Flower Image Classification Using CNN, Transfer Learning, and VGG19

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Abstract

Machine learning and deep learning, among the most influential fields, have significantly enhanced various facets of our lives. Convolutional Neural Networks (CNN) stand out as a powerful category, particularly in addressing real-world challenges. Notably, pre-trained models such as Transfer Learning and VGG play a pivotal role in image classification applications. While existing algorithms have demonstrated success in classifying images in grayscale datasets like FASHION MNIST11], this research aims to focus on a flower dataset. The dataset comprises 14 distinct types of flower images, encompassing 13,618 training images and 98 validation images. This study explores the effectiveness of Convolutional Neural Networks (CNN), Transfer Learning using InceptionV3, and VGG19 in the classification of flower images. The objective is to contribute to environmental research by facilitating the accurate identification of these 14 different flower species. To assess the models' performance in this specific domain, various performance metrics will be employed, providing insights into their efficacy for flower image classification.

1 Introduction

Flower classification is pivotal for understanding ecosystems and environmental health. Accurate flower classification models have the potential to assist researchers and conservationists in assessing the health of plant populations in specific regions. What distinguishes one flower from another can be also challenging. One of the most challenging multi-classes classification problems is flower image classification in which labels are separated with the images which are in two folders and high depth of flowers categorization as well. This study explores three distinct models – Convolutional Neural Networks (CNN), Transfer Learning (InceptionV3), and VGG19 – for classifying 14 diverse flower types. The primary objectives include evaluating model performance, comparing their efficacy, and assessing their potential contribution to environmental studies.

2 Literature Review

Prior studies have demonstrated the success of deep learning models, particularly CNN, in various image classification tasks. There are some research in[2],[3] Transfer Learning, using pre-trained models like InceptionV3 and VGG19, which has exhibited effectiveness in diverse domains. However, applying these models to flower classification within the context of environmental research is an underexplored area. This study aims to bridge this gap and contribute to the existing literature.

3 Data Collection and Preprocessing

The dataset comprises labeled images of 14 different flower types. Preprocessing involves resizing images to 128x128 pixels, normalizing pixel values to [0, 1], and employing data augmentation techniques. A thorough organization of the dataset into training and validation sets ensures proper labeling and structure for subsequent model training.

4 Model Architecture

```python
# code block 12
# Define the model
def build_model():
    model = models.Sequential([
        layers.Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3)),
        layers.MaxPooling2D((2, 2)),
        layers.Conv2D(64, (3, 3), activation='relu'),
        layers.MaxPooling2D((2, 2)),
        layers.Conv2D(128, (3, 3), activation='relu'),
        layers.MaxPooling2D((2, 2)),
        layers.Flatten(),
        layers.Dense(128, activation='relu'),
        layers.Dense(14, activation='softmax')  # Use softmax for multi-class classification
    ])
    return model
```

CNN model building

The CNN architecture consists of convolutional layers, max-pooling layers, and fully connected layers. InceptionV3 and VGG19 leverage pre-trained weights to extract hierarchical features from flower images. Each model is designed to capture intricate details of various flower species.

5 Hyperparameter Tuning

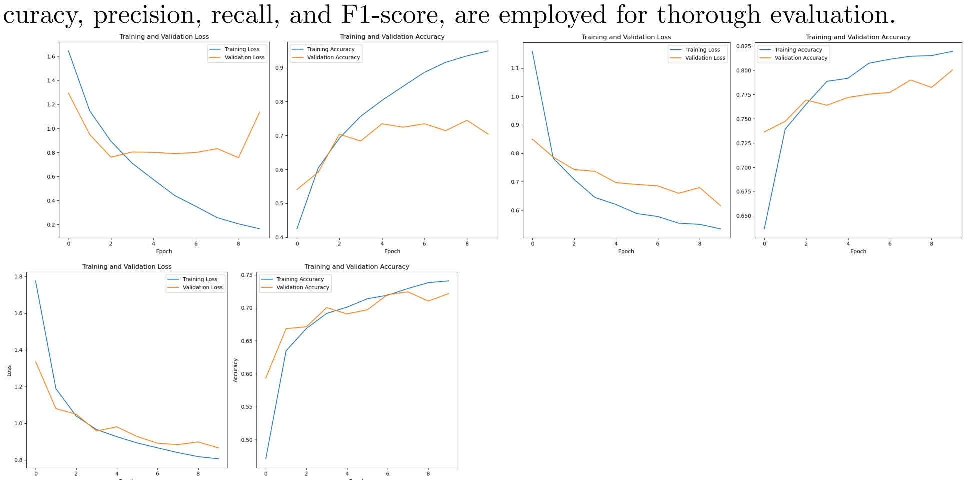
Hyperparameter optimization is performed to fine-tune each model for flower classification. Parameters, including learning rates, batch sizes, and epochs, undergo a systematic grid search. The best hyperparameters, determined based on validation set performance, ensure optimal convergence during training.For the CNN model, the best hyperparameters are as follows: **best_hyperparameters = {'batch_size': 32, 'epochs': 20, 'learning_rate': 0.001}**

```
%%time
param_grid = {
    'learning_rate': [0.001],
    'batch_size': [16, 32],
    'epochs': [10, 20]
}

grid = ParameterGrid(param_grid)

best_accuracy = 0
best_hyperparameters = {}

for params in grid:
    print(f"Training with hyperparameters: {params}")

    model = build_model()
    optimizer = tf.keras.optimizers.Adam(learning_rate=params['learning_rate'])
    model.compile(optimizer=optimizer,
                  loss='sparse_categorical_crossentropy',
                  metrics=['accuracy'])

    history = model.fit(train_dataset, epochs=params['epochs'], batch_size=params['batch_size'], validation_data=val_dataset)

    _, accuracy = model.evaluate(val_dataset)

    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_hyperparameters = params

print("Best Hyperparameters:", best_hyperparameters)
```

Hyperparameter Tuning

6 Training and Results

Model training involves feeding preprocessed data into each architecture and monitoring performance on the validation set. The training process converges based on the best hyperparameters, and comprehensive metrics, including accuracy, precision, recall, and F1-score, are employed for thorough evaluation.



The figure(1,1) is CNN loss and accuracy The figure(1,2) is TransferLearning Inception V3 loss and accuracy The figure(2,1) is VGG 19 loss and accuracy

7 Model Comparison

A comparative analysis of the CNN, Transfer Learning (InceptionV3), and VGG19 models provides insights into their respective strengths and weaknesses. The assessment includes each model's ability to capture intricate features of different flower species, shedding light on their effectiveness for flower image classification.

7.1 CNN Performance

The CNN exhibits the following performance metrics:

- Validation Accuracy: 0.7041
- Precision: 0.7271
- Recall: 0.7041
- F1-score: 0.6942

7.2 Transfer Learning Inception V3

For the Transfer Learning InceptionV3 model, the performance metrics are as follows:

- Validation Loss: 0.6491
- Validation Accuracy: 0.7991

7.3 VGG 19

The VGG19 model demonstrates the following performance metrics:

- Validation Loss: 0.8575
- Validation Accuracy: 0.7279

Model	**Test Accuracy**
CNN using Softmax activation function	0.7041
Transfer Learning Inception V3	0.7991
VGG 19	0.7279

Table 1: Test Accuracy for Different Models.

8 Discussion

8.1 CNN Performance

The CNN model achieved a validation accuracy of 0.7041, demonstrating its capability to capture intricate features of various flower species. The precision, recall, and F1-score metrics indicate a balanced performance in positive predictions and the minimization of false positives and false negatives. However, the moderate accuracy suggests potential areas for improvement.

8.2 Transfer Learning (InceptionV3)

In contrast, Transfer Learning with InceptionV3 showcased superior performance with a validation accuracy of 0.7991. Leveraging pre-trained models appears to be particularly effective in this context, outperforming the standalone CNN model. This emphasizes the importance of leveraging existing knowledge encoded in pre-trained models for improved flower image classification.

8.3 VGG19 Performance

The VGG19 model, while still providing a respectable validation accuracy of 0.7279, demonstrated a slightly lower performance compared to Transfer Learning. The observed differences in accuracy highlight the nuanced nature of flower features captured by different architectures.

9 Conclusion and Future Work

Further investigation into the intricacies of flower features that challenge the models may guide future research and model refinement. Future studies could explore additional architectures, hyperparameter tuning, or ensemble methods to enhance accuracy.

In conclusion, this research not only provides insights into individual model performances but also highlights the potential for advancements in flower image classification. The implications of this research extend to the development of specialized models contributing to the accurate identification and monitoring of diverse flower species in natural ecosystems. This study lays the groundwork for future research aimed at refining and expanding the applicability of flower image classification models.

10 References

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