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Classification of Green Apple Varieties Using Convolutional Neural Network Based on RGB Color with Mobilenetv2

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Abstract

Manual classification of green apple varieties is often time-consuming, labor-intensive, and prone to human subjectivity. This study aims to develop an automatic classification model based on RGB color features using the MobileNetV2 Convolutional Neural Network (CNN) architecture. The dataset consists of 1,170 images of three green apple varieties: Golden Delicious, Granny Smith, and Manalagi. The preprocessing process includes cropping, resizing, background removal, and conversion to RGB format. The model is trained using 5-fold cross-validation to ensure robustness and generalization ability. The experimental results show an average accuracy of 96%, with precision, recall, and F1-Score values of 96.33% each. The model is implemented in a web-based application using the Flask framework, and tested on new images. The test results show a confidence level of 80.92% for Granny Smith, 87.38% for Manalagi, and 78.43% for Golden Delicious. This study shows that the combination of MobileNetV2 CNN and RGB color features can effectively classify green apple varieties, and make significant contributions to technology-based agricultural automation and quality control systems.

Keywords: Green Apple Classification; Apple Varieties; Convolutional Neural Network; RGB Color; MobileNetV2;

1. INTRODUCING

Technological advancements have significantly improved the ability to classify visual objects, particularly in agricultural domains where accurately identifying fruit varieties is essential. Fruits play a vital role in human nutrition due to their high vitamin and dietary fiber content, which contributes to overall health and well-being [1]. Apples are among the most widely consumed fruits globally due to their taste and nutritional benefits. Green apple varieties, such as Golden Delicious, Granny Smith, and Manalagi, are especially popular due to their distinctive color and flavor. Green apples are appreciated not only for their fresh taste, but also for their health benefits. They contain high levels of pectin, bioactive polyphenols, and dietary fiber, which contribute to cholesterol management and other health improvements [2]. Green apples, such as Golden Delicious, Granny Smith, and Manalagi, are widely consumed varieties due to their taste and health benefits [3] [4] [5].

Each variety has distinctive visual characteristics, but subtle color differences are often difficult for humans to consistently distinguish. Computer vision-based technologies, particularly the Convolutional Neural Network (CNN) approach, offer a solution to

Alnofri Rano Masiku: *Corresponding Author

automate this classification process efficiently and accurately [6]. Several previous studies have applied CNN in fruit classification or disease detection. Research by [7] developed an apple leaf disease classification system using RGB color features and achieved an accuracy of 86.67%. However, this study focuses on disease detection, not fruit variety classification. Another study, described in [8] used CNN to classify the ripeness level of oranges based on RGB images, and achieved an accuracy of 96%. This study focuses on the level of ripeness of oranges. Meanwhile [9] applied CNN in apple freshness detection using an RGB normalization approach with an accuracy of 90%. The study applied CNN in apple freshness detection using RGB normalization approach, but did not discuss variety classification. Furthermore, research by [10] developed a method for classifying wax layers on apples using CNN and achieved an accuracy of 85%. This study focuses on the classification of wax layers on apples. Another study referred to in [11] discusses the implementation of CNN to detect the freshness level of apples, with an accuracy of 93%. This study focuses on detecting the level of freshness in apples.

However, there are not many studies that specifically classify green apple varieties using RGB color features with lightweight CNN architectures such as MobileNetV2, which are designed for computational efficiency and are suitable for implementation on resource-constrained devices [12]. Therefore, this study aims to develop an automatic classification system for green apple varieties using MobileNetV2 based on RGB color features, and implement it in a web form to support the apple classification process quickly and practically. By automatically classifying three green apple varieties, this study provides a practical solution to reduce dependence on manual assessment which tends to be subjective and time-consuming. This benefit is important in the effort to digitize smart farming systems, especially in the process of sorting fruits based on variety quality.

2. METHODOLOGY

2.1. Dataset Collection

This research uses a dataset comprising 1,170 images of three varieties of green apples: Golden Delicious, Granny Smith, and Manalagi. The images were collected to provide a balanced and comprehensive representation of each variety, ensuring the classification model can effectively learn its distinctive features. Each apple was photographed under controlled lighting conditions to maintain color consistency, which is critical since the classification is based on RGB color features.

a. Golden Delicious *b. Granny Smith* *c. Manalagi*

Figure 1. Green Apple Classification

The dataset was carefully curated to include variations in apple orientation, size, and slight color differences within each variety, thereby enhancing the model's robustness against real-world variability.

