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Pepper Color Classification Using Deep Learning

Afnan A. Mezied and Samy S. Abu-Naser

Department of Information Technology,
Faculty of Engineering and Information Technology,
Al-Azhar University, Gaza, Palestine

Abstract: *Color classification of bell peppers is essential in determining ripeness, nutritional value, and market grade. Traditional manual sorting methods are inefficient, error-prone, and unsuitable for large-scale agricultural operations. As automation and precision farming continue to advance, the demand grows for intelligent systems capable of reliable and real-time classification. This study proposes a deep learning-based solution using transfer learning with the VGG16 convolutional neural network to classify bell peppers into three color categories: green, red, and yellow. A dataset of 1,776 training images and 592 test images was used with minimal preprocessing. The model achieved 100% test accuracy, indicating strong potential for deployment in automated agricultural workflows.* While the results are promising, the model's performance likely benefits from the dataset's consistency. Future work will focus on evaluating generalization under real-world conditions and implementing the system on resource-constrained devices for use in smart farming environments.

Keywords: Deep Learning, Convolutional Neural Networks, Pepper Classification, Agriculture.

1. INTRODUCTION

In modern agricultural supply chains, particularly in horticultural production, visual quality assessment remains a cornerstone of post-harvest handling and market classification. The physical appearance of fruits and vegetables, including shape, size, and color, directly influences consumer preference and economic value. Among these factors, color is one of the most critical attributes, as it often signifies maturity, freshness, and nutritional content. For bell peppers (Capsicum annuum), color serves not only as a visual cue but also as an essential indicator of ripeness stages, biochemical composition, and market readiness. Bell peppers transition from green to red, yellow, or orange as they mature, undergoing significant biochemical transformations. These include elevated levels of antioxidants, carotenoids, and vitamins A and C, which contribute to their health benefits and shelf life.

Traditionally, color sorting has relied on manual labor, particularly in small to medium-sized farms. However, manual classification is inherently subjective, labor-intensive, and prone to error. Factors such as operator fatigue, varying lighting conditions, and inconsistent visual standards contribute to inaccurate or inconsistent sorting. Furthermore, increasing labor costs and the global shift toward automated and precision agriculture have exposed the limitations of manual sorting systems.

Recent technological advances particularly in computer vision and machine learning have enabled significant improvements in automation for agriculture. Deep learning, especially Convolutional Neural Networks (CNNs), has emerged as a powerful tool for image-based classification tasks. CNNs automatically extract spatial features from raw image data without requiring handcrafted feature engineering.

Among CNN architectures, VGG16 has gained widespread use due to its structured and uniform design, deep feature extraction capacity, and compatibility with transfer learning workflows. Transfer learning, which involves adapting a pre-trained model to a new but related task, allows practitioners to achieve high accuracy even with limited labeled data and computing resources [53], [59].

In this study, we propose an automated pepper color classification system based on deep learning, utilizing transfer learning with the VGG16 architecture. The model is trained on a curated dataset of bell pepper images categorized into three color classes green, red, and yellow representing distinct ripeness stages.

The objective is to develop a robust, accurate, and scalable model that can be integrated into smart farming environments to improve post-harvest sorting, quality assurance, and agricultural workflow automation.

By minimizing the need for human intervention, this system has the potential to enhance productivity, reduce waste, and support data-driven decision-making in the agri-food supply chain.

2. STUDY OBJECTIVES

1- Develop a CNN-based classification model capable of recognizing bell pepper color.

2- Apply the VGG16 architecture through transfer learning to enhance model performance.

3- Evaluate model accuracy on a real-world pepper dataset.

4- Assess the generalization ability of the model under minimal preprocessing conditions.

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3. DATASET

Figure 1: Dataset Samples

The dataset used in this study consists of labeled bell pepper images categorized into three classes [65]:

Training Dataset:

- Green: 444 images
- Red: 666 images
- Yellow: 666 images

Total: 1,776 images

Testing Dataset:

- Green: 148 images
- Red: 222 images
- Yellow: 222 images

Total: 592 images

All images were resized to 256×256 pixels. Initially, minimal preprocessing was applied. Later, data augmentation techniques such as rotation, flipping, and translation were introduced to enhance generalization. This configuration resulted in optimal classification performance.

The model achieved a classification accuracy of 100.0% on the test set.

4. THE ARTIFICIAL CONVOLUTIONAL NEURAL NETWORKS: AN INTRODUCTION

Convolutional Neural Networks (CNNs) are a specialized class of deep learning models designed to process data with a grid-like structure, such as images. Unlike traditional neural networks, CNNs exploit the spatial hierarchy in image data by learning features directly from pixel intensities through a series of convolutional and pooling operations. This architecture has revolutionized visual recognition tasks in fields such as medical imaging, surveillance, autonomous driving, and more recently, precision agriculture [3], [19], [28], [41].

CNNs are particularly well-suited for image classification tasks because of their ability to automatically extract low- to high-level features, which are essential for distinguishing objects, textures, and patterns relevant to agricultural products. The following components form the building blocks of a CNN architecture:

Design

A typical CNN consists of a sequence of layers, including convolutional layers, activation functions, pooling layers, and fully connected layers. This hierarchical design enables the network to detect increasingly abstract features as data passes through the layers. Early layers might detect edges or color gradients, while deeper layers recognize shapes, textures, or even specific features such as the curvature or color patterns found in ripe bell peppers. This modularity and progressive learning make CNNs ideal for differentiating between visually similar categories, such as green, red, and yellow peppers [55, 59].

Convolutional

At the heart of a CNN lies the convolutional layer, which applies a set of learnable filters (also called kernels) across the input image. These filters perform element-wise multiplications with small local regions of the input, detecting specific patterns such as color transitions or edges. As the network learns, these filters specialize in identifying features critical for classification, such as the color blobs that define a pepper’s hue [53], [56].

Each filter generates a feature map that highlights the presence of a learned feature at different spatial locations. Stacking multiple filters allows the model to capture a rich set of visual cues relevant for distinguishing pepper color categories.

Pooling

Pooling layers are responsible for reducing the spatial dimensions of the feature maps while preserving the most important information. The most common pooling operation is Max Pooling, which selects the maximum value in each local neighborhood. This process achieves three goals:

- Reduces computational cost.
- Controls overfitting.
- Introduces spatial invariance to small translations or distortions.

By applying pooling, the network retains dominant features such as large patches of red or green while discarding minor noise or variations caused by lighting or camera position.

Fully Connected

Following the convolutional and pooling stages, the final layers of a CNN are typically fully connected (dense) layers, which treat the extracted features as inputs to a traditional neural network. These layers consolidate the learned representations and make decisions about class membership.

In this study, the final layer uses the softmax activation function to produce probabilities for each of the three target classes: green, red, and yellow. The class with the highest probability is selected as the model's prediction [53], [60].

Receptive Field

The receptive field of a neuron in a CNN refers to the specific region of the input image that influences that neuron's output. In the early layers, the receptive field is small, allowing the network to capture fine-grained details such as color boundaries or texture variations. As the depth increases, the receptive field expands, allowing deeper neurons to integrate broader contextual information crucial for identifying complex shapes or patterns like the overall color distribution of a pepper [59], [61].

The concept of receptive fields is essential for understanding how CNNs combine both local and global information to make accurate classifications.

Weights

CNNs learn by adjusting the weights associated with each filter and connection. During training, these weights are updated using backpropagation to minimize the classification error. One of the key innovations in CNNs is weight sharing, where the same filter is applied across all spatial locations in the input. This drastically reduces the number of parameters, enabling the model to learn position-invariant features and generalize better across varied image layouts [Over time, the network converges to a set of weights that best capture the distinguishing visual characteristics of the training data, in this case, the color properties of bell peppers.

5. METHODS

The model was implemented using the Keras API with TensorFlow as the backend. Transfer learning was employed by utilizing the pre-trained VGG16 model trained on the ImageNet dataset. To adapt it for the bell pepper color classification task, the top layers were removed (include_top=False), and a custom classifier head was added for three-class output (green, red, yellow).

Note: All images were kept in RGB format; grayscale images were not used in this study. All input images were RGB with three color channels and resized to 256×256 pixels. The dataset was preprocessed using VGG16's preprocessing function to ensure compatibility with the base model. No grayscale conversion was applied, and all training was conducted using full-color imagery. To enhance generalization, data augmentation was incorporated during training. The following augmentation techniques were used:

- Random rotations
- Horizontal and vertical flipping
- Width and height shifts

These transformations were configured using the ImageDataGenerator module. The dataset was split into training and validation sets using a 70:30 stratified sampling ratio. Training was conducted for 25 epochs using the Adam optimizer with a learning rate of 0.0001. The categorical crossentropy loss function was used due to the multi-class nature of the problem. Model performance was evaluated using accuracy and F1 score as metrics.

The best model weights were saved using a checkpoint mechanism that monitored validation loss. This ensured that the final model retained the optimal parameters for generalization.

6. MODEL

The classification model was built using the pre-trained VGG16 network with its convolutional base frozen to preserve learned features from ImageNet. A custom classification head was added, consisting of a Global Max Pooling layer, a Dense layer with 256 ReLU units, and a final Dense layer with 3 softmax units to predict pepper color classes: green, red, and yellow.

This architecture offers a balance between accuracy and computational efficiency, making it suitable for deployment in automated agricultural systems. By freezing the base model and training only the new layers, the model reduces overfitting and speeds up training.

The model achieved 100% test accuracy, highlighting its effectiveness, though further testing on external datasets is encouraged to validate generalization.

Table 1: Model Architecture Summary.

Layer (type)	**Output Shape**	**Param #**
input_layer (InputLayer)	(None, 256, 256, 3)	0
block1_conv1 (Conv2D)	(None, 256, 256, 64)	1,792
block1_conv2 (Conv2D)	(None, 256, 256, 64)	36,928
block1_pool (MaxPooling2D)	(None, 128, 128, 64)	0
block2_conv1 (Conv2D)	(None, 128, 128, 128)	73,856
block2_conv2 (Conv2D)	(None, 128, 128, 128)	147,584
block2_pool (MaxPooling2D)	(None, 64, 64, 128)	0
block3_conv1 (Conv2D)	(None, 64, 64, 256)	295,168
block3_conv2 (Conv2D)	(None, 64, 64, 256)	590,080
block3_conv3 (Conv2D)	(None, 64, 64, 256)	590,080
block3_pool (MaxPooling2D)	(None, 32, 32, 256)	0
block4_conv1 (Conv2D)	(None, 32, 32, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 32, 32, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 32, 32, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 16, 16, 512)	0
block5_conv1 (Conv2D)	(None, 16, 16, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 16, 16, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 16, 16, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 8, 8, 512)	0
global_max_pooling2d (GlobalMaxPooling2D)	(None, 512)	0
dense (Dense)	(None, 3)	1,539
Total Parameters: 14,716,227	Trainable Parameters: 14,716,227	Non-trainable Parameters: 0

7. DATA VISUALIZATIONS

To evaluate the model’s performance, learning behavior, and generalization ability, a detailed visual analysis of training metrics was conducted over multiple epochs. Visualization plays a crucial role in understanding how the model optimizes its parameters, how effectively it captures underlying patterns in the data, and whether it tends to overfit or underfit. By comparing training and validation curves for both loss and accuracy, we gain insights into the model's convergence behavior, its stability during learning, and the impact of techniques such as data augmentation. The following plots illustrate these aspects clearly, showing how the model evolved throughout the training process and how well it was able to generalize its learning to unseen validation samples.

1- Training vs Validation Loss (Initial Model):

The initial model was trained for 20 epochs without data augmentation. As shown in Figure 2, both training and validation loss decreased steadily. The validation loss plateaued slightly earlier than the training loss, indicating that the model started to overfit after a few epochs. Nonetheless, the general alignment between the curves suggests that the model was able to learn effectively.

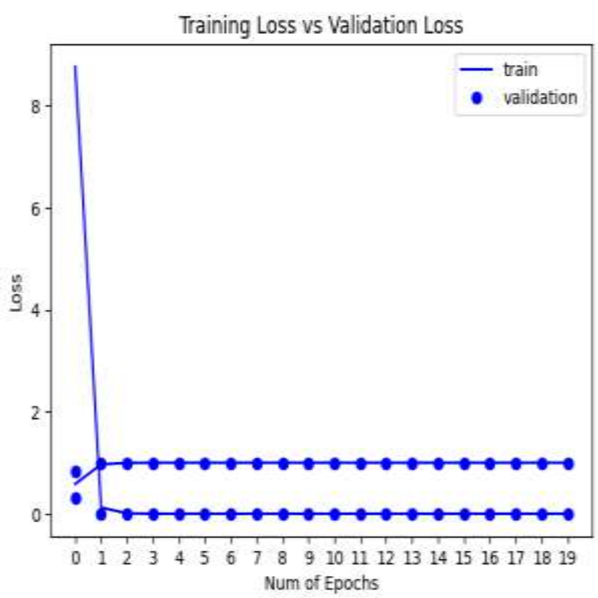

Figure 2: Training Loss vs Validation Loss. The model demonstrates effective learning with minimal divergence between training and validation losses in the early epochs.

2- Training vs Validation Accuracy:

As illustrated in Figure 3, the training and validation accuracy both reached 100% within the first five epochs. This indicates that the model quickly captured the key features required for accurate classification of the three pepper classes. The parallel progression of both curves suggests minimal overfitting.

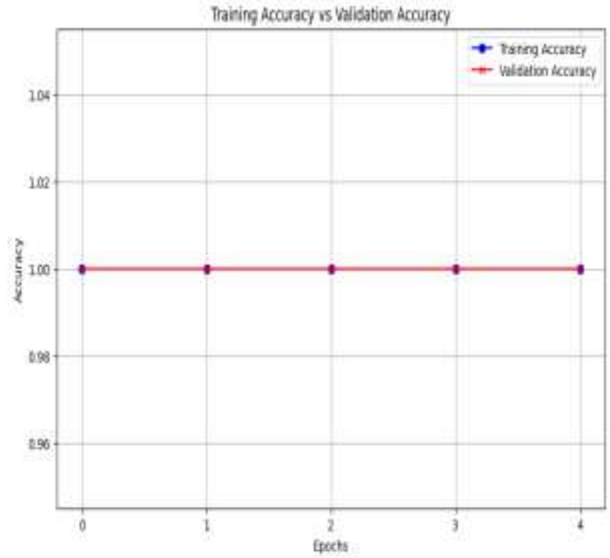

Figure 3: Training Accuracy vs Validation Accuracy. Both training and validation accuracies rapidly converge to 100%, reflecting the model's high capacity and well-separated class features.

3- Improved Model Loss Curve:

To further enhance generalization, a refined version of the model was trained using data augmentation. As shown in Figure 4, the loss for both training and validation sets decreased smoothly and remained closely aligned. This suggests improved generalization and reduced overfitting due to regularization effects introduced by augmentation.

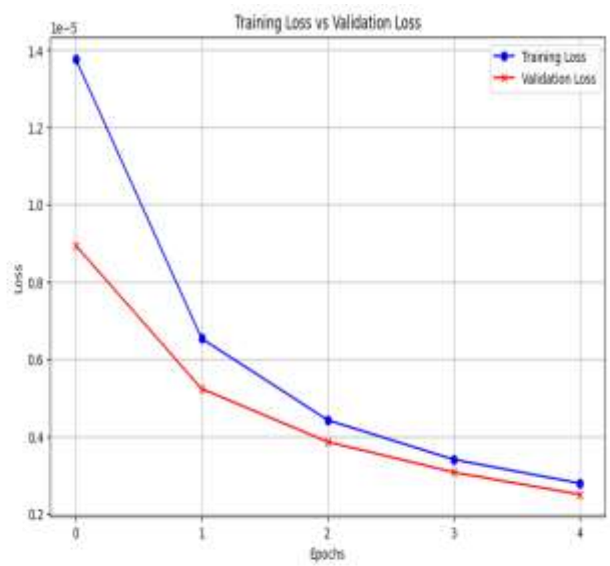

Figure 4: Improved Training Loss vs Validation Loss. The close alignment between training and validation losses reflects stable learning and stronger generalization performance under data augmentation.

CONCLUSION

This study demonstrated the effectiveness of a deep learning approach specifically the VGG16 architecture with transfer learning for the classification of bell pepper colors. The model achieved 100% accuracy on a held-out test set, indicating strong potential for deployment in automated agricultural systems. However, such exceptional performance may reflect the uniformity of the dataset rather than true generalization ability.

To address this, future work should focus on enhancing the model's robustness by incorporating k-fold cross-validation, which offers a more reliable estimate of performance across diverse subsets of data. Additionally, testing the model on external datasets captured under varying environmental conditions such as changes in lighting, background complexity, and image quality will be essential to validate its effectiveness in real-world applications. Expanding the dataset and exploring deployment on resource-constrained edge devices will also contribute to the development of practical, scalable solutions for smart farming and post-harvest automation.

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