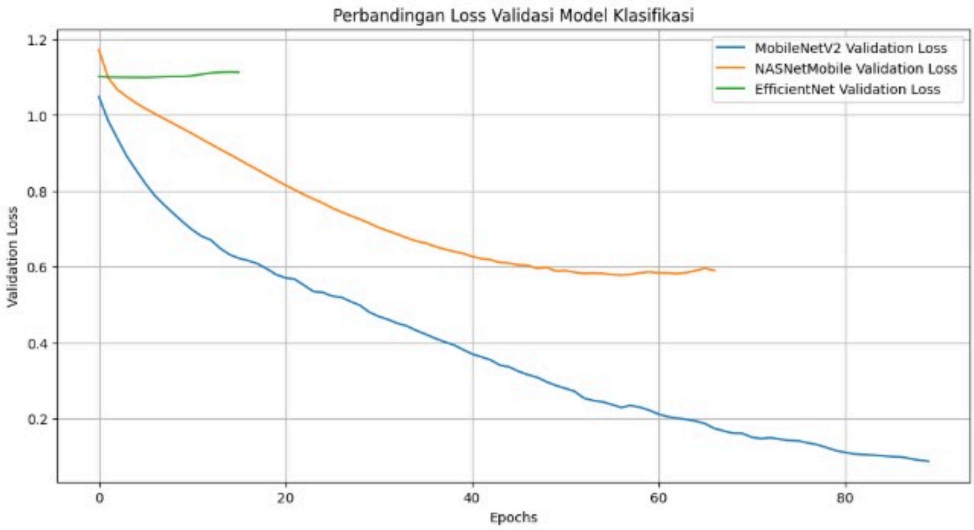

Figure 9. Combined Validation Loss Graph of Various Feature Extractors

Following the feature extraction process using MobileNetV2, the classification stage was performed using several machine learning algorithms, namely Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN). These models were evaluated using the extracted feature vectors to determine the most suitable classifier. As shown in Table 3.

Table 3. Comparison of Classification Models

Model	Total Parameter	Accuracy	Inference speed	Model size
Random Forest	2.257.984	91%	0.04 ms/pic	27.78 MB
Artificial Neural Network (ANN)	2.257.984	73%	0.00 ms/pic	27.11 MB
Support Vector Machine (SVM)	2.257.984	50%	0.20 ms/pic	36.33 MB

From the results, Random Forest outperformed the other classifiers in terms of validation accuracy, classification consistency across chili categories, and training speed. Therefore, Random Forest was selected as the final classification algorithm for this system.

Based on the two-stage evaluation, this study employed a hybrid combination of MobileNetV2 as the feature extractor and Random Forest as the classification model. This combination proved to deliver high accuracy and efficient classification performance, as well as robustness in handling visual variations of bird's eye chili images.

3.2 Confusion Matrix Evaluation Results

The performance evaluation of the classification models in this study not only relies on accuracy and inference efficiency but also requires a more detailed analysis using the confusion matrix. The confusion matrix provides an in-depth view of each model's ability to correctly classify chili categories, highlighting the number of correct predictions (True Positives) and incorrect predictions (False Positives and False Negatives) for each class.

1) Confusion Matrix of the Random Forest

The Random Forest model demonstrated excellent and consistent classification performance, as shown in Figure . This is evident from the strong dominance of diagonal values in the confusion matrix, indicating that most instances were correctly classified into their respective categories. High true positive counts were recorded for several classes, including red-dry, red-medium, and red-fresh.

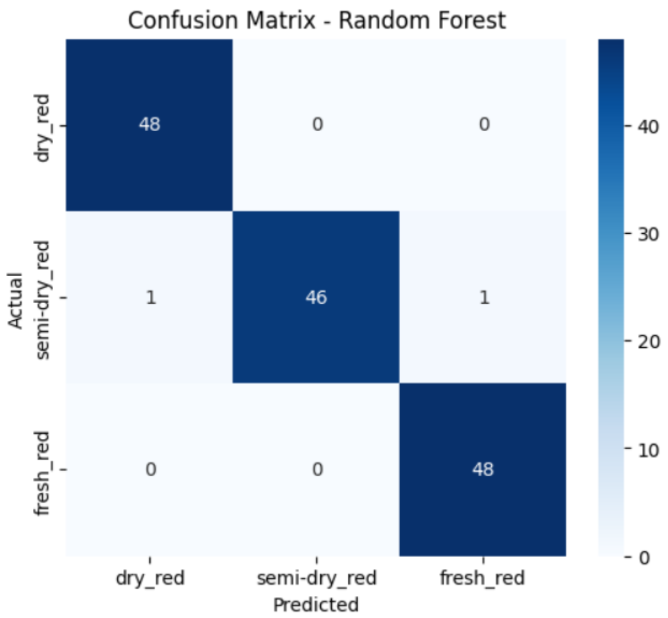

Figure 10. Confusion Matrix of the Random Forest

2) Confusion Matrix of the ANN

The Artificial Neural Network (ANN) model exhibited a more variable performance, as shown in Figure . While it successfully classified instances from.