Table 1. Table Name (Table Fomat)

Apple Variety	Number of Images
Golden Delicious	390
Granny Smith	390

Alnofri Rano Masiku: *Corresponding Author

JURNAL TEKNOINFO
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Manalagi	390
Total	**1,170**

This table reflects the balanced dataset composition used in the research, with an equal number of images per class (390 images each), totaling 1,170 images. This balance supports unbiased training and evaluation, especially when employing K-Fold Cross Validation [13]. The images in the dataset underwent several preprocessing steps, including cropping to focus on the apple region, resizing to a uniform dimension suitable for CNN input, and background removal to isolate the apple from the surrounding area. These steps enhance the quality of the input data by emphasizing color features critical to classification.

2.2. Image Pre-Processing

Image preprocessing is a crucial step in enhancing the quality and relevance of input data for a Convolutional Neural Network (CNN) model [14]. In this study, several preprocessing techniques were applied to raw images of green apples to prepare them for effective feature extraction based on RGB color information. The preprocessing pipeline includes the following stages namely:

a. Cropping

Each image was cropped to focus solely on the apple and remove unnecessary background areas. This step reduces noise and irrelevant information that could adversely affect model training.

b. Resizing

The cropped images were resized to 224×224 pixels, aligning with the MobileNetV2 architecture's input size requirement. Standardizing the image size ensures uniformity in the data fed into the CNN.

c. Background removal

Background removal techniques were applied to further isolate the apple from its surroundings. This process enhances the apple's color features by eliminating distracting background pixels.

d. RGB Conversion

All images were converted to and maintained in the RGB color space because the classification model relies on RGB color channel information to differentiate apple varieties.

These preprocessing steps improve the signal-to-noise ratio of the dataset, enabling the CNN to learn features that are more discriminative of color and texture.

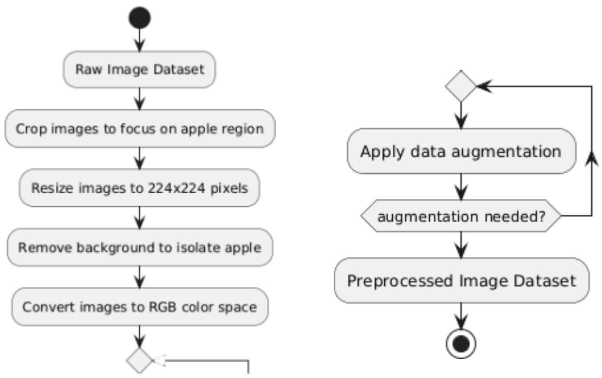

Figure 2. Image Data Pre-Processing Steps

As illustrated in the flowchart, data augmentation is an iterative process applied after initial preprocessing steps, such as cropping, resizing, background removal, and RGB

Alnofri Rano Masiku: *Corresponding Author

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conversion. The objective of data augmentation is to artificially augment the diversity and size of the training dataset by generating modified versions of the original images. This process assists in enhancing the model's capacity for generalization and robustness by subjecting it to a broader spectrum of visual variations [15].

2.3. Model Architecture MobileNetV2

MobileNetV2 is a lightweight deep learning architecture specifically designed for mobile and embedded vision applications. This architecture is known for its efficient use of computational resources while maintaining high accuracy, making it suitable for deployment in environments with limited processing power.

