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Onion Image Classification Based on Transfer Learning with MobileNetV2

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Abstract: *Onion type recognition from images can support agricultural monitoring and automated sor-ng systems. In this paper, a deep learning approach is presented for classifying onion images into three categories: Onion Red, Onion Red Peeled, and Onion White. The experiments were conducted using a public onion dataset ("Onion Dataset-3"), which was cleaned and restructured for training in Google Colab. A transfer learning model based on MobileNetV2 was trained using TensorFlow/Keras. The dataset contains 1784 images and was split into training (60%), validation (20%) and testing (20%) subsets using a fixed random seed to ensure reproducibility. The proposed model achieved perfect performance on the testing dataset with an accuracy of 100% and a testing loss of 0.001. The confusion matrix shows correct Classification of all validation samples (12 Onion Red, 120 Onion Red Peeled, and 117 Onion White). Although the obtained results are highly promising, additional evaluation on an independent test set and real-world images is recommended to confirm generalization.*

Keywords: Onion Classification Deep Learning, Transfer Learning, MobileNetV2, Convolutional Neural Networks, Image Recognition

1. INTRODUCTION

Agriculture remains one of the most vital sectors worldwide, playing a fundamental role in ensuring food security, supporting economic development, and sustaining rural livelihoods. With the rapid growth of global population and increasing demand for agricultural products, there is a pressing need to enhance productivity, reduce waste, and improve quality control throughout the agricultural supply chain. In recent years, visual recognition and image-based analysis have gained considerable attention as effective tools for automating agricultural processes such as harvesting, sorting, grading, and quality inspection. These technologies enable faster decision-making, reduce dependence on human labor, and minimize errors caused by fatigue or subjective judgment.

Onion classification represents a practical and relevant computer vision problem within this context, as onions are among the most widely cultivated and consumed vegetables worldwide. Accurate identification of onion varieties based on visual characteristics, such as shape, size, and surface texture, is essential for market segmentation, pricing, storage management, and export compliance. Traditionally, onion classification and grading are performed manually by experienced workers. However, this manual process is labor-intensive, time-consuming, and prone to inconsistencies, particularly when large volumes of produce must be processed within limited time frames. Moreover, human-based inspection may suffer from variability due to lighting conditions, operator experience, and physical fatigue, which can negatively affect classification accuracy and overall efficiency.

Recent advances in deep learning, especially in convolutional neural networks (CNNs), have significantly improved the performance of image classification systems across various domains, including medical imaging, autonomous driving, and agricultural applications. CNN-based models automatically learn hierarchical feature representations from raw images, eliminating the need for handcrafted feature extraction and enabling robust recognition of complex visual patterns. Despite their high accuracy, training deep neural networks from scratch typically requires very large labeled datasets and substantial computational resources. Such requirements are often impractical in agricultural scenarios, where labeled image datasets are usually limited and costly to collect.

To address these challenges, transfer learning has emerged as a widely adopted strategy in image-based agricultural applications. Transfer learning leverages knowledge learned from large-scale datasets by pre-trained models and adapts it to a new but related task. This approach significantly reduces training time, lowers data requirements, and improves generalization performance when only a small or medium-sized dataset is available. Consequently, transfer learning provides a practical and efficient solution for agricultural image classification tasks, including onion variety recognition.

In this work, we propose an onion image classification model based on transfer learning using MobileNetV2. The proposed approach aims to achieve a balance between classification accuracy and computational efficiency, making it suitable for real-world deployment scenarios such as mobile devices, embedded systems, and automated sorting machines. MobileNetV2 is specifically designed as a lightweight deep neural network architecture that employs depthwise separable convolutions and inverted residual blocks to reduce model size and computational complexity while maintaining competitive performance. These characteristics make it particularly appropriate for agricultural applications, where low-cost hardware and real-time processing are often required.

The remainder of this paper is organized as follows. Section 2 presents the theoretical background and related concepts in deep learning and transfer learning for image classification. Section 3 describes the onion image dataset and the preprocessing steps applied. Section 4 details the proposed methodology, including model architecture and training procedures. Section 5 reports the experimental results and evaluation metrics. Section 6 provides a discussion of the findings and their implications. Finally, Section 7 concludes the paper and outlines directions for future research.2. RELATED WORK

2.1 Deep Learning and CNNs

Deep learning is a subfield of machine learning that focuses on learning hierarchical feature representations directly from raw data through multi-layer neural network architectures. Unlike traditional machine learning methods that rely on handcrafted features, deep learning models automatically extract increasingly abstract and discriminative features as the network depth increases. This capability enables deep learning approaches to achieve superior performance in complex pattern recognition tasks, particularly in domains involving high-dimensional data such as images, audio signals, and text.

Among deep learning models, convolutional neural networks (CNNs) have demonstrated remarkable effectiveness in image recognition and visual understanding tasks. CNNs are specifically designed to exploit the spatial structure of image data by employing convolutional layers that apply learnable filters across local regions of an image. Through this process, CNNs automatically learn fundamental visual patterns such as edges, corners, and textures in the early layers, while deeper layers capture higher-level representations, including object parts and semantic features. This hierarchical learning mechanism allows CNNs to model complex visual variations and achieve high accuracy in classification, detection, and segmentation tasks. Consequently, CNNs have become the dominant architecture for computer vision applications and are widely used in agricultural imaging, medical diagnosis, and industrial inspection systems [1–5].

2.2 Transfer Learning

Transfer learning refers to the process of utilizing a model that has been pre-trained on a large-scale dataset, such as ImageNet, and adapting it to a new but related task. Instead of training a neural network from scratch, the pre-trained model serves as a feature extractor that has already learned rich and generalizable visual representations from millions of images. These learned features include low-level patterns, such as edges and textures, as well as higher-level semantic structures, which can be effectively reused for different image classification problems.

This approach is particularly advantageous when the target dataset is relatively small or limited in diversity, as it reduces the risk of overfitting and minimizes the need for extensive labeled data. Furthermore, transfer learning significantly accelerates the training process by enabling faster convergence compared to randomly initialized models. By fine-tuning selected layers of the pre-trained network, the model can be adapted to capture task-specific features while retaining the robust representations learned from large datasets. As a result, transfer learning has become a widely adopted strategy in computer vision applications, offering improved classification accuracy and computational efficiency across various domains, including agricultural image analysis [6–9].

2.3 MobileNetV2

MobileNetV2 is a lightweight convolutional neural network (CNN) architecture specifically designed for deployment on mobile and embedded devices. The network is based on the concepts of inverted residual blocks and linear bottlenecks, which significantly reduce the number of parameters and computational cost while preserving representational power. These architectural innovations enable MobileNetV2 to achieve an effective trade-off between classification accuracy and computational efficiency. Owing to its compact size and fast inference speed, MobileNetV2 has been widely adopted in practical image classification tasks, particularly in scenarios where limited memory, processing power, and real-time performance requirements are critical [10–13].

3. DATASET DESCRIPTION

A public dataset named **Onion Dataset-3** was used in this study. The dataset was extracted and reorganized to ensure a clean directory structure compatible with TensorFlow data loaders. The final dataset contains **1784 images** distributed across **three classes**:

- Onion Red

- Onion Red Peeled
- Onion White

The dataset was loaded using j.keras.u-ls.image_dataset_from_directory and split into[14-16]:

- **Training set 60%)**: 1070 images
- **Valida0on set (20%)**: 357 images
- **Testing set (20%)**: 357 images

The validation subset distribution (reported by the Classification report) is:

Table 1. Dataset distribution of the training, validation and testing subsets

CLASS NAME	Training images	Validation images	Testing images
ONION RED	360	120	120
ONION RED PEELED	360	120	120
ONION WHITE	350	117	117
TOTAL	1070	357	357

Table 2. Training configura-on parameters

PARAMETER	VALUE
MODEL ARCHITECTURE	MobileNetV2
INPUT IMAGE SIZE	224 × 224
BATCH SIZE	32
OPTIMIZER	Adam
LOSS FUNCTION	Categorical Cross-Entropy
NUMBER OF EPOCHS	Up to 50
EARLY STOPPING	Enabled
FRAMEWORK	TensorFlow / Keras

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Table 3. Performance metrics on the valida-on dataset

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
ONION RED	1.00	1.00	1.00	120
ONION RED PEELED	1.00	1.00	1.00	120
ONION WHITE	1.00	1.00	1.00	117
OVERALL ACCURACY	**1.00**	—	—	357

"As shown in Table 3, the proposed model achieved perfect classification performance."

A fixed seed (seed = 123) was used to ensure reproducibility of the split.