Misclassifications were also observed in the red-dry and red-fresh classes. Although the ANN model showed reasonable performance for certain categories, it lacked the stability and precision offered by the Random Forest model.

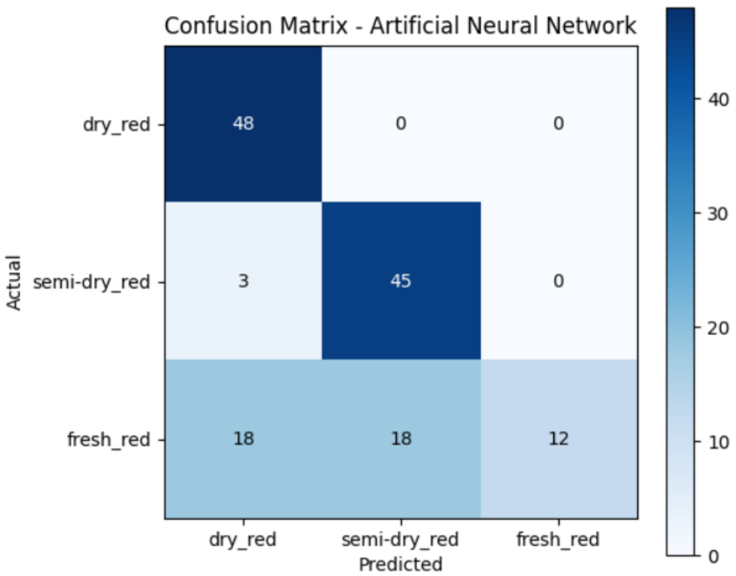

Figure 11. Confusion Matrix of the Artificial Neural Network

3) Confusion Matrix of the SVM

In contrast to the other models, the Support Vector Machine (SVM) showed the weakest performance, as shown in Figure 5. According to the confusion matrix, its performance on some classes was notably poor.

The model also produced substantial errors in the red-fresh and red-medium categories. These results suggest that SVM was unable to effectively separate data in the high-dimensional feature space produced by MobileNetV2. The high rate of misclassification across nearly all categories indicates that SVM is not a suitable choice for this chili quality classification system.

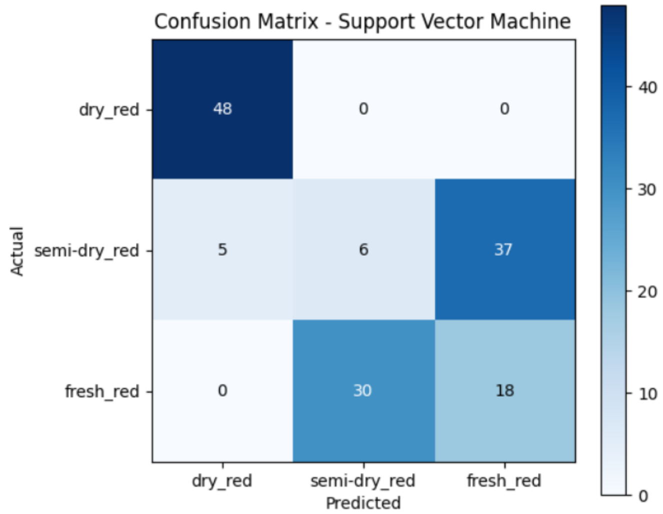

Figure 5. Confusion Matrix of the Support Vector Machine

3.3 Discussion

The experimental results of this study demonstrate the effectiveness of the hybrid classification model combining MobileNetV2 for feature extraction and Random Forest for classification. The performance was evaluated using several key metrics which Accuracy, Precision, Recall, and F1-Score.

Among the five deep learning models evaluated for feature extraction MobileNetV2, EfficientNetB0, and NASNetMobile, consistently outperformed the others in terms of both classification accuracy and computational efficiency. As shown in Table 2, MobileNetV2 achieved a validation accuracy of 96%, with the shortest inference time and the smallest model size, making it optimal for mobile deployment.

After the feature extraction phase, four classification algorithms were compared which, Random Forest, Artificial Neural Network (ANN), and Support Vector Machine (SVM). Random Forest produced the highest validation accuracy at 91%, with superior performance across all evaluation metrics and the most consistent classification across chili categories.