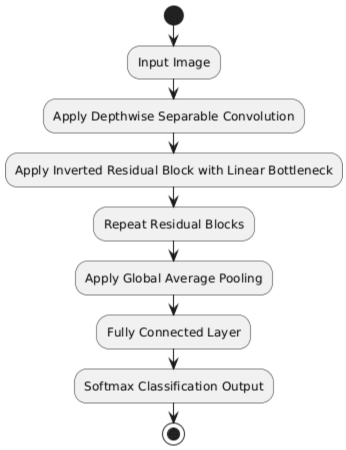

Figure 3. MobileNetV2 Workflow

Table 2. MobileNetV2 Configuration for Green Apple Classification

Parameter	Value / Configuration	Description
Architecture	MobileNetV2	Lightweight CNN architecture suitable for mobile and embedded devices.
Pre-trained Weights	ImageNet	Initial weights were pre-trained on the ImageNet dataset and then fine-tuned for green apple classification.
Input Size	224 × 224 pixels	Resized input images to match the MobileNetV2 architecture requirements.
Optimizer	Adam	Used for training the network.
Learning Rate	0.001	Rate at which the model learns during training.
Batch Size	32	Number of images processed in each iteration during training.
Epochs	50	Number of complete passes through the training dataset.
Loss Function	(Not specified, but likely Cross-Entropy)	A loss function that quantifies the penalty for inaccurate classifications.
Data Augmentation	Rotation, Zoom, Flipping	Applied to increase dataset diversity and reduce overfitting.

The model was initialized with weights pretrained on the ImageNet dataset. This transfer learning approach leverages knowledge gained from a large dataset to improve performance on the smaller apple dataset. Furthermore, the pretrained model was fine-tuned on the apple image dataset using the training parameters outlined in Section 2.4.

2.4. Training and Validation

Alnofri Rano Masiku: *Corresponding Author

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This section delineates the training and validation process employed to develop the green apple classification model using MobileNetV2 architecture. The methodology ensures robust model performance and generalization through systematic data partitioning, parameter tuning, and evaluation metrics.

Data Partitioning and K-Fold Cross Validation

In order to maximize the use of the available dataset and minimize the risk of overfitting, the model training utilized 5-Fold Cross Validation (K=5). This technique partitions the dataset, which consists of 1,170 images, into five subsets, or folds. In each iteration of the process, four folds (80% of the data) are utilized for training, while the remaining fold (20%) is designated as the validation set. This process is repeated five times, with each fold utilized precisely once for validation. The results from all folds are then averaged to provide a reliable estimate of the model's performance. This approach mitigates bias from random train-test splits and ensures the model's ability to generalize across unseen data.

Training Configurations

The MobileNetV2 model was initialized with pretrained ImageNet weights and fine-tuned on the apple dataset. The training parameters were set as follows:

Table 3. Training Parameters

Parameter	Value	Description
Optimizer	Adam	Adaptive learning rate optimizer
Learning Rate	0.001	Step size for weight updates
Batch Size	32	Number of samples per training batch
Epochs	50	Number of complete passes through data
Loss Function	Categorical Cross-Entropy	Suitable for multi-class classification

During the training process, data augmentation techniques such as rotation, zoom, horizontal flipping, and brightness adjustment were employed to artificially enhance dataset diversity and mitigate the risk of overfitting.

To provide a clearer and more comprehensive picture of the stages carried out in this classification system, Figure 4. presents a flowchart of the method used in the study. This diagram summarizes the process starting from the input of raw apple images, pre-processing stages, training the CNN model using the MobileNetV2 architecture, to the output in the form of classification results accessed through a web interface.

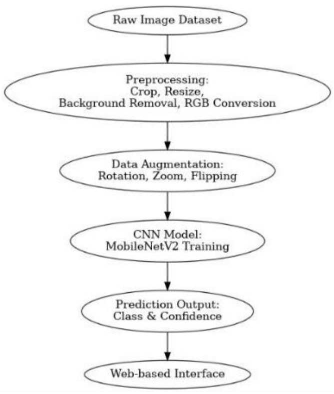

Figure 4. Green Apple Classification Workflow Diagram

This diagram shows the complete flow of the green apple variety classification process developed in this study. The process starts from the raw image dataset which is processed

Alnofri Rano Masiku: *Corresponding Author

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through cropping, resizing, background removal, and RGB conversion stages. Furthermore, data augmentation is carried out to increase the diversity of the dataset. The processed images are then used in training the CNN model using the MobileNetV2 architecture. The classification results in the form of variety labels and confidence scores are displayed through a web-based interface.

Performance Evaluation

Performance evaluation constitutes a critical phase in assessing the effectiveness and reliability of the green apple classification model developed using the MobileNetV2 architecture. This section provides a thorough exposition of the evaluation metrics, confusion matrix analysis, and testing on new images, thereby facilitating a comprehensive understanding of the model's predictive capabilities.

