"Advancements in Flower Recognition and Classification Techniques: A Comprehensive Literature Review"

The following report consists of overview of research papers with recent advancements in Flower Classification techniques.

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A vision-based hybrid approach for identification of Anthurium flower cultivars

Link: https://www.sciencedirect.com/science/article/abs/pii/S0168169918309232?via%3Dihub

The paper focuses on the development of a hybrid approach for the accurate classification of Anthurium flower cultivars using computer vision techniques. It employs the Viola-Jones object detection algorithm for spadix region detection and multi-template matching for cultivar identification.

Methodology: The paper introduces a novel approach to classify Anthurium flower cultivars. It uses the Viola-Jones object detection algorithm to identify the spadix region and subsequently matches it with various templates representing different cultivars. The process relies on normalized cross-correlation (NCC) to determine the best match, thus identifying the cultivar.

Results: The research yielded impressive results. The proposed approach achieved high accuracy in both spadix region detection and cultivar classification, with a computation time of less than 0.5 seconds, making it suitable for real-time applications. The classification accuracy exceeded 99%, demonstrating the effectiveness of the method.

Strengths and Weaknesses: The strengths of the paper lie in its innovative approach to Anthurium cultivar classification, the combination of Viola-Jones and multi-template matching, and its high accuracy in real-time classification. However, potential weaknesses include the reliance on specific image processing algorithms, which may have limitations in handling complex and diverse real-world conditions. This paper provides a foundation for further research and improvement, particularly in developing more robust and adaptable methods for flower classification.

A Lightweight Attention-Based Convolutional Neural Networks for Fresh-Cut Flower Classification

Link: https://ieeexplore.ieee.org/document/10042302

This paper introduces an innovative approach to classifying fresh-cut flowers using a combination of ShuffleNet V2, data augmentation, and an attention mechanism. It reports impressive classification accuracy and speed results, offering significant advantages over traditional methods. The study focuses on classifying 434 rose flowers in an industrial setting, and it is valuable for future work on multichannel data applications.

Methodology: The paper collects RGB images and depth information data from rose flowers using a stereo depth camera. It then develops data augmentation techniques to enhance limited samples and employs the ShuffleNet V2 network, transfer learning, and an attention mechanism to classify flowers based on their specifications.

Results: The proposed network structure achieves high accuracy, with 98.891% on the 3-channel dataset and 99.915% on the 4-channel dataset, along with a remarkable classification speed of 0.020 seconds per flower. This surpasses current market fresh-cut flower classification machines, making it a strong candidate for practical applications.

Strengths: The paper presents a novel approach to fresh-cut flower classification, addressing both accuracy and speed. The data augmentation techniques enhance model robustness. The results demonstrate superior performance in terms of accuracy and speed, offering a competitive advantage over existing methods, particularly in an industrial context.

Weaknesses: The paper has a limited scope, focusing primarily on rose flowers and lacking a comprehensive comparative analysis with other models. It doesn't thoroughly explore the robustness of the model under diverse environmental conditions. Hardware details are somewhat lacking, and the reliance on transfer learning is not extensively discussed. More testing in real-world environments would provide valuable insights.

A New Improved Convolutional Neural Network Flower Image Recognition Model

Link: https://ieeexplore.ieee.org/document/9003016

This paper proposes A-LDCNN, a novel convolutional neural network model for flower image recognition. It utilizes a pre-trained VGG-16 network from ImageNet for feature learning on preprocessed flower images. An attention mechanism is introduced, combining local features from intermediate convolution layers with global features from the fully connected layer to create the final classification feature. Additionally, the paper introduces an innovative LD-loss function based on Latent Dirichlet Allocation (LDA) to minimize the feature distance within classes and maximize it between classes, addressing inter-class similarity and intra-class differences in flower image classification.

Methodology: A-LDCNN leverages pre-trained VGG-16 for feature extraction and incorporates an attention mechanism to fuse local and global features. It introduces LD-loss, which combines LDA to create a loss function aimed at optimizing feature distances between and within classes during CNN training.

Results: The classification experiments reveal that A-LDCNN achieves an accuracy of 87.6%, outperforming other traditional networks, and excels at recognizing flower images under natural conditions.

Strengths: The paper presents a novel approach that combines attention mechanisms and LD-loss in a CNN, effectively addressing challenges in flower image classification. It leverages the power of pre-trained models for feature extraction, improving accuracy under real-world conditions.

Weaknesses: The paper's accuracy, while improved, might still leave room for higher performance. It could benefit from more extensive comparative analyses with other models. Further exploration of the impact of different flower datasets and diverse environmental conditions could enhance the model's robustness. More details about the image preprocessing and practical applications would be valuable.

FlowerPhenoNet: Automated Flower Detection from Multi-View Image Sequences Using Deep Neural Networks for Temporal Plant Phenotyping Analysis

Link: https://www.mdpi.com/2072-4292/14/24/6252

Methodology: The paper introduces FlowerPhenoNet, a deep learning system for detecting and monitoring flowers in plant image sequences. It uses YOLOv3 for flower detection and introduces a novel set of temporal flower-based phenotypes. A benchmark dataset, FlowerPheno, comprising multiview image sequences of three flowering plant species, is also provided for performance evaluation.

