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Research Article

Multiclass Meat Classification Using a Hybrid Machine Learning Approach

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Abstract: Image classification is a key field in digital image processing with broad applications, such as object recognition and disease detection. The use of artificial neural network architectures, such as MobileNetV2, has significantly advanced pattern recognition in large datasets. However, in small datasets, challenges related to accuracy and generalization are often encountered. This study explores an RGB-based approach utilizing MobileNetV2 for image feature extraction and Support Vector Machine (SVM) as the classifier. MobileNetV2 is applied to extract features from RGB images, which are then further processed by SVM to determine image classes. The results indicate that this model achieves an accuracy of 91.67%, precision of 0.9163, recall of 0.9167, and F1-score of 0.9161. Based on the confusion matrix analysis, the model effectively distinguishes between classes, despite slight overlaps. This research contributes to the development of intelligent image classification systems that can be applied in various fields, including the food industry. With these achievements, the RGB approach integrating MobileNetV2 and SVM has proven effective in enhancing image classification accuracy, even with relatively small datasets. These findings open opportunities for applying similar methods in other image processing tasks that require high accuracy in object or disease detection and classification.

Keywords: Classification; Image; MobileNetV2; RGB; SVM

1. Introduction

Image classification is a fundamental domain in digital image processing and artificial intelligence, with diverse applications, including object recognition, disease detection, and security surveillance (Hidayat et al., 2022; Nurhalisa et al., 2025). Over the past decades, advancements in neural network architectures, such as MobileNetV2, have significantly improved pattern recognition and image classification, demonstrating exceptional performance on large-scale datasets like ImageNet (Indraswari et al., 2022). However, despite the robustness of these models, their deployment on domain-specific datasets with limited samples presents challenges, particularly concerning accuracy and generalization (Dani & Handayani, 2024).

One of the primary challenges in image classification on small datasets is the lack of sufficient data to train models optimally, which can lead to overfitting or inaccurate predictions (Ma et al., 2023), (Budi et al., 2024). A study applying convolutional neural networks (CNN) with the MobileNetV2 architecture for mobile applications demonstrated its effectiveness in detecting beef freshness. The model was trained on 2,080 images (1,040 fresh, 1,040 spoiled) and evaluated using a confusion matrix, achieving an accuracy of 94%. This application effectively assists users in ensuring meat quality and reducing health risks (Tirtana & Irawan, 2024). MobileNetV2, designed for efficiency and high performance, can

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extract representative features from images. On the other hand, the Support Vector Machine (SVM) method is known for its strong classification capabilities, particularly when handling feature-based data with limited samples, making it an effective complementary approach for image-based analysis (Kurniawan & Ariatmanto, 2024) (Ilmadina et al., 2023). In the classification of meat images, SVM was employed as the classifier and evaluated using a confusion matrix. The experimental results indicate that the highest accuracy was achieved for goat meat at 91.4%, the highest precision was observed for goat meat at 80%, the highest recall was recorded for beef at 81.3%, and the highest F1-score was obtained for beef at 0.76 (Christyono & others, 2024).

Research on meat image processing demonstrates significant potential for deep learning applications (Cahyo et al., 2023; Hidayat, 2025; Hidayat et al., 2022; Lasniari et al., 2022; Tirtana & Irawan, 2024). The integration of transfer learning with pre-trained models has been explored for meat image classification, revealing that transfer learning not only accelerates the training process but also enhances model accuracy. Furthermore, class imbalance remains a major challenge in image classification, as an imbalanced dataset may cause the model to overlook classes with fewer samples (Ramadhan et al., 2024).

This study aims to evaluate image classification performance by comparing two primary approaches: RGB+MobileNetV2 and RGB+MobileNetV2+SVM, as well as identifying the strengths and limitations of each method. The first approach involves training the RGB+MobileNetV2 model end-to-end using a neural network architecture for direct classification. The second approach utilizes MobileNetV2 as a feature extractor, followed by classification using SVM to generate predictions. These approaches are compared based on performance metrics such as accuracy, precision, recall, and F1-score to determine the effectiveness and efficiency of each method.

This research focuses on classifying three types of meat beef, pork, and goat, using MobileNetV2 as the primary model. Challenges in meat image classification include data imbalance and visual variations that are difficult to recognize manually. Therefore, this study adopts a more comprehensive approach, incorporating data augmentation techniques, class weighting, and evaluation using various performance metrics to ensure the model's accuracy and reliability in meat image classification. This approach is expected to make a significant contribution to supporting the automation of the food industry through intelligent technology.

Additionally, this research aims to contribute to the development of more effective and efficient image classification models, particularly for applications with limited datasets. The findings of this study may also serve as a reference for researchers and practitioners in selecting the optimal combination of methods to maximize image classification performance across various application domains. The developed model is evaluated using performance metrics such as accuracy, precision, recall, and F1-score to ensure accurate meat image classification. To analyze the model's prediction distribution on test data, a confusion matrix is employed, which is particularly useful given the challenges related to class imbalance. Image normalization techniques and class weighting are applied to address data imbalance issues and ensure proportional attention to each category during model training.

2. Research Method

Image classification is a fundamental task in computer vision, aiming to categorize image data into specific classes based on available visual content (Susanto et al., 2023). In image classification, machine learning techniques are employed to develop models capable of learning patterns from image data and making predictions on new inputs (Bansal et al., 2023). Several commonly used approaches for image classification include convolutional neural networks (CNN) and support vector machines (SVM) (Dinesh et al., 2024).

The research methodology employed in this study consists of several stages designed to achieve the research objectives, namely classifying images using a machine learning model based on a Convolutional Neural Network (CNN) with a transfer learning approach utilizing MobileNetV2, as well as evaluating model performance using Support Vector Machine (SVM) and calculating various evaluation metrics. This methodology involves data collection, data processing, model training, and result analysis, as illustrated in Figure 1.

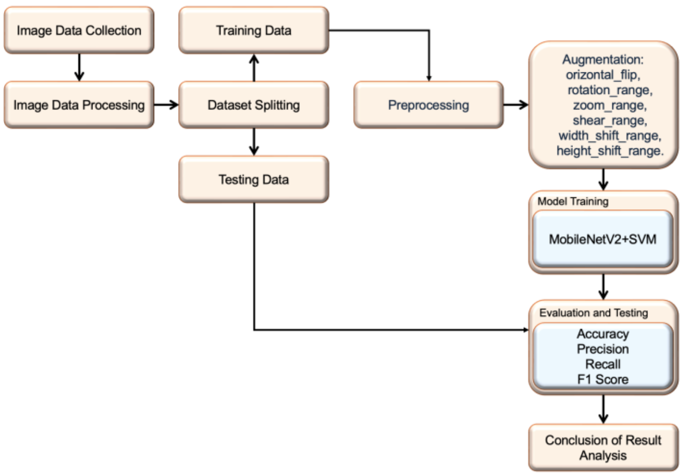

Figure 1. Research Workflow

2.1. Image Data Collection

The dataset used in this study is categorized into three classes: beef images, pork images, and goat meat images. This dataset is a primary dataset collected by the researcher and was previously utilized in image classification research (Hidayat et al., 2022). Each image in the dataset has varying dimensions; however, for consistency in processing, all images were resized to 224×224 pixels to match the input requirements of MobileNetV2. The dataset consists of 480 images, with each class containing 120 images (Table 2). Sample images from the dataset are presented in Figure 2.

Figure 2. Sample Image Data

Table 1. Image Data Classes

Image Data Class	Quantity
Pork Meat Images	160
Beef Images	160
Goat Meat Images	160
Total	480

2.2 Preprocessing Data

The next step involves converting the images into arrays to facilitate processing. The images are then further processed by normalizing pixel intensity values to a range between 0 and 1. Additionally, the dataset is split into two subsets: training data and testing data, with a ratio of 80% for training and 20% for testing (Table 3).

Table 2. Image Data Distribution

Image Data	Quantity
Training Images	384
Testing Images	96
Total	480

Data augmentation is performed to enrich the training dataset by generating variations of the original images. The augmentation process includes transformations such as image shifts (horizontal and vertical), rotation, zoom, and horizontal flipping. These augmentations help the model learn to recognize patterns from a more diverse set of images and mitigate the risk of overfitting. The augmented image dataset is presented in Figure 3 below.

Figure 3. Augmented Image Data

2.2 Model Training

During the model training phase, MobileNetV2, a pre-trained CNN model trained on the ImageNet dataset, is utilized as the foundation for feature extraction. MobileNetV2 operates in transfer learning mode, where the pre-trained weights from a large-scale dataset are retained, and only the upper layers are fine-tuned to adapt to the specific dataset used in this study. This model was selected due to its efficiency and ability to process smaller-sized images effectively.

After image data preprocessing, the next step is feature extraction, where the processed images are fed into MobileNetV2 to generate feature vectors that encapsulate essential information from the images. These extracted features are then used as input for the classification model. In the subsequent stage, SVM classification training is performed using the standardized feature vectors. A linear kernel SVM is employed, as it is well-suited for this dataset due to its relatively simple and well-structured nature. The training process is conducted on the training data, and the trained model is then used to predict the image categories in the test dataset.

3. Result And Discussion

As illustrated in Figure 5, MobileNetV2 was employed as the primary feature extractor for image data. This model leverages pre-trained weights from the ImageNet dataset. In this study, MobileNetV2 functions exclusively as a feature extractor, while the classification task is handled by SVM. The model consists of a total of 2,257,984 parameters, which is relatively large. However, the number of trainable parameters is zero, as the MobileNetV2 model is used solely for feature extraction without fine-tuning. This approach significantly reduces training time and model complexity while still harnessing MobileNetV2's feature extraction capabilities.

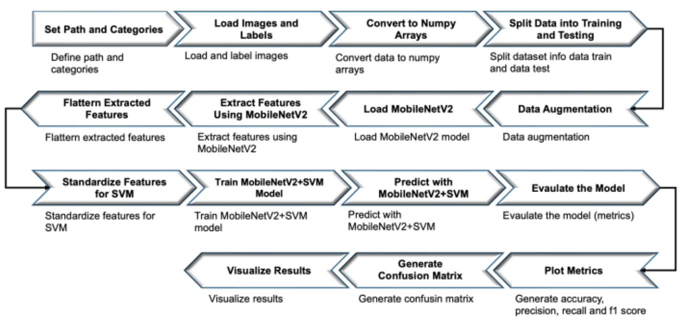

Figure 5. Research Process Overview

After extracting features with MobileNetV2, the SVM model was trained using the training dataset to predict image classes in the test dataset. Evaluation results indicate that the model achieves high classification performance, demonstrating its effectiveness in the given classification task.

Table 4. Performance Metrics of MobileNetV2+SVM Model

Evaluation Metric	Value
Accuracy	0.9167 (91.67%)
Precision	0.9163
Recall	0.9167
F1 Score	0.9161
Loss	0.1751

Table 4 demonstrates that the MobileNetV2+SVM model achieves strong performance, with an accuracy of 91.67%, precision of 0.9163, recall of 0.9167, F1-score of 0.9161, and a loss value of 0.1751. These metrics indicate that the model is highly capable of classifying data effectively, with a well-balanced distribution of errors between precision and recall. This suggests that the model is not only accurate in predicting the correct classes but also successfully minimizes false positives and false negatives. Overall, the model delivers highly satisfactory results, with nearly identical scores for accuracy, precision, recall, and F1-score, indicating that the SVM classifier effectively classifies images without overemphasizing or neglecting any specific class.

Additionally, the confusion matrix further illustrates the distribution of model predictions on the test dataset. Based on the obtained values (Figure 6), the model demonstrates a strong ability to distinguish between different classes in the dataset, with minimal misclassification. This confirms that the features extracted by MobileNetV2 are highly relevant and can be effectively leveraged for image classification using SVM.

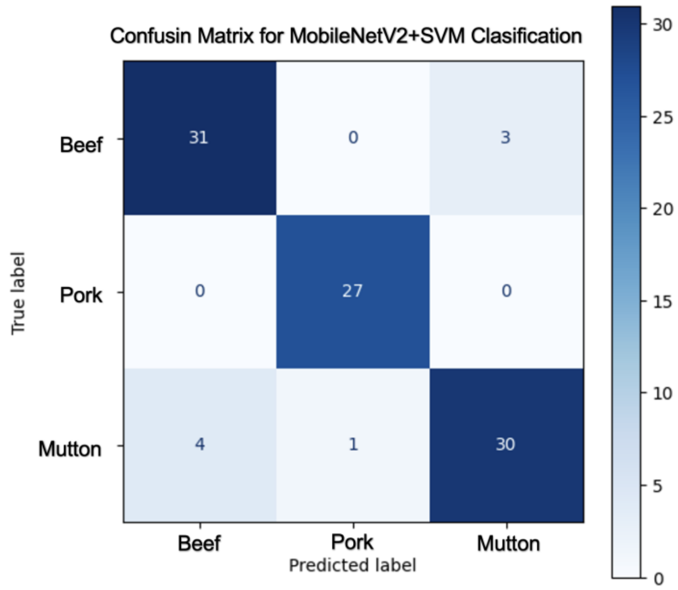

Figure 6. Confusion Matrix of Classification Results

Table 5. Comparison of Research Results

Aspect	**Previous Research** (Hidayat et al., 2022)	Current Study
Model Used	ResNet152V2	MobileNetV2 + SVM
Image Data	585 images for training and 15 images for testing	384 images for training and 96 images for testing
Number of Image Classes	3 classes: pork, goat, beef	3 classes: pork, goat, beef
Accuracy	80.00%	91.67%
Precision	0.8200	0.9163
Recall	0.8000	0.9167
F1 Score	0.7967	0.9161
Loss	0.4000	0.1751

Based on Table 5, the follow-up study utilizing MobileNetV2 + SVM demonstrates a significant improvement over the previous research that employed ResNet152V2. Although both studies used the same dataset and identical class categories (pork, goat, and beef), the follow-up study achieved an accuracy of 91.67%, surpassing the 80% accuracy reported in the previous study. Additionally, precision, recall, and F1 score also showed notable improvements, indicating that the model is more effective in accurately identifying and classifying images. This improvement can be attributed to the efficiency of MobileNetV2 and the suitability of SVM as a classification technique.

Moreover, the follow-up study exhibited a lower loss value (0.1751) compared to the previous research (0.4000), signifying better training efficiency and convergence. The use of 384 images for training and 96 images for testing in the follow-up study provided a more representative and accurate evaluation, compared to the previous study, which used 585 training images but only 15 testing images. Overall, the follow-up study employing MobileNetV2 + SVM delivered superior results in terms of both accuracy and training efficiency, making it a more effective approach for red meat image classification.

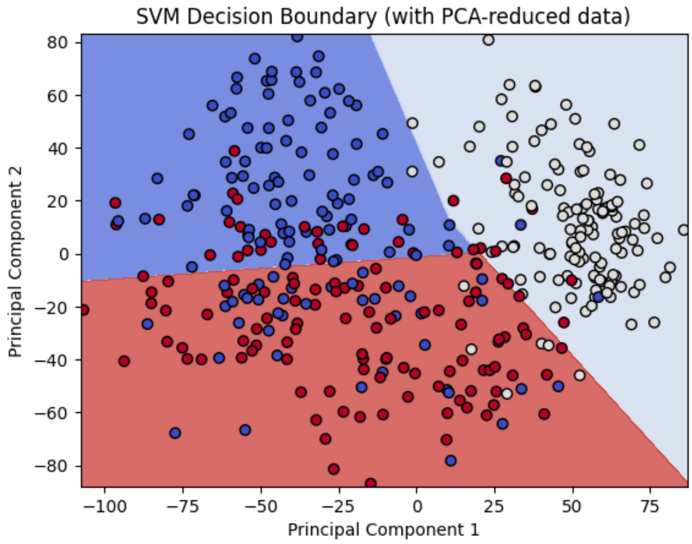

Figure 7. PCA Model Results

Based on Figure 7, the use of Principal Component Analysis (PCA) for dimensionality reduction of features extracted from the MobileNetV2 model offers several advantages, particularly in terms of visualization and model interpretability. By reducing the dimensionality to two, PCA enables the visualization of the decision boundary of the SVM model in a two-dimensional space. This approach facilitates the analysis of how SVM differentiates between the classes in the dataset while reducing computational complexity without significantly losing relevant information. This makes the analysis and visualization simpler yet still informative.

Additionally, visualizing the decision boundary using PCA provides a clear perspective on how SVM separates the different classes within the data. By plotting the prediction results in a two-dimensional space, the models decision boundary can be easily visualized. The plot indicates that SVM effectively distinguishes between classes, although some overlap remains. This overlap suggests certain areas where predictions are more challenging, highlighting potential areas for model improvement in future research.

4. Conclusion

This study successfully demonstrates that the combination of MobileNetV2 as a feature extractor and SVM as a classification model yields highly effective results in image classification. With an accuracy of 91.67% and well-balanced precision, recall, and F1-score values, the model exhibits consistent performance in correctly classifying data. MobileNetV2, leveraging pre-trained weights from ImageNet, effectively extracts essential features without requiring fine-tuning, thereby reducing training complexity. Additionally, the use of PCA for visualizing SVM's decision boundaries provides deeper insights into the model's performance while identifying areas that are more challenging to predict.

Although the model has shown excellent performance, there are several areas for potential improvement to achieve even better results. Fine-tuning MobileNetV2 is recommended to extract more dataset-specific features. Furthermore, exploring additional data augmentation techniques and experimenting with different SVM kernels could contribute to further accuracy enhancements. For a more in-depth analysis, data visualization techniques such as t-SNE or UMAP could be utilized to understand data distribution in lower-dimensional spaces. With further advancements in this methodology, the model is expected to handle more complex and diverse image classification tasks with even greater accuracy and efficiency.

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