Evaluation Metrics

The model's performance was quantified using standard classification metrics, which provide insight into different aspects of the classification quality:

a. Accuracy
Measures the overall correctness of the model by calculating the ratio of correctly classified samples to the total number of samples.

b. Precision
Indicates the proportion of true positive predictions among all positive predictions, reflecting the model's ability to

avoid false positives.

c. Recall (Sensitivity)
Quantifies the proportion of actual positives correctly identified, highlighting the model's ability to detect true

positives.

d. F1-Score
Harmonic mean of precision and recall, balancing the trade-off between these two metrics.

These metrics were computed for each fold in the 5-Fold Cross Validation and averaged to provide robust performance estimates.

3. RESULT AND DISCUSSIONS

3.1. Data preprocessing

Data preprocessing is a fundamental stage in this research to prepare the raw apple images for effective feature extraction and classification by the MobileNetV2 CNN model. The preprocessing pipeline included several key steps: cropping, resizing, background removal, and RGB color conversion. These steps were designed to enhance the quality and consistency of the input images, focusing on the relevant features necessary for accurate classification.

b. Cropping
The cropping process involved isolating the apple from the original image by removing unnecessary background areas. This step is critical to minimize noise and irrelevant information that could interfere with the model's learning process. Figure 5 illustrates the cropping applied to sample images, showing how the apple region is tightly framed.

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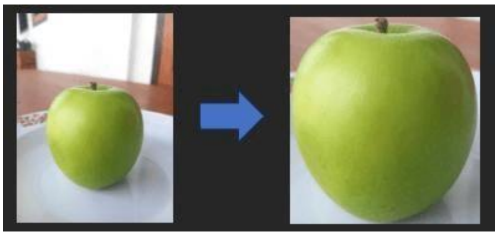


Figure 5. Cropping

c. Resizing

After cropping, all images were resized to a uniform dimension of 224×224 pixels. This resizing aligns with the input size requirement of the MobileNetV2 architecture, ensuring compatibility and consistent input dimensions for the CNN. Figure 6 in the thesis depicts the resized images ready for further processing.

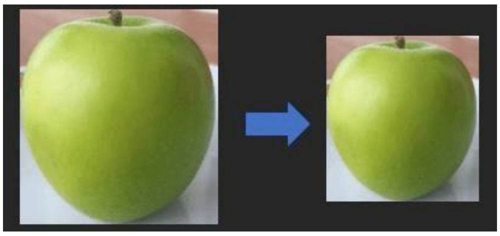


Figure 6. Resizing

d. Background Removal

To further enhance the focus on the apple, background removal techniques were applied. This process isolates the apple from its environment, removing distracting background elements and improving the clarity of color features. Figure 7 in the thesis shows examples of images before and after background removal, highlighting the apple as the sole object of interest.

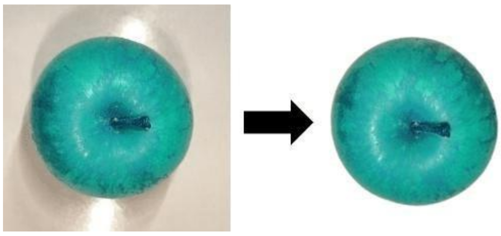
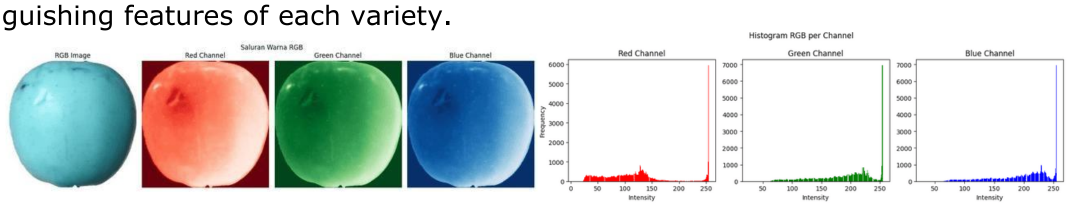


Figure 7. Background Removal

e. RGB Color Conversion

The images were converted and maintained in the RGB color space, as the classification model relies on RGB color channels to distinguish between apple varieties. The color distribution per channel was analyzed to understand the distinguishing features of each variety.



Alnofri Rano Masiku: *Corresponding Author

JURNAL TEKNOINFO
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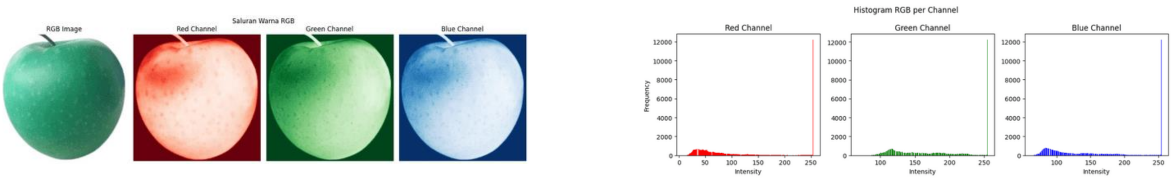
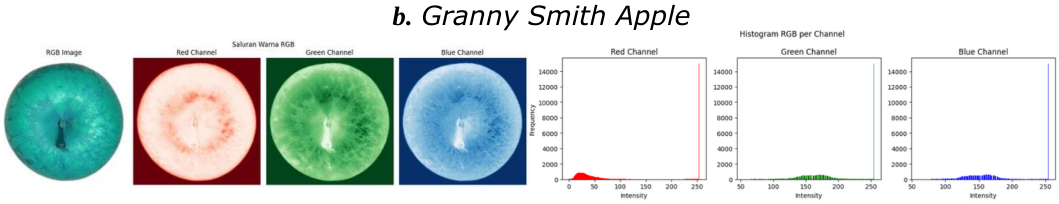
a. Golden Delicious Apple



b. Granny Smith Apple



c. ManalagiApple

Figure 8. RGB Conversion and Histogram per Apple

The histograms of RGB channels revealed distinct color intensity patterns among Golden Delicious, Granny Smith, and Manalagi apples, validating the choice of RGB-based feature extraction for this classification task.

3.2. Model Performance

The performance of the green apple variety classification model using the MobileNetV2 architecture was rigorously evaluated through a 5-Fold Cross Validation approach to ensure robustness and generalizability. The dataset of 1,170 images was partitioned into five subsets, with each fold serving as a validation set once while the remaining four folds were used for training.

Evaluation Metrics

The model's effectiveness was assessed using four key metrics, thus, the average performance metrics across the five folds are summarized in the table below:

Table 4. Average Performance Metrics from 5-Fold Cross Validation

Metric	Average Score (%)
Accuracy	96.00
Precision	96.33
Recall	96.33
F1-Score	96.33

These results indicate that the MobileNetV2 model achieved high accuracy and balanced precision and recall, demonstrating its strong capability in correctly classifying the three green apple varieties: Golden Delicious, Granny Smith, and Manalagi.

3.1 Confusion Matrix Analysis

The confusion matrix is a vital tool for evaluating the performance of the classification model by providing a detailed breakdown of the model's predictions. It visualizes the instances of correct and incorrect classifications for each class, allowing for a nuanced understanding of the model's strengths and weaknesses.

Analysis of the Average Confusion Matrix

Table 5 presents the average confusion matrix across all validation folds.

JURNAL TEKNOINFO
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Table 5. Average Confusion Matrix Across Validation Folds

Actual \ Predicted	Golden Delicious	Granny Smith	Managagi
Golden Delicious	375	8	7
Granny Smith	6	380	4
Manalagi	5	7	378

Golden Delicious out of 390 actual Golden Delicious apples, 375 were correctly classified, while 8 were misclassified as Granny Smith and 7 as Manalagi. Granny Smith out of 390 actual Granny Smith apples, 380 were correctly classified, while 6 were misclassified as Golden Delicious and 4 as Manalagi. Manalagi out of 390 actual Manalagi apples, 378 were correctly classified, while 5 were misclassified as Golden Delicious and 7 as Granny Smith. These results indicate a high degree of accuracy in classifying each apple variety. The misclassifications are relatively low, suggesting that the model effectively distinguishes between the three classes based on RGB color features.

The classification results show that the MobileNetV2 model is able to achieve an average accuracy of 96%, with precision, recall, and F1-score values balanced above 96%. This performance shows that this model is accurate in distinguishing the three green apple varieties, namely Golden Delicious, Granny Smith, and Manalagi. Compared to the study by [7] which only achieved an accuracy of 86.67% for apple leaf disease classification using RGB, this result shows a significant improvement. The study [8] has an accuracy of 96% for orange ripeness classification, but does not focus on the classification of apple varieties with high visual similarity. Meanwhile, studies [9], [10], and [11] discuss freshness detection and fruit condition classification with an accuracy of 85–93%, but do not develop a green apple variety classification system.

The confusion matrix in Fold 1 also shows excellent classification performance. Out of 63 Golden Delicious samples, 62 samples were correctly classified and only 1 sample was misclassified. For Granny Smith, 59 out of 62 samples were correctly classified with only 3 misclassifications. Most notable was the Manalagi class where the model was able to correctly classify all 63 samples without error.

Table 6. Classification Test Set Report

Classification Report	Precision	Recall	F1 - Score	Support
Golden Delicious	1.00	0.94	0.97	78
Granny Smith	0.97	0.95	0.96	78
Manalagi	0.92	1.00	0.96	78
Accuracy			0.96	234
Macro Avg	0.98	0.98	0.98	234
Weighted	0.98	0.98	0.98	234

Alnofri Rano Masiku: *Corresponding Author

JURNAL TEKNOINFO
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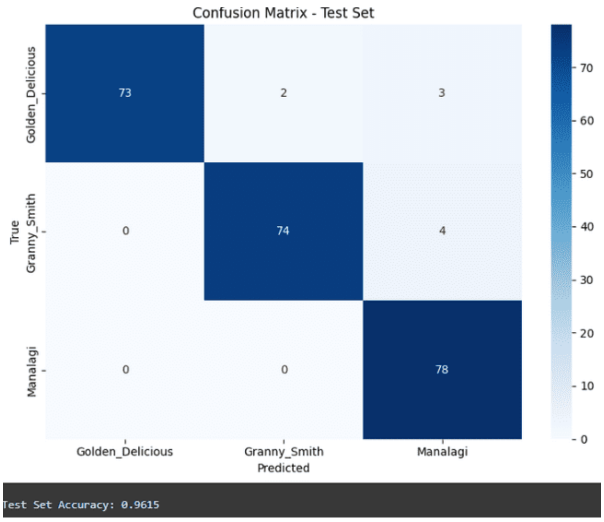

Figure 9. Test Set Confusion Matrix

Based on the confusion matrix in Figure 10, it can be seen that the classification model has shown a very good performance in classifying the three apple classes, namely Golden Delicious, Granny Smith, and Manalagi. Confusion Matrix shows that in the Golden delicious class, 73 Golden delicious images were correctly classified as Golden delicious, 2 Golden delicious images were incorrectly classified as Granny smith and 3 images were classified as Manalagi. For the Granny smith class, 74 Granny smith images were correctly classified as Granny smith, and 4 images were classified as Manalagi, then no images were classified as Golden delicious. Furthermore, in the Manalagi class there are 78 Manalagi images that are correctly classified as Manalagi, then there are no images classified as Granny smith and Golden delicious.

The main difference in this study is the use of the lightweight MobileNetV2 architecture that can be applied to devices with limited resources, as well as its implementation in an easy-to-use web form. In addition, this study also uses a cross-validation approach (K-Fold Cross Validation) with a value of K = 5 to ensure the robustness and generalization of the model to varying data.

Implementation and Web Application Testing

The trained MobileNetV2 model was deployed as a web-based application to facilitate real-world testing and validation. This deployment aimed to assess the model's practical utility in classifying green apple varieties under conditions that mimic actual usage scenarios.

Web Application Interface

The web application, built using the Flask framework, provides a user-friendly interface consisting of two main pages:

Main Page

Users can upload an image of a green apple. On this page, users can upload images of green apples to be classified.

JURNAL TEKNOINFO
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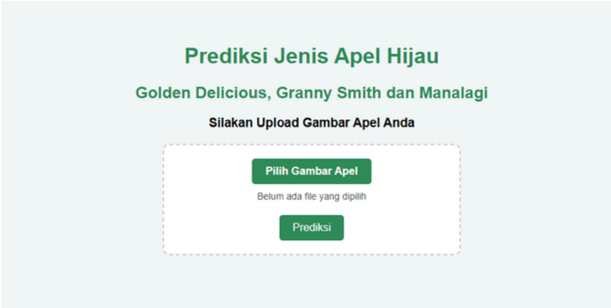

1. *Figure 11. Main Page*

Figure 11 shows the main page of the green apple type prediction system. There is a "Select Apple Image" button thatallows users to select an image file from the device. After the image is successfully uploaded, the system will display the image for confirmation before the prediction process is carried out. The "Predict" button will be active after the image is selected, and the user can click it to start the classification process using the trained model.

a. Prediction Result Page
Displays the classification result, indicating the predicted apple variety along with a confidence score

2. *Figure 12. Result Page*

Figure 12 shows the classification results after the user uploads a green apple image into the system. Based on the CNN model analysis, the image is predicted as a Granny Smith type with a confidence level of 74.19%. In addition to displaying the main results, the system also displays two other types of apples that have similarities based on the confidence value, namely Manalagi (18.60%) and Golden Delicious (7.21%).

Testing Methodology

New, unseen images of green apples were used to test the deployed model. These images were separate from the training and validation sets, ensuring an unbiased evaluation of the model's generalization ability. The testing process involved uploading each image through the web interface and recording the model's prediction and confidence score.

Results and Analysis

Alnofri Rano Masiku: *Corresponding Author

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The classification confidence scores for the tested apple varieties are presented in Table 8

Table 8. Classification Confidence on New Images in Web Application

Apple Variety	Test Images	Confidence (%)
Granny Smith		80.92
Manalagi		87.38
Golden Delicious		78.43

The model classified Granny Smith apples with an average confidence of 80.92%. This relatively high confidence suggests that the model can reliably identify this variety based on its distinct green color and shape. Manalagi apples were classified with the highest confidence, averaging 87.38%. This may be attributed to the unique yellowish-green hue of Manalagi apples, making them easily distinguishable from the other two varieties. The model showed a slightly lower confidence in classifying Golden Delicious apples, with an average of 78.43%. This could be due to the color variability of Golden Delicious apples, which can range from greenish-yellow to golden, causing some confusion with other varieties.

Discussion

The results obtained in this study demonstrate the effectiveness of the MobileNetV2 model, which leverages RGB color features to classify green apple varieties with high accuracy. This research addresses the challenge of distinguishing between visually similar apple varieties—Golden Delicious, Granny Smith, and Manalagi—by utilizing subtle differences in color information. The model achieved an average accuracy of 96% across 5-Fold Cross Validation, with precision, recall, and F1-score values consistently above 96%. These results indicate the model’s strong ability to correctly identify apple varieties while minimizing false positives and false negatives, an essential factor for reliable and practical implementation in the agricultural sector. The use of RGB color histograms proved effective in capturing the distinct visual patterns among the three apple varieties, which the model successfully learned and used for accurate classification. Furthermore, the deployment of the model as a web application enabled real-world testing, where the confidence scores for previously unseen images demonstrated the model's generalization capabilities. Although direct comparisons with other studies focusing specifically on green apples are limited, the model's performance is competitive with existing fruit classification studies using CNNs. Overall, the combination of high accuracy, computational efficiency, and real-world usability suggests that MobileNetV2 is a promising solution for automated fruit classification in resource-constrained environments, such as mobile or embedded systems, thereby supporting the automation of sorting and quality control processes in agriculture

Alnofri Rano Masiku: *Corresponding Author

4. CONCLUSION

This study successfully developed an automated classification model for green apple varieties—Golden Delicious, Granny Smith, and Manalagi—based on RGB color features using the MobileNetV2 Convolutional Neural Network (CNN) architecture. The dataset under consideration contained 1,170 images, which were meticulously preprocessed through a series of steps. These steps included cropping, resizing to 224×224 pixels, background removal, and RGB conversion to enhance feature quality. The model was trained and evaluated using 5-Fold Cross Validation, achieving an average accuracy of 96.00%, with precision, recall, and F1-Score all at 96.33%. The metrics reveal a classification performance that is both highly effective and balanced. Confusion matrix analysis further confirmed minimal misclassification among the three apple varieties, thereby demonstrating the model's robustness. The trained model was deployed as a web-based application using the Flask framework, enabling practical, real-time classification. The model's performance was further assessed through testing on previously unseen images, yielding confidence scores of 80.92% for Granny Smith, 87.38% for Manalagi, and 78.43% for Golden Delicious apples. These results serve to validate the model's generalizability and applicability in real-world settings. This research demonstrates that MobileNetV2, when combined with RGB color-based image preprocessing, provides an accurate, efficient, and deployable solution for green apple variety classification. This finding has the potential to benefit agricultural quality control and sorting automation

5. REFERENCES

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