To facilitate practical usage, the selected MobileNetV2 + Random Forest model was integrated into an Android-based mobile application. Users can upload chili images via the camera or gallery, and the system will classify them into three categories, fresh_red, semi-dry_red, and dry_red. The application also provides moisture content estimation, which supports quality assurance and post-harvest decision-making.

3.4 Limitations and Future Work

This study has several limitations that should be acknowledged. First, the dataset comprises 300 original chili images captured from 30 samples over 10 drying cycles, which may limit generalization across variations in cultivar, illumination, background, camera sensors, and drying methods. Second, the evaluation relies on a single hold-out split (80/20) without cross-validation or external test sets; therefore, the reported performance may be optimistic. Third, images were acquired from a top-down view in a controlled setting, whereas real-world deployment may introduce occlusion, motion blur, and illumination changes. Future work will expand the dataset across different devices and acquisition conditions, apply k-fold cross-validation and out-of-distribution testing, and investigate domain adaptation to improve robustness across cultivars and environments. In addition, integrating multimodal signals (e.g., temperature and humidity during drying) will be explored to better separate the semi-dry_red and dry_red categories [17].

4. CONCLUSION

This study developed a hybrid classification pipeline that combines MobileNetV2 as a feature extractor and Random Forest as the final classifier to assess the quality of bird's eye chili during drying using digital images. The proposed approach achieved 94% validation accuracy during the feature-extraction stage and 91% accuracy at the final classification stage, demonstrating reliable discrimination among fresh_red, semi-dry_red, and dry_red classes. The model also produced strong precision, recall, and F1-score with limited misclassification, indicating stable performance under the evaluated conditions. Furthermore, the MobileNetV2+RF pipeline was integrated into an Android application to enable on-device, offline inference from smartphone photos, supporting practical postharvest decision-making by reducing subjectivity and improving inspection efficiency. Future improvements will focus on enlarging and diversifying the dataset, incorporating additional features or multimodal signals, and applying more rigorous validation (e.g., cross-validation and external testing) to strengthen generalization across cultivars and acquisition environments.

REFERENCE

[1] O. Cruz-Domínguez *et al.*, "A novel method for dried chili pepper classification using artificial intelligence," *J Agric Food Res*, vol. 3, Mar. 2021, doi: 10.1016/j.jafr.2021.100099.

[2] Y. A. Azis, N. Khuriyati, and A. Suyantohadi, "Classification of Dried Chilli Quality Using Image Processing," in *IOP Conference Series: Earth and Environmental Science*, IOP Publishing Ltd, Mar. 2021. Doi: 10.1088/1755-1315/686/1/012058.

[3] Y. F. Sihombing, A. Septiarini, A. H. Kridalaksana, and N. Puspitasari, "Chili Classification Using Shape and Color Features Based on Image Processing," *Scientific Journal of Informatics*, vol. 9, no. 1, pp. 42–50, May 2022, doi: 10.15294/sji.v9i1.33658.

[4] Z. Shu, X. Li, and Y. Liu, "Detection of Chili Foreign Objects Using Hyperspectral Imaging Combined with Chemometric and Target Detection Algorithms," *Foods*, vol. 12, no. 13, Jul. 2023, doi: 10.3390/foods12132618.

[5] Y. Noutfia and E. Ropelewska, "Exploration of Convective and Infrared Drying Effect on Image Texture Parameters of 'Mejhoul' and 'Boufeggous' Date Palm Fruit Using Machine Learning Models," *Foods*, vol. 13, no. 11, Jun. 2024, doi: 10.3390/foods13111602.

[6] D. Lopez-Betancur *et al.*, "Evaluating CNN Models and Optimization Techniques for Quality Classification of Dried Chili Peppers (Capsicum annuum L.)," *International Journal of Combinatorial Optimization Problems and Informatics*, vol. 15, no. 2, pp. 13–25, Jun. 2024, doi: 10.61467/2007.1558.2024.v15i2.462.

[7] H. B. Patel and N. J. Patil, "An Intelligent Grading System for Automated Identification and Classification of Banana Fruit Diseases Using Deep Neural Network," *International Journal of Computing and Digital Systems*, vol. 15, no. 1, pp. 761–773, 2024, doi: 10.12785/ijcds/150155.
[8] Sneha Ramdas Shegar and Dr. Pawan Bhambu, "Fruit Quality Analysis and Disease Detection using Deep Learning Techniques," 2024. Doi: https://doi.org/10.52783/jes.1372.
[9] E. H. Rachmawanto, A. Susanto, R. Raad, A. Al-Jawry, I. Utomo, and R. R. Ali, "Green Chili Quality Classification based on HSV Color Feature with SVM," *APIT) Application of Information Technology*, vol. 1, no. 1, pp. 27–32, 2022, doi: 10.12487/AMRI.v1i1.xxxxx.
[10] L. Goel and J. Nagpal, "A Hybrid Convolutional Neural Network–Random Forest Model for Plant Disease Diagnosis," in *Smart Innovation, Systems and Technologies*, Springer Science and Business Media Deutschland GmbH, 2023, pp. 509–517. Doi: 10.1007/978-981-19-7447-2_45.
[11] N. H. Nguyen *et al.*, "Rating pome fruit quality traits using deep learning and image processing," *Plant Direct*, vol. 8, no. 10, Oct. 2024, doi: 10.1002/pld3.70005.
[12] D. C. P. Ambrose, R. Naik, and H. Patil, "Studies on the drying behaviour of red chilli and it's effect on quality," *Journal of Applied Horticulture*, vol. 26, no. 2, pp. 182–185, 2024, doi: 10.37855/jah.2024.v26i02.34.
[13] P. Gong, Y. Ma, C. Li, X. Ma, and S. H. Noh, "Understand Data Preprocessing for Effective End-to-End Training of Deep Neural Networks," Apr. 2023, doi: doi.org/10.48550.
[14] J. Liang, Y. Liu, and V. Vlassov, "The Impact of Background Removal on Performance of Neural Networks for Fashion Image Classification and Segmentation," in *Proceedings – 2023 Congress in Computer Science, Computer Engineering, and Applied Computing, CSCE 2023*, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 1960–1968. Doi: 10.1109/CSCE60160.2023.00323.
[15] L. Perez and J. Wang, "The Effectiveness of Data Augmentation in Image Classification using Deep Learning," Dec. 2017, doi: 10.48550/arXiv.1712.04621.
[16] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," *J Big Data*, vol. 6, no. 1, Dec. 2019, doi: 10.1186/s40537-019-0197-0.
[17] V. R. Joseph, "Optimal ratio for data splitting," *Stat Anal Data Min*, vol. 15, no. 4, pp. 531–538, Aug. 2022, doi: 10.1002/sam.11583.
[18] Achmad Naila Muna Ramadhani, Galuh Wilujeng Saraswati, Rama Tri Agung, and Heru Agus Santoso, "Performance Comparison of Convolutional Neural Network and MobileNetV2 for Chili Diseases Classification," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 7, no. 4, pp. 940–946, Aug. 2023, doi: 10.29207/resti.v7i4.5028.
[19] D. Purbasari et al. , "MICROWAVE DRYING CHARACTERISTICS OF CHILIES BASED ON DIFFERENT VARIETIES (Capsicum frustescens dan Capsicum annum) AND MICROWAVE POWER," Jurnal Penelitian Sains dan Teknologi Indonesia , vol. 3, no. 2, 2024, doi: 10.19184/jpsti.v3i2.4144.
[20] D. Navarro-Solís et al. , "Analysis of Convolutional Neural Network Models for Classifying the Quality of Dried Chili Peppers (Capsicum Annuum L)," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) , Springer Science and Business Media Deutschland GmbH, 2024, pp. 116–131. doi: 10.1007/978-3-031-51940-6_10.
[21] N. M. Hussin , M. N. S. Zainudin , W. H. M. Saad, M. R. Kamarudin , S. Muhammad, and M. S. J. A. Razak, "Chili fruits maturity estimation using various convolutional neural network architecture," Indonesian Journal of Electrical Engineering and Computer Science , vol. 33, no. 1, pp. 557–567, Jan. 2024, doi: 10.11591/ijeecs.v33.i1.pp557-567.
[22] A. A. Abdul Manan, M. A. Mohd Razman , I. Mohd Khairuddin, and M. N. A. Shapiee , "Chili Plant Classification using Transfer Learning models through Object Detection," MEKATRONIKA , vol. 2, no. 2, pp. 23–27, Dec. 2020, doi: 10.15282/mekatronika.v2i2.6743.
[23] N. Ma, Y. Wu, Y. Bo, and H. Yan, "Chili Pepper Object Detection Method Based on Improved YOLOv8n," Plants , vol. 13, no. 17, p. 2402, Aug. 2024, doi: 10.3390/plants13172402.
[24] A. Albanese, M. Nardello , and D. Brunelli , "Automated Pest Detection with DNN on the Edge for Precision Agriculture," IEEE J Emerg Sel Top Circuits Syst , vol. 11, no. 3, pp. 458–467, Sep. 2021, doi: 10.1109/JETCAS.2021.3101740.

[25] M. S. Uzer , “Deep Learning-Based Classification Consisting of Pre-Trained Models and Proposed Model Using K-Fold Cross-Validation for Pistachio Species,” Applied Sciences (Switzerland) , vol. 15, no. 8, Apr. 2025, doi: 10.3390/app15084516.