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Review of Flower Image Classification

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Abstract

Flower image classification poses a challenging task in computer vision due to the diverse varieties of flowers and their intricate visual characteristics. Convolutional neural networks (cnns) have emerged as powerful tools in recent years for addressing this challenge. Additionally, deep learning techniques have proven valuable in this context. This paper aims to provide an overview of various strategies and methodologies currently employed for categorizing floral images using deep learning approaches.

Keywords: Image classification, Deep learning, Flower classification, Transfer learning, Neural network.

1. Introduction

The classification of flower images is a significant process utilized across various disciplines such as agriculture, botany, and environmental monitoring. Traditional methods of flower classification relied on manual feature extraction and shallow learning algorithms, which often overlooked the nuanced complexities and variations present in floral photographs. This field has undergone a profound transformation with the advent of deep learning, enabling automatic feature extraction and the construction of hierarchical structures directly from pixel-level data.

Flower classification using transfer learning applies a pre-trained deep learning model to categorize photographs of flowers into multiple classes. Initially trained on extensive datasets of generic images like imagenet, these pre-trained models are subsequently fine-tuned using smaller datasets of flower photographs, such as the Oxford Flowers 17 and Oxford Flowers 102 datasets. The Oxford Flowers 102 dataset, for instance, consists of images depicting 102 distinct flower species and is commonly used for refining pre-trained models. During fine-tuning, the final layer of the pre-trained model is often replaced with a new layer tailored to generate the specific number of flower categories. Subsequently, the model undergoes training on the flower dataset using transfer learning techniques. This approach allows the model to leverage knowledge gained from the broader dataset during the pre-training phase, resulting in a more precise and efficient model for flower classification.

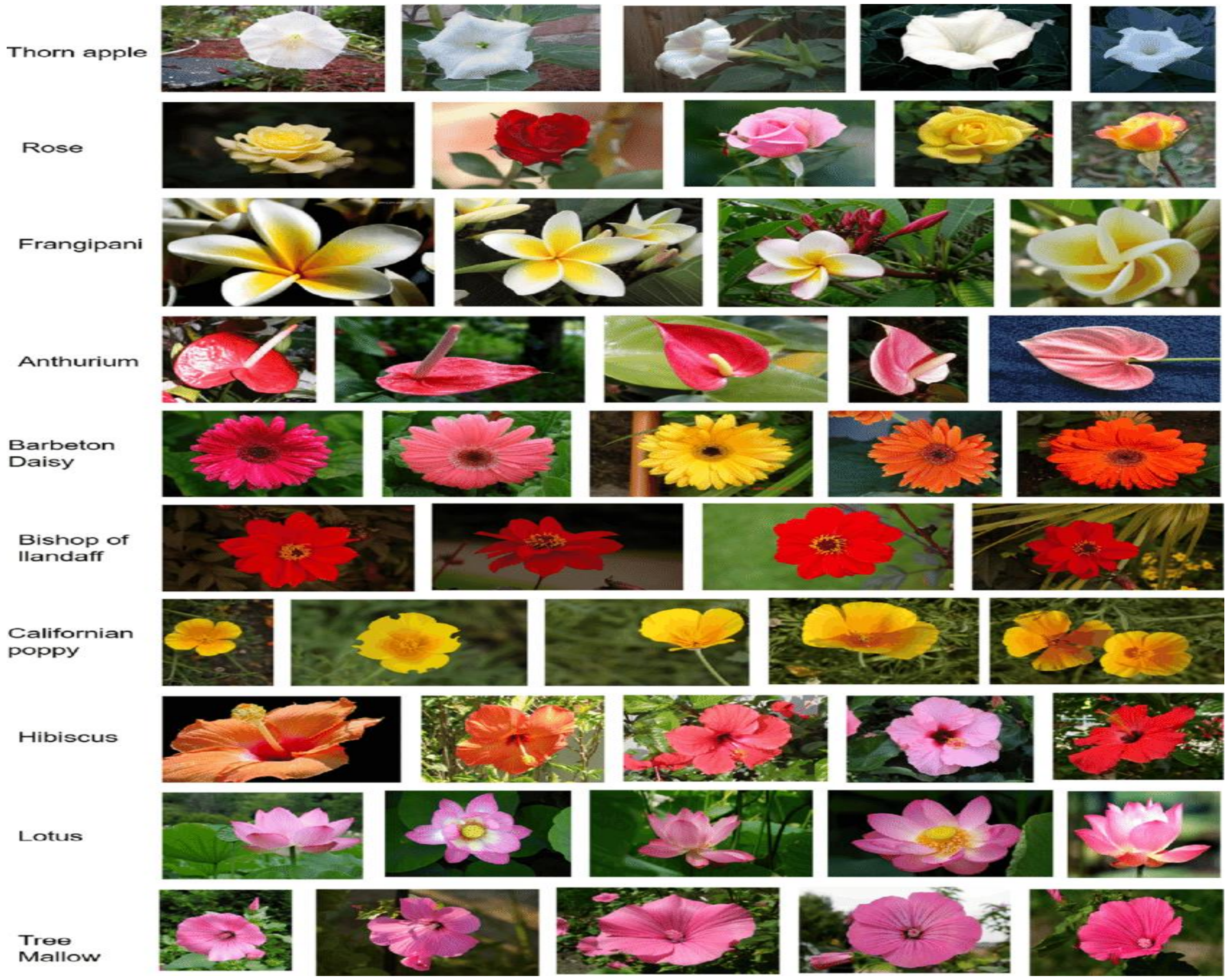

Figure 1: Illustrative flower dataset from Oxford University [10]