Results: FlowerPhenoNet successfully detects and monitors flowers in image sequences of sunflower, canna, and coleus plants. It computes various flower-based phenotypes, including the emergence of the first flower, total number of flowers, highest number of bloomed flowers, and flower growth and blooming trajectories.

Strengths:
Novel Contribution: The paper introduces FlowerPhenoNet, a unique deep learning framework for flower-based plant phenotyping, addressing an important aspect of plant growth monitoring.
Benchmark Dataset: It provides the FlowerPheno dataset, a valuable resource for developing and evaluating algorithms in the field.
Potential Applicability: FlowerPhenoNet can be applied to various flower species with different shapes, architectures, and growth patterns.

Weaknesses:
Single Object Detector: The paper uses YOLOv3 for flower detection, which may have limitations in detecting small or occluded flowers. It would be beneficial to explore newer object detection networks for improved accuracy. Size Estimation Challenges: Estimating flower size accurately in 2D images is a challenge, especially when flowers change orientation or are occluded. Future work should consider 3D model reconstruction for precise size estimation. Expanding Dataset: Expanding the FlowerPheno dataset to include more plant species and diverse conditions would enhance the applicability and representativeness of the system.

Flower classification based on single petal image and machine learning methods

Link: https://ieeexplore.ieee.org/document/8393382

Methodology: The paper presents a novel automatic flower classification system. It involves acquiring 157 petal images of three categories using a digital camera. After pre-processing, color features and wavelet entropies are extracted from these petal images. Principal component analysis (PCA) is applied to reduce feature dimensionality. Four different classifiers (Support Vector Machine, Weighted k Nearest Neighbors, Kernel based Extreme Learning Machine, and Decision Tree) are trained to categorize the petals. The performance of these classifiers is evaluated using 5-fold cross-validation.

Results: Weighted k-Nearest Neighbors achieved the highest overall accuracy of 99.4% among the four classifiers. The proposed system demonstrated efficiency in identifying flower categories and outperformed existing state-of-the-art methods.

Strengths: High Accuracy: The system achieved an impressive overall accuracy of 99.4% in classifying flower petals, which indicates the effectiveness of the approach. Novelty: The paper introduces a new method for flower classification using a combination of color features, wavelet entropies, and PCA. Comparative Evaluation: The use of multiple classifiers and cross-validation provides a robust assessment of the system's performance.

Weaknesses: Limited Dataset: The paper doesn't specify the size and diversity of the dataset used for experimentation. A larger and more diverse dataset could enhance the system's robustness. Classifier Choice: While Weighted k-Nearest Neighbors performed the best, it's essential to explore whether other classifiers might yield even better results.

Four-Dimension Deep Learning Method for Flower Quality Grading with Depth Information

Link: https://www.mdpi.com/2079-9292/10/19/2353

Methodology: The paper presents a deep learning-based method for classifying the quality of fresh cut flowers based on maturing status. It collects RGB images and depth information of flower buds, fuses this data into a four-dimensional (4D) input, and uses convolutional neural networks (VGG16, ResNet18, MobileNetV2, InceptionV3) to classify flower maturing status. The models are trained and evaluated, and the depth information significantly improves classification accuracy.

Results: Depth information improves flower maturing status classification accuracy. inceptionV3 with depth data achieved the highest classification accuracy (up to 98%). Traditional machine learning methods had lower accuracy compared to deep learning. Proposed deep learning method outperforms other deep learning methods, achieving the highest classification accuracy.

Strengths and Weaknesses: The paper introduces a novel approach for flower quality grading with deep learning. Fusing depth information with RGB data enhances classification accuracy. The proposed method outperforms traditional machine learning methods. The depth of analysis and comparison with other deep learning methods provides valuable insights. Limited details on the specific architecture and hyperparameters of the neural networks used. The paper primarily focuses on flower maturing status classification and does not address broader flower quality features. The dataset is relatively small and may not fully represent the diversity of flower varieties and conditions. The paper does not discuss real-world implementation or scalability to large-scale flower grading.

SMARTFLORA Mobile Flower Recognition Application Using Machine Learning Tools

Link: https://ieeexplore.ieee.org/document/9781961

Methodology: The paper introduces the "SMARTFLORA Mobile Flower Recognition" application, which uses machine learning tools to enable users to identify three types of flower species: daisies, roses, and sunflowers. The system architecture involves training machine learning models using a Kaggle dataset and Teachable Machine Learning platform. The trained models are then exported to TensorFlow Lite Models and integrated into Android Studio to build the mobile application.

Results: The paper reports that the application achieved an accuracy of 88% in recognizing the specified flower species. It also discusses the methodology for developing the application, including the use of Kaggle datasets, Teachable Machine Learning, and TensorFlow Lite.

Strengths: The paper addresses the valuable need for a flower recognition application to help users identify various flower species. It leverages machine learning tools and TensorFlow Lite, which can be beneficial for creating mobile applications. The paper provides insights into the methodology used for training the recognition model.

