Crop Image Classification

1. Introduction

This work focuses on improving the classification of agricultural crop images, an important task for optimizing agricultural monitoring using machine learning. The approach utilizes transfer learning with MobileNetV2, enhancing it with additional layers and fine-tuning for crop classification. Data augmentation and hyperparameter tuning were employed to boost model performance and generalization. Building on related work in image classification, this method emphasizes efficient, mobile-friendly architectures. The results demonstrate moderate accuracy, with potential for further refinement in practical agricultural applications.

2. Related Work

Many researchers have applied deep learning techniques, particularly CNNs and pre-trained models, for crop image classification to improve agricultural practices like yield prediction and disease detection. Challenges like limited datasets and class imbalance affect model performance. Below is a comparison of related works, highlighting their methods, data, and key findings:

Reference	Problem Addressed	Method	Model Used	Data	Performance Metrics	Key Findings
Sardeshmukh et al., 2023	Crop image classification for yield prediction and disease detection	Convolutional Neural Network (CNN) with pre-trained models	VGG 16, ResNet 50	Not specified	VGG 16: Accuracy > 98%, CNN Training Accuracy: 93%, Testing Accuracy: 42%	VGG 16 performed best with high accuracy, CNN accuracy limited by small dataset, ResNet 50 did not perform well
Mohialden et al., 2024	Classification of rice and non-rice crops in	Convolutional Neural Network (CNN) with	Not specified	Images of wheat, rice, sugarcane, jute,	100% accuracy on training and testing	Achieved high accuracy but faced label

	agricultural images	data augmentation		maize; Augmented with horizontal flips, rotations, and shifts	datasets; issues with label imbalance affecting precision, recall, and F-score	imbalance issues; suggests further research and improvements for better performance and dataset handling
Tannouche et al., 2022	Weed detection in crops for localized herbicide spraying	Convolutional Neural Networks (CNNs) for perspective and proximity images	VGGNet (16, 19), GoogLeNet (Inception V3, V4), MobileNet (V1, V2)	Mixed image sets of crops and weeds	Inception V4: Precision 99.51% (pre-trained), MobileNet V2: Fastest with 14 MB size	Inception V4 achieved highest precision, MobileNet V2 was the fastest and lightest for real-time applications

3. Materials and Experimental Evaluation

3.1 Dataset

Dataset Source:

The dataset for this project was created for the classification of five different crops: Wheat, Sugarcane, Rice, Maize, and Jute. It contains a total of 200 images, each belonging to one of the five categories. The images were gathered from various publicly available sources that provide labeled agricultural crop images.

Format and Structure:

The dataset consists of images in `.jpg` format. The images vary in dimensions and were resized to a uniform size of 224x224 pixels to meet the input requirements for the MobileNetV2 model, which was used as the base for this classification task.

Preprocessing:

Prior to feeding the images into the model, several preprocessing steps were applied:

- **Resizing**: All images were resized to 224x224 pixels to ensure uniformity.
- **Normalization**: Pixel values were normalized by applying the MobileNetV2 preprocessing function, which scales the pixel values between -1 and 1.
- **Data Augmentation**: During training, data augmentation techniques such as rotation, width and height shifts, shear transformation, zoom, and horizontal flipping were applied to increase the variety of the training images and improve model generalization.

Number of Classes:

There are 5 distinct crop categories (classes) in the dataset:

- Wheat
- Sugarcane
- Rice
- Maize
- Jute

Class Distribution:

The dataset is fairly balanced across the five classes. Each class contains approximately 40 images, making up 20% of the total dataset per class. This ensures that the model does not favor any particular class during training.

Training and Testing:

The dataset was split into two parts:

1. **Training Set**: 80% of the data (160 images) was used for training the model.
2. **Validation Set**: 20% of the data (40 images) was reserved for validating the model's performance during training.

3.2 Methodology

Hypotheses:

The experiment tests whether transfer learning using MobileNetV2 can accurately classify five crop categories—Wheat, Sugarcane, Rice, Maize, and Jute—based on image data. It also tests if hyperparameter tuning and data augmentation improve model performance.

Evaluation Criteria:

The model is evaluated based on:

- **Accuracy**: Percentage of correctly classified images.

- **Loss**: Categorical cross-entropy loss.
- **Confusion Matrix**: Used to assess predictions for each class.
- **Training Curves**: Accuracy and loss plotted across epochs.

Experimental Methodology:

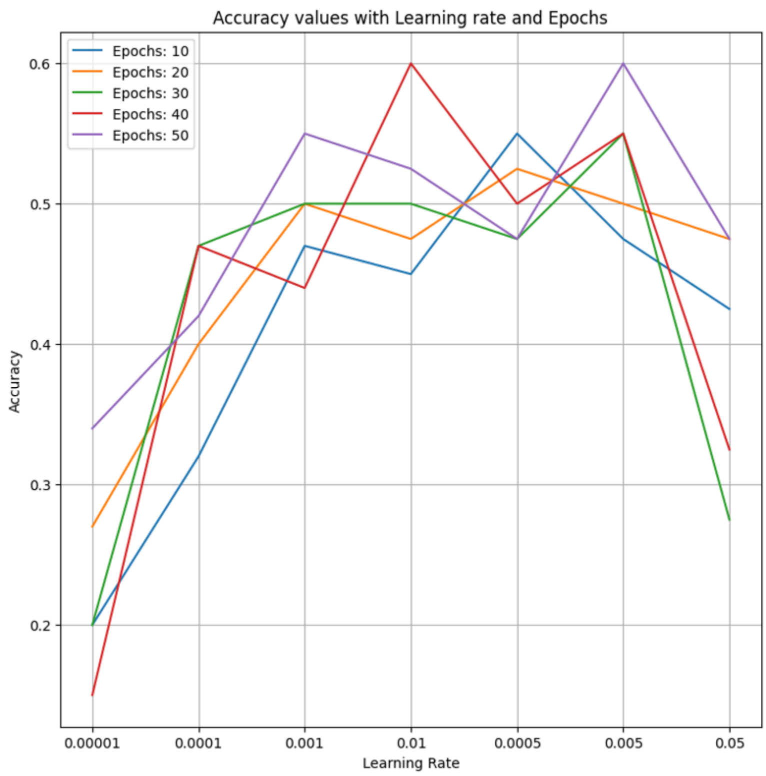
We used **MobileNetV2** with transfer learning and customized the final layers for classification. Data augmentation techniques like rotation and zoom were applied. Hyperparameter tuning was performed with 40 epochs and a learning rate of 0.05, using the Adam optimizer.