2. Literature Survey

1. The Earth's biodiversity is vast and diverse, encompassing approximately 360,000 species that collectively contribute to the planet's ecological balance. Many of these species share similar physical characteristics such as shape, size, and color, making accurate species identification a challenging endeavor. For instance, the Iris flower species includes three subspecies: Setosa, Versicolor, and Virginica, all of which share common floral features. Shukla et al. [1]
2. Chose to utilize the Iris dataset due to its accessibility and simplicity. This dataset comprises three categories, each containing fifty instances, and serves as a foundational dataset for applying machine learning algorithms to automatically classify Iris flower subclasses. The study focuses on leveraging Machine Learning techniques to achieve precise flower classification, bypassing approximation. The implementation of this approach involves three key phases: segmentation, feature extraction, and validation processes. In the realm of plant species, the adoption of deep learning techniques is increasingly prevalent. Tog acaar et al. [2]
3. Introduced a hybrid approach that combines feature selection techniques with Convolutional Neural Network (CNN) models to achieve desired outcomes. CNN models are employed for feature extraction,

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and various feature selection strategies are integrated to identify the most effective characteristics. The goal is to distinguish and categorize overlapping characteristics gathered through feature selection techniques, with experimental results assessing the impact of feature intersections on classification performance. Deep neural networks, renowned for their effectiveness in pattern recognition within images, have significantly impacted computer vision applications. Object detection tasks in computer vision, such as recognizing faces, vehicles, plant leaves, and surveillance videos, are particularly challenging due to intra-class similarities and variations. Abbas et al. [3]

4. Conducted research utilizing an optimized deep convolutional neural network equipped with Faster-Recurrent Convolutional Neural Network (Faster-RCNN) and Single Shot Detector (SSD) to localize, recognize, and classify objects of interest. They trained pre-existing models like resnet 50, resnet 101, Inception V2, and mobilenet on a dataset of two thousand images to achieve robust results. Flowers not only hold scientific value but also play significant roles in our lives. Traditional methods of flower classification often relied on human-selected features like shape, color, and texture, leading to limited classification accuracy. Wu et al. [4]
5. Introduced an effective flower classification strategy utilizing a convolutional neural network in tandem with transfer learning. Models like VGG-16, VGG-19, Inception-v3, and resnet50 were compared between network initialization and transfer learning approaches, highlighting transfer learning's potential to mitigate issues such as local optima and overfitting in deep convolutional networks. The utilization of pretrained models in problem-solving was underscored in the study by CENGİL et al. [5]
6. focusing on image categorization using transfer learning. This technique leverages pretrained deep learning models like alexnet, googlenet, VGG16, densenet, and resnet, emphasizing the efficiency and accuracy advantages of starting classification tasks with pretrained rather than randomly initialized networks. The findings demonstrate satisfactory model performance, with VGG16 achieving optimal results. Flower classification presents challenges due to the vast diversity among flower species in terms of shape, color, and overall appearance. Applications of deep learning techniques, including cnns and transfer learning, were extensively reviewed and analyzed by Narvekar et al. [6].
7. They applied a prototype CNN model architecture and transfer learning approach on architectures such as VGG16, mobilenet2, and resnet50 for flower classification using publicly available datasets. The significance of deep learning techniques extends to complex tasks such as image extraction, segmentation, and semantic classification. Alipour et al. [7]
8. Conducted research employing a powerful deep learning algorithm to classify 102 different flower types, employing transfer learning based on the densenet121 architecture to enhance model accuracy compared to earlier methods. Their preprocessing steps and training efforts led to achieving 98.6% accuracy over 50 epochs, surpassing previous deep learning systems. In domains like botany, agriculture, and pharmaceuticals, there is a growing demand for algorithms capable of classifying flowers based on photographs. Desai et al. [8]
9. proposed a flower classification technique using a convolutional neural network and transfer learning, utilizing features extracted from a VGG19 convolutional neural network architecture. They achieved a validation accuracy of 91.1% and a training accuracy of 100%, highlighting the efficacy of their approach. Hiary et al. [9]
10. Introduced a novel two-step deep learning classifier for identifying flowers across various species, incorporating automatic floral area division for bounding box identification and a binary classifier within a fully convolutional network architecture for floral segmentation. Their unique training processes aimed

to achieve robust, accurate, and real-time flower classification Data set This article provides a comprehensive review of publicly available floral image datasets, encompassing widely recognized datasets such as Oxford Flowers-17 [10]

11. Oxford Flowers-102, and tacos. These datasets vary in the number of categories, image resolutions, and diversity of flower species, facilitating the evaluation and comparison of different classification methodologies.

3. Evaluation Metrics

The paper explores common evaluation metrics employed to assess the performance of models for floral image classification, such as accuracy, precision, recall, F1-score, and confusion matrices. It underscores the importance of considering class imbalance and domain-specific challenges during the evaluation phase.

4. Conclusion and Future Scope

The advancements in flower image categorization using deep learning have been significantly boosted by the availability of extensive datasets, robust computational capabilities, and innovative model architectures. This study aims to provide insights into current state-of-the-art methods, challenges, and future prospects in this field. These findings are pertinent to various applications, including biodiversity conservation, horticulture, and related domains.

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