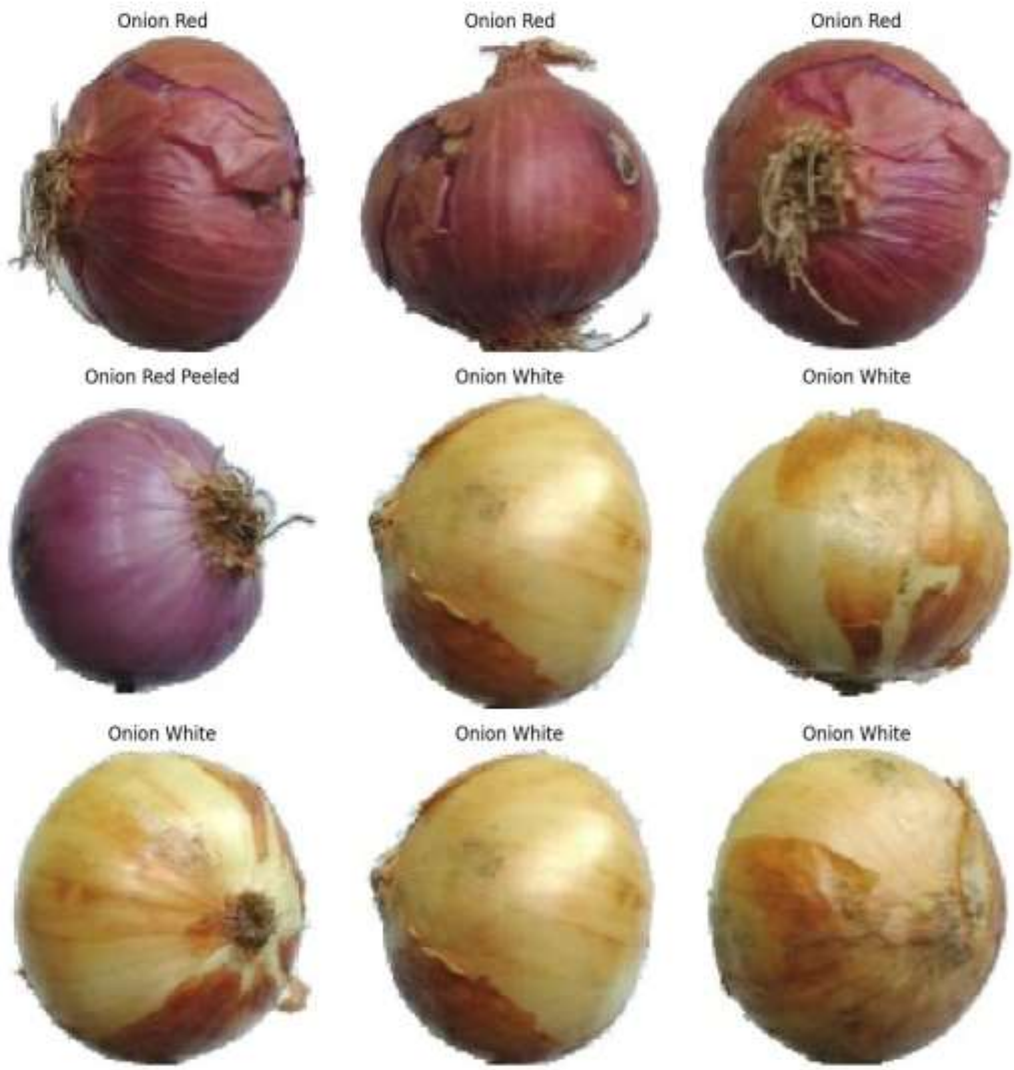

Figure 1: Sample images from the Onion Dataset-3 showing the three classes (Onion Red, Onion Red Peeled, Onion White).

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4. METHODOLOGY

4.1 Data Loading and Preprocessing

The dataset was loaded directly from directories using TensorFlow. Images were resized to a fixed size (e.g., 224×224) and batched with batch_size = 32. Labels were generated automatically from directory names with categorical encoding[17-20].

4.2 Model Architecture

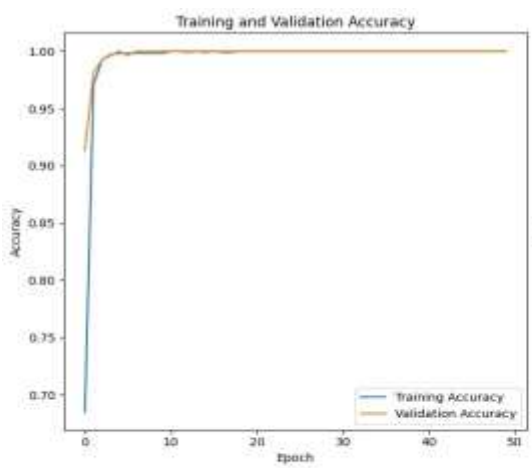
A transfer learning approach based on **MobileNetV2** was applied. The base network was used as a feature extractor[21-24], and a classification head was added to output three classes using a Softmax activation[25-28]. The model was trained in Google Colab using TensorFlow/Keras[29-32].