Weaknesses: The paper focuses on a limited set of flower species (daisies, roses, sunflowers) and may not cover a broader range of flowers. It does not discuss potential challenges or limitations of the application. The paper does not delve into the user experience or broader applications beyond the specified flower types.

Automatic recognition of flowers through color and edge-based contour detection

Link: https://ieeexplore.ieee.org/document/6469535

Methodology: The paper introduces an automatic flower recognition system for smartphone users. When a user submits a flower image to the server, the server performs image processing and searching. The server detects the flower's contour using both color-based and edge-based contour detection. It then classifies color groups and contour shapes using k-means clustering and history matching. The server compares the input image with reference images stored on the server. The paper also addresses image recognition failures due to lighting and camera angles through partial recognition and image recovery. The experiments involve 500 images from 100 species of Korean natural flowers, achieving a recognition success rate of 94.8%.

Results: The paper reports a recognition success rate of 94.8% for 500 images from 100 species of Korean natural flowers. The use of both color and contour information, as well as the elimination of user interaction in the recognition process, contributes to this high success rate. The methodology is shown to be effective in handling images influenced by environmental factors.

Strengths: The paper presents an efficient automatic flower recognition system for smartphone users, addressing the challenges of complex and irregular flower shapes. It achieves a high recognition success rate (94.8%) for a diverse set of flower images. The methodology combines color and contour information, reducing user interaction and handling images in natural conditions.

Weaknesses: The paper's focus is on Korean natural flowers, and it might not cover a broader range of flower species. While it addresses lighting and camera angle issues, there may be room for further improvement in handling challenging environmental conditions. The paper does not discuss potential real-time or mobile application development aspects.

Flower Identification System Using Vision Based Technique

Link: https://ieeexplore.ieee.org/document/9760663

Methodology: The paper presents a flower recognition system that uses computer vision and machine learning techniques for identifying flower species. It utilizes image properties extracted from flower images to classify them. The method focuses on features like flower color and shape, extracted from a dataset using machine learning algorithms, including Tensor Flow. Neural networks are employed for image classification. The paper utilizes a dataset of flower images, stored and trained using Tensor Flow, and deploys an online database. The proposed system integrates Amazon Web Services (AWS) to enable remote access. Flower identification results are based on the features identified by the neural network.

Results: The paper discusses the experimental results of the proposed flower recognition system, although specific details are not provided. The system employs neural networks, machine learning, and computer vision to successfully identify flower species. It appears to be a promising vision-based technique for flower recognition.

Strengths: The paper addresses the issue of flower species recognition, which is challenging for common individuals due to the vast variety of flower species. The utilization of machine learning, neural networks, and computer vision demonstrates a promising approach to flower identification. The use of cloud services (AWS) and online databases enhances accessibility and scalability.

Weaknesses: The paper lacks specific details on the experimental results, making it challenging to evaluate the system's performance comprehensively. The work focuses on the classification of flower images based on color and shape, potentially leaving room for additional feature extraction and enhancement. There may be potential challenges in deploying such a system in real-world applications, which could be further discussed.

Detection and classification of opened and closed flowers in grape inflorescences using Mask R-CNN

Link: https://ieeexplore.ieee.org/document/9290720

Methodology: The paper presents a deep learning approach using the Mask R-CNN neural network to accurately classify and count opened and closed flowers in grape inflorescence images. To train the model, image datasets containing annotated instances of opened and closed flowers were used. The model is capable of segmenting individual flowers and distinguishing between the two classes, addressing challenges such as the similarity in shape, color, and texture between opened and closed flowers. A partitioned frame approach was employed for image preprocessing.

Results: The study demonstrated the effectiveness of the Mask R-CNN model for detecting and classifying opened and closed flowers in grape inflorescences. Correlation results showed a strong relationship between the predicted and actual total numbers of flowers and the ratio of opened to closed flowers. While the model performed well, outliers in the results were identified, such as blurry image sections and the presence of mature fruits that were incorrectly classified as closed flowers.

Strengths: The paper introduces an innovative application of Mask R-CNN in the agriculture domain, specifically for grapevine inflorescence analysis. The methodology leverages deep learning to tackle the challenging task of distinguishing visually similar objects (opened and closed flowers) in varying conditions. The study provides valuable insights into the application of deep learning for flower counting and classification, which can have broad applications in phenological studies.

Weaknesses: The dataset used for training and evaluation is relatively small, which could impact the model's generalizability to different conditions and stages of flower development. Outliers in the results, particularly due to blurry image sections and the presence of mature fruits, indicate areas for further improvement. The paper does not compare its approach to existing methods, making it challenging to assess its performance relative to alternative techniques.

Convolution Neural Network based Transfer Learning for Classification of Flowers

Link: https://ieeexplore.ieee.org/document/8600536

Methodology: The paper addresses the challenge of accurately classifying flowers, which have varied shapes, structures, and appearances. Traditional flower classification methods based on color, shape, and texture features have limitations in accuracy due to manual feature selection. The authors propose the use of CNNs and transfer learning to improve flower classification. The paper uses pre-trained CNN models (VGG-16, VGG-19, Inception-v3, and ResNet50) on the ImageