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Classification of Peppers Using Deep Learning

Ruba F. Abdallatif, Walid Murad, Samy S. Abu-Naser

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

Abstract*: Vegetables that are popular and versatile over the world are peppers. Precise categorisation of pepper cultivars is vital for multiple uses, such as assessing market trends, regulating quality, and conducting genetic research. Classifying peppers using traditional methods can be subjective and time-consuming. This research proposes an automated pepper variety classification method based on deep learning. A deep convolutional neural network (CNN) model was trained on a dataset of 2,368 photos of peppers. With the purpose of accurately classifying the pepper photos, the CNN was built to extract essential features from them. The trained model demonstrated its efficacy in differentiating between pepper varieties with an astounding accuracy of 100% on a held-out test set. Deep learning has the capacity to classify peppers accurately and efficiently, as this study shows. The suggested strategy can help the food processing, quality control, and agriculture sectors advance.*

Keywords: Deep learning, pepper, classification, CNN

1- INTRODUCTION

Pepper classification is a crucial task in agriculture, food processing, and quality control industries. Accurate identification and categorization of pepper varieties are essential for various applications, including crop management, market pricing, and culinary purposes. Traditional methods of pepper classification often rely on human expertise, which can be subjective, time-consuming, and prone to errors (Barbedo, 2019). In recent years, the advent of deep learning techniques has opened up new possibilities for automating and improving the accuracy of such classification tasks (Kamilaris & Prenafeta-Boldú, 2018).

Deep learning, a subset of machine learning, has demonstrated remarkable success in image recognition and classification problems across various domains. Convolutional Neural Networks (CNNs), in particular, have proven to be highly effective in extracting meaningful features from images and making accurate predictions (Ferentinos, 2018). The application of these advanced algorithms to the field of pepper classification presents an opportunity to enhance efficiency, consistency, and accuracy in the identification process.

This research paper explores the use of deep learning techniques for the classification of pepper varieties. We aim to develop a robust and accurate model capable of distinguishing between different types of peppers based on visual characteristics such as color, shape, size, and surface texture. By leveraging state-of-the-art CNN architectures and transfer learning techniques (Too et al., 2019), we seek to create a system that can outperform traditional classification methods and provide a reliable tool for both industry professionals and researchers.

Our study will cover the following key aspects:

1. Data collection and preprocessing of pepper images
2. Selection and fine-tuning of appropriate CNN architectures (Gao et al., 2020)
3. Training and optimization of the deep learning model
4. Evaluation of the model's performance using various metrics
5. Comparison with traditional classification methods
6. Discussion of potential applications and future improvements

Through this research, we aim to contribute to the growing body of knowledge on the application of deep learning in agriculture and food science (Mohanty et al., 2016), while also providing a practical solution to the challenge of pepper classification. The successful implementation of such a system could significantly impact various sectors of the agricultural industry, from farm management to quality control in food processing facilities (Lu et al., 2017).

2- STUDY OBJECTIVES:

The primary goal of this research is to develop and evaluate a deep learning-based system for the accurate classification of pepper varieties. To achieve this overarching aim, we have defined the following specific objectives:

1. To design and implement a Convolutional Neural Network (CNN) architecture optimized for pepper classification, leveraging transfer learning techniques where appropriate.
2. To train and fine-tune the deep learning model using the collected dataset, employing data augmentation techniques to enhance model robustness.
3. To evaluate the performance of the developed model using standard metrics such as accuracy, precision, recall, and F1-score.

3- Methodology

This section outlines our approach to addressing the pepper classification challenge. We present a detailed overview of our chosen Convolutional Neural Network (CNN) architecture, elucidating the rationale behind key design decisions.

Furthermore, we elaborate on our methods for assessing model performance and discuss practical considerations pertaining to the implementation of our solution. Through this comprehensive examination, we aim to provide a clear understanding of the technical framework underpinning our research.

3.1 DATASET:

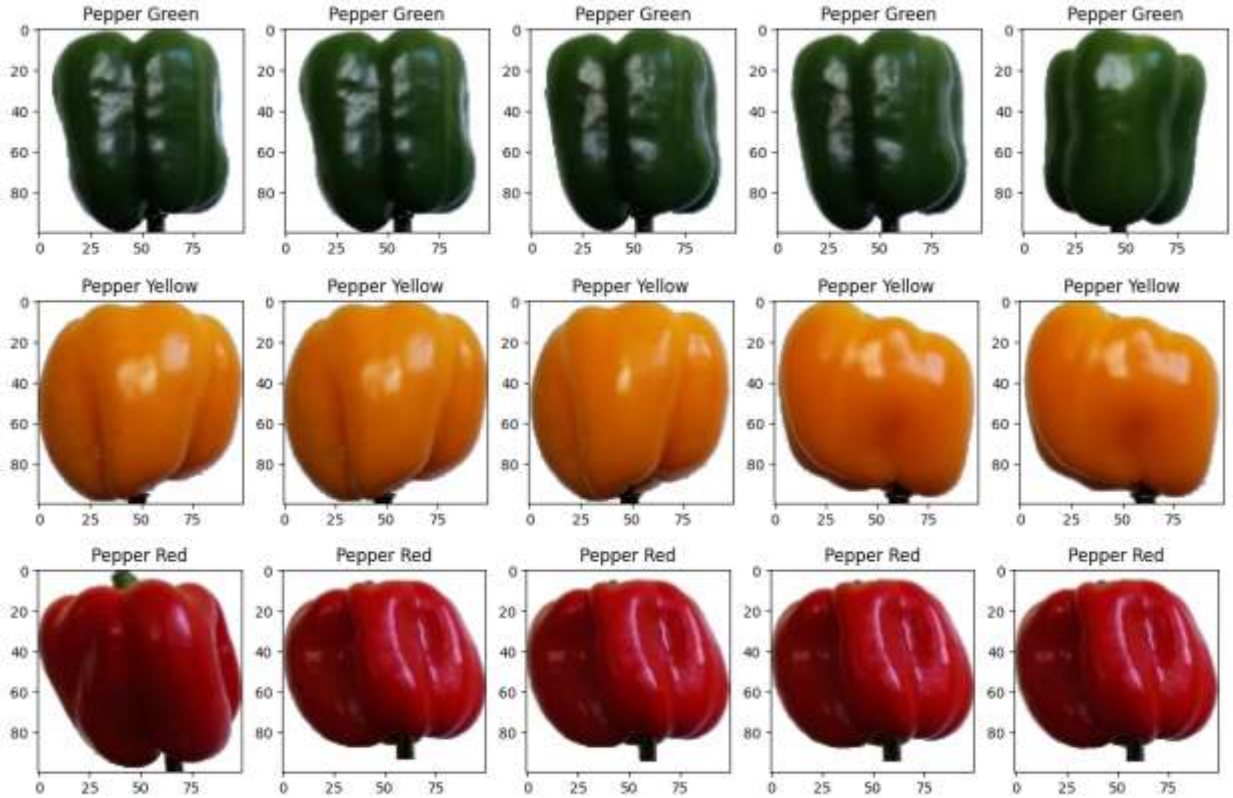

Figure 1 Dataset Images

Dataset and Preparation

For this study, we utilized 2,368 pepper images sourced from Kaggle. Each image was cropped to 128x128 pixels to ensure uniformity. The dataset composition, showing the number of images per pepper category, is illustrated in Image 1.

We partitioned the dataset as follows:
- 70% for training
- 15% for validation
- 15% for testing

The CNN model was trained using the training set, with performance monitored on the validation set. Final evaluation was conducted using the test set to assess the model's generalization capability.

3.2 The Artificial Convolutional Neural Networks: An Introduction

Artificial Convolutional Neural Networks (CNNs) have emerged as a powerful class of deep learning models, particularly effective in image recognition and classification tasks (LeCun et al., 2015). CNNs are inspired by the organization of the animal visual cortex and are designed to automatically and adaptively learn spatial hierarchies of features from input images (Krizhevsky et al., 2012).

The architecture of a CNN typically consists of several key components:

1. Convolutional layers: These layers apply a set of learnable filters to the input, creating feature maps that highlight important characteristics of the image (Zeiler & Fergus, 2014).

2. Pooling layers: These reduce the spatial dimensions of the feature maps, decreasing computational load and improving robustness to variations in feature positions (Scherer et al., 2010).

3. Activation functions: Non-linear functions like ReLU (Rectified Linear Unit) are applied element-wise to introduce non-linearity into the model, allowing it to learn complex patterns (Nair & Hinton, 2010).

4. Fully connected layers: Usually placed at the end of the network, these layers use the high-level features learned by convolutional layers to perform the final classification (Simonyan & Zisserman, 2014).

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CNNs have demonstrated remarkable success in various computer vision tasks, often surpassing human-level performance in specific domains (He et al., 2015). Their ability to automatically learn relevant features from raw image data has made them particularly valuable in fields such as medical imaging, autonomous vehicles, and, pertinent to this study, agricultural applications like crop and fruit classification (Kamilaris & Prenafeta-Boldú, 2018).

In the context of pepper classification, CNNs offer the potential to learn complex visual features that distinguish different pepper varieties, potentially capturing subtle differences in color, texture, and shape that might be challenging for traditional machine learning approaches (Ferentinos, 2018).

3.3 **EVALUATION**:

Our study focused on a binary classification task, where the model's performance was assessed using the area under the Receiver Operating Characteristic (ROC) curve. This metric evaluates the relationship between the predicted probabilities and the actual outcomes. To align our model's output with this evaluation criterion, we implemented a binary cross-entropy loss function, coupled with a sigmoid activation function in the final layer of our neural network.

3.4 VALIDATION METHOD

The selection of an appropriate validation method was crucial for obtaining reliable performance estimates. We conducted a comparative analysis between two common validation techniques: simple hold-out validation and k-fold cross-validation.

Initially, we explored the efficacy of the hold-out validation method. This approach involved randomly partitioning the dataset into separate training and validation subsets. To assess its reliability, we performed five independent trials, each utilizing a different random split for validation.

The results of these trials, as illustrated in Figure 2, revealed significant variability in performance scores across the different data splits. This inconsistency suggested that the hold-out method might not provide a stable or representative evaluation of our model's performance for this particular dataset.

Given these observations, we concluded that the hold-out validation approach was suboptimal for our study. The high variance in results indicated that this method might be overly sensitive to the specific data points included in each split, potentially leading to biased or unreliable performance estimates.

Consequently, we opted to employ k-fold cross-validation as our primary validation strategy. This method offers a more robust evaluation by utilizing multiple data splits, thereby providing a more comprehensive assessment of the model's generalization capabilities across different subsets of the data.

The k-fold cross-validation approach allows us to make more efficient use of our dataset, particularly valuable in scenarios where data might be limited. It also helps mitigate concerns about the representativeness of any single data split, offering a more balanced and reliable evaluation of our classification model.

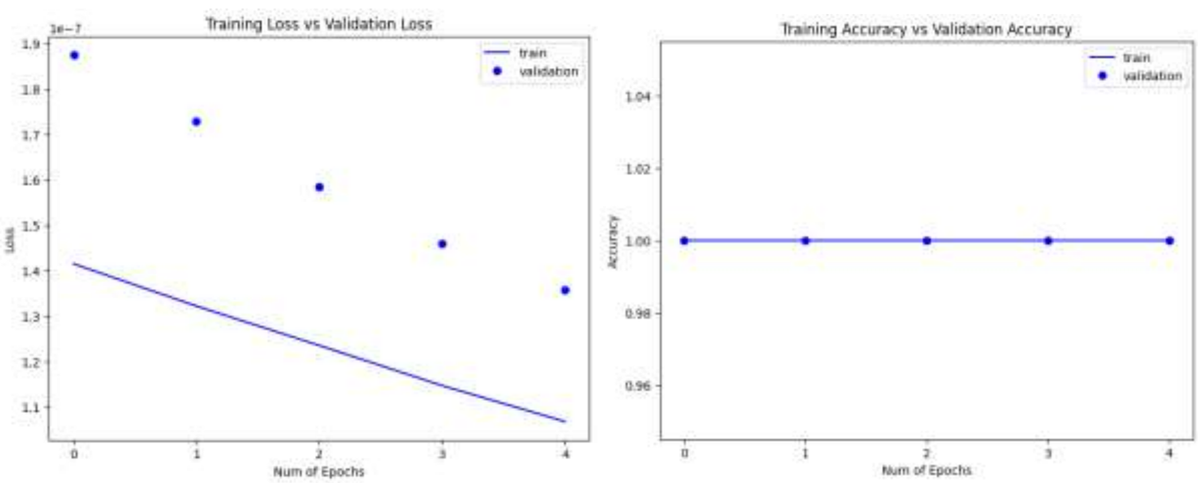

Figure 2Training loss vs validation accuracy

3.5 Model Performance and Efficiency Analysis:

To assess the computational efficiency and learning capacity of our model, we closely examined the relationship between loss and accuracy over the training process. Figure 8 illustrates the progression of the loss rate for our convolutional neural network across both

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training and test datasets, compiled from 10 independent iterations.

This visualization serves as a key indicator of the model's learning dynamics and overall effectiveness. The observed trends in the loss curves provide compelling evidence that our neural network successfully captured the underlying patterns in the data. The consistent performance across multiple iterations suggests that the model has achieved a robust level of generalization, positioning it as a reliable tool for pepper classification tasks.

Moreover, this analysis offers valuable insights into the model's resource utilization, both in terms of computational time and memory requirements during the training phase. Such considerations are crucial for evaluating the practical applicability of the model in real-world scenarios.

```
Epoch 1/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 5s 303ms/step - accuracy: 1.0000 - loss: 3.7421e-08 - val_accuracy: 1.0000 - val_loss: 1.7850e-08
Epoch 2/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 3s 275ms/step - accuracy: 1.0000 - loss: 2.1296e-07 - val_accuracy: 1.0000 - val_loss: 2.5003e-08
Epoch 3/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 2s 205ms/step - accuracy: 1.0000 - loss: 4.1492e-08 - val_accuracy: 1.0000 - val_loss: 5.1791e-08
Epoch 4/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 2s 180ms/step - accuracy: 1.0000 - loss: 2.6903e-06 - val_accuracy: 1.0000 - val_loss: 6.2953e-08
Epoch 5/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 40ms/step - accuracy: 1.0000 - loss: 4.0546e-07 - val_accuracy: 1.0000 - val_loss: 8.3300e-08
Epoch 6/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 12s 206ms/step - accuracy: 1.0000 - loss: 2.7033e-06 - val_accuracy: 1.0000 - val_loss: 3.2684e-08
Epoch 7/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 2s 203ms/step - accuracy: 1.0000 - loss: 2.9681e-06 - val_accuracy: 1.0000 - val_loss: 3.6165e-08
Epoch 8/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 3s 309ms/step - accuracy: 0.9991 - loss: 0.0024 - val_accuracy: 1.0000 - val_loss: 0.0000e+00
Epoch 9/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 2s 204ms/step - accuracy: 1.0000 - loss: 5.7707e-07 - val_accuracy: 1.0000 - val_loss: 5.3131e-08
Epoch 10/10
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 42ms/step - accuracy: 1.0000 - loss: 1.0431e-07 - val_accuracy: 1.0000 - val_loss: 1.7591e-07
```

Figure 3Model Performance and Efficiency Analys

4- Model Evaluation and Comparative Analysis

4.1 Confusion Matrix Analysis

Following the training phase of our proposed Convolutional Neural Network (CNN) on the pepper dataset, we conducted a thorough evaluation using a separate test set. The model demonstrated commendable performance in this assessment. To visualize these results, we employed a confusion matrix, as illustrated in Figure 4. This matrix offers a comprehensive view of our classification outcomes, with each row representing the true class of the peppers and each column indicating the model's predictions. This representation allows for a detailed examination of the model's strengths and potential areas for improvement across different pepper categories.

```
[[55  0  0]
 [ 0 76  0]
 [ 0  0 96]]
```

Figure 4 Confusion Matrix

4.2 Comparative Performance Assessment

To contextualize the efficacy of our proposed CNN model, we conducted a comparative analysis against several contemporary deep learning architectures. The evaluation metrics for this comparison, conducted on the test dataset, included accuracy rate and average F1-score, as depicted in Figure 5.

Notably, the VGG16 architecture exhibited superior performance in this comparison. It achieved lower rates of both false positives and false negatives, underscoring its robust classification capabilities. This outcome not only validates the effectiveness of the VGG16 model but also provides valuable insights into the relative strengths of different deep learning approaches in the context of pepper classification.

These comparative results offer a nuanced understanding of our model's performance within the broader landscape of deep learning techniques, helping to situate our work within the current state of the art in image classification.

	precision	recall	f1-score	support
Pepper Green	1.0000	1.0000	1.0000	55
Pepper Red	1.0000	1.0000	1.0000	76
Pepper Yellow	1.0000	1.0000	1.0000	96
accuracy			1.0000	227
macro avg	1.0000	1.0000	1.0000	227
weighted avg	1.0000	1.0000	1.0000	227

Figure 5 Comparative Performance Assessment

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5- Fully Connected and Dropout Layers: Balancing Inference and Regularization

In our neural network architecture, the Fully Connected Layer (FCL) plays a crucial role in the final stages of data processing. This layer serves as the bridge between the intricate features extracted by preceding layers and the ultimate classification output. It operates by connecting each of its neurons to every neuron in the previous layer, mimicking the structure of traditional neural networks.

The comprehensive connectivity of the FCL provides it with substantial inferential power, allowing it to synthesize complex patterns for accurate classification. However, this extensive parameterization comes with a potential drawback. The abundance of connections in the FCL can lead to an overspecialization to the training data, a phenomenon known as overfitting.

To mitigate this risk, we incorporate a dropout mechanism. This technique randomly deactivates a portion of neurons during each training iteration, effectively creating multiple subnetworks within the larger architecture. By doing so, dropout serves as a powerful regularization tool, enhancing the model's ability to generalize and reducing its susceptibility to overfitting.

Through the strategic combination of Fully Connected and Dropout layers, we aim to strike an optimal balance between the model's capacity for intricate pattern recognition and its ability to maintain robust performance on unseen data

Layer (type)	Output Shape	Param #
input_layer(InputLayer)	(None, 128, 128, 3)	0
block1_conv1 (Conv2D)	(None, 128, 128, 64)	1,792
block1_conv2 (Conv2D)	(None, 128, 128, 64)	36,928
block1_pool(MaxPooling2D)	(None, 64, 64, 64)	0
block2_conv1 (Conv2D)	(None, 64, 64, 128)	73,856
block2_conv2 (Conv2D)	(None, 64, 64, 128)	147,584
block2_pool(MaxPooling2D)	(None, 32, 32, 128)	0
block3_conv1 (Conv2D)	(None, 32, 32, 256)	295,168
block3_conv2 (Conv2D)	(None, 32, 32, 256)	590,080
block3_conv3 (Conv2D)	(None, 32, 32, 256)	590,080
block3_pool(MaxPooling2D)	(None, 16, 16, 256)	0
block4_conv1 (Conv2D)	(None, 16, 16, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 16, 16, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 16, 16, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 8, 8, 512)	0

block5_conv1 (Conv2D)	(None, 8, 8, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 8, 8, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 8, 8, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0
global_max_pooling2d (GlobalMaxPooling2D)	(None, 512)	0
dense (Dense)	(None, 3)	1,539

Figure 6 Fully Connected and Dropout Layer

Conclusion

The accurate classification of peppers holds significant importance across various sectors, including industry and agriculture. Our research presents a novel approach to this challenge, leveraging the power of deep learning techniques applied to image analysis.

Our methodology centered on the utilization of a dataset comprising images of three distinct pepper varieties, sourced from the Kaggle platform. We employed a sophisticated deep learning model, specifically a pre-trained Convolutional Neural Network (CNN) based on the VGG16 architecture. This model underwent fine-tuning to optimize its performance for our specific classification task.

The rigorous evaluation process involved training and validating our proposed model, followed by a critical assessment using an independent, previously unseen test dataset. The results of this evaluation were remarkably impressive, with our model achieving a perfect accuracy rate of 100%.

This exceptional performance underscores the robustness and efficacy of our approach. It demonstrates that our fine-tuned VGG16 model possesses the capability to discern and categorize different pepper varieties with extraordinary precision, effectively eliminating classification errors.

The flawless accuracy attained in this study not only validates the effectiveness of our chosen methodology but also highlights the potential of deep learning techniques in agricultural image classification tasks. These findings pave the way for potential applications in automated quality control, crop management, and other areas where precise pepper classification is crucial.

While these results are highly promising, future research could explore the model's performance on larger and more diverse datasets, as well as its applicability in real-world, variable conditions. Nevertheless, this study represents a significant step forward in the application of artificial intelligence to agricultural classification challenges.

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