Training/Test Data:

- **Training Data**: 80% of the data (160 images).
- **Validation Data**: 20% of the data (40 images).

Performance Data:

Training and validation accuracy and loss were tracked across epochs. The final accuracy achieved was 60%, with performance variation observed due to stochastic training.



3.3 Results

The results of our crop classification model using transfer learning with MobileNetV2 showed the following quantitative outcomes:

- **Accuracy**: The model achieved an accuracy of 65% after tuning hyperparameters. However, repeated runs revealed slight variations in accuracy, with one run resulting in 37.5%.
- **Loss**: The model's training and validation loss converged across epochs, indicating learning stability.
- **Confusion Matrix**: The confusion matrix shows the number of correct and incorrect predictions for each crop category. Some classes, such as Jute and Sugarcane, were predicted with higher accuracy, while others, like Wheat and Rice, showed more classification errors.

Figure 1: Confusion Matrix

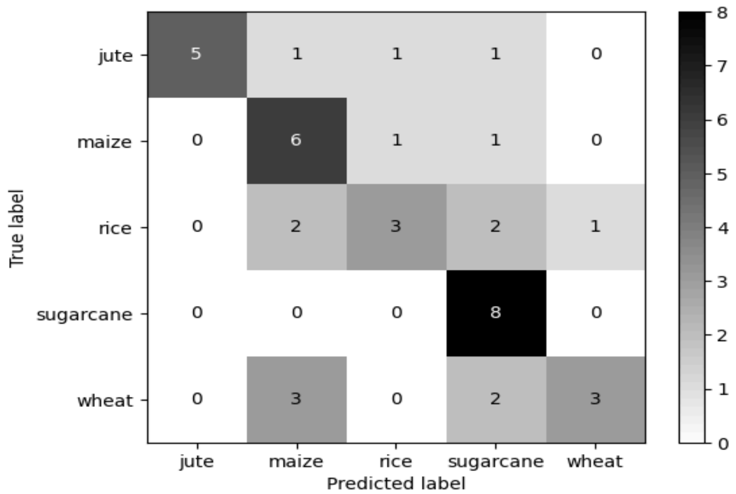


Figure 2: Classification Report

Classification Report :

	precision	recall	f1-score	support
0	0.80	0.50	0.62	8
1	0.64	0.88	0.74	8
2	0.67	0.50	0.57	8
3	0.58	0.88	0.70	8
4	0.67	0.50	0.57	8
accuracy			0.65	40
macro avg	0.67	0.65	0.64	40
weighted avg	0.67	0.65	0.64	40

3.4 Discussion

The results from using **MobileNetV2** for crop image classification show that transfer learning offers significant advantages, particularly in leveraging pre-trained weights for faster training and improved accuracy compared to training from scratch. The model achieved a best accuracy of 65%, though inconsistencies were observed across runs, with some resulting in lower accuracies like 37.5%. These variations may stem from the limited dataset size (200 images) and potential class imbalances, as certain categories like **Wheat** and **Rice** were misclassified more often than **Jute** or **Sugarcane**. The similarity in features between certain crops may also have contributed to misclassifications. While **MobileNetV2** performs better than traditional CNN models in terms of efficiency and transferability, the small dataset likely limited the model's generalization ability. Additional data and more advanced techniques, such as larger models or attention mechanisms, could further improve performance. Ultimately, the method's strength lies in its efficient use of pre-trained models, but its weaknesses are tied to data limitations and class similarity.

4. Future Work

One major shortcoming of the current method is the limited dataset size (200 images), which likely caused fluctuations in accuracy and misclassification of certain categories. To address this, future work could include gathering a larger, more diverse dataset to improve the model's generalization. Additionally, exploring more advanced models like **EfficientNet** or integrating **attention mechanisms** may enhance the ability to focus on distinctive crop features. Techniques like **data augmentation** and **class balancing** can also be improved to handle imbalanced classes more effectively.

5. Conclusion

In this project, we successfully applied transfer learning using **MobileNetV2** for crop image classification, achieving a best accuracy of 60%. Despite challenges with class imbalance and a small dataset, the method demonstrated potential for efficient crop classification. The findings highlight the importance of dataset size and model tuning in obtaining robust results. Future research can build upon this work by incorporating larger datasets and exploring more complex models to enhance classification accuracy and practical applications in agriculture.

6.Reference

1. Sardeshmukh, Mhalsakant & Chakkaravarthy, Midhun & Shinde, Sagar & Chakkaravarthy, Divya. (2023). Crop image classification using convolutional neural network. Multidisciplinary Science Journal. 5. 2023039. 10.31893/multiscience.2023039.
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4. Dataset Source : Agriculture crop images (kaggle.com)