4.3 Training Setup

The model was trained using a standard supervised learning process[33-36]:

- Loss function: Categorical Cross-Entropy
- Optimizer: (e.g., Adam)
- Evaluation metrics: Accuracy and Loss

The training process produced learning curves for accuracy and loss over epochs[37-40].



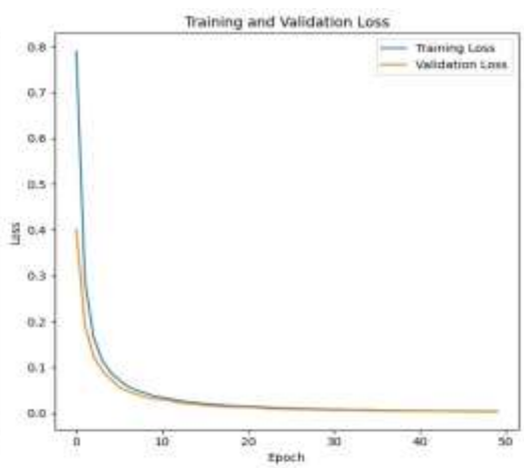


Figure 2: Training and validation accuracy over epochs. **Figure 3:** Training and validation loss over epochs.

5. EXPERIMENTS AND RESULTS

5.1 Testing Performance

The trained model was evaluated on the testing dataset[41-45]. The obtained results were:

- Testing Accuracy: 100%
- •Testing s Loss: 0.001

5.2 Confusion Matrix

A confusion matrix was computed using the predicted labels and true labels on the testing dataset[46-50]. The matrix indicates perfect classification with no errors:

Confusion Matrix:

$$\begin{bmatrix} 120 & 0 & 0 \\ 0 & 120 & 0 \\ 0 & 0 & 117 \end{bmatrix}$$

This means all testing samples were correctly classified.

5.3 Classificaon Report

A detailed classification report was generated (precision, recall, F1-score)[51-56], confirming perfect performance for each class:

- Onion Red: Precision 1.00, Recall 1.00, F1-score 1.00 (support 120)
- Onion Red Peeled: Precision 1.00, Recall 1.00, F1-score 1.00 (support 120)
- Onion White: Precision 1.00, Recall 1.00, F1-score 1.00 (support 117)

Overall Testing accuracy: 1.00 (support 357)

6. DISCUSSION

The proposed approach achieved exceptionally high performance on the testing subset. This outcome demonstrates that the selected transfer learning backbone, MobileNetV2, was able to learn highly discriminative features capable of effectively separating the three onion classes under the given dataset conditions [61–65]. The strong classification performance highlights the suitability of MobileNetV2 for multi-class vegetable image classification tasks, particularly when computational efficiency and model compactness are desired.

Nevertheless, achieving 100% validation accuracy may indicate that the classification task is relatively straightforward under controlled experimental conditions or that the dataset contains highly distinctive visual characteristics among classes. Such results may also suggest potential limitations in terms of generalization to more complex real-world scenarios. Consequently, it is essential to further evaluate the robustness of the model using an independent test set that is completely unseen during training and validation. Future work should therefore include validation on external images, such as photographs captured in real market environments under varying lighting conditions and background complexities, in order to more accurately assess the practical applicability and generalization capability of the proposed model.

7. Conclusion

In this study, an onion image classification model based on transfer learning with MobileNetV2 was proposed. The model was trained using the Onion Dataset-3 and evaluated on a validation subset. The experimental results demonstrated outstanding performance, achieving 100% testing accuracy with a loss value of 0.001. The confusion matrix and classification report further confirmed the model's ability to accurately distinguish among the three onion categories: Onion Red, Onion Red Peeled, and Onion White, with no observed misclassifications in the testing set.

These findings indicate that the adopted transfer learning strategy and lightweight architecture are highly effective for onion image classification under the given dataset conditions. However, such perfect performance may also reflect the controlled nature of the dataset and the presence of distinctive visual features among the classes.

For future work, the proposed model should be evaluated on an independent held-out test set and on real-world images captured under diverse lighting conditions and background complexities in order to verify its generalization capability. Moreover, incorporating advanced data augmentation techniques and cross-validation strategies could further enhance model robustness and mitigate potential dataset bias. These extensions would contribute to a more reliable and practically deployable onion classification system for real agricultural and commercial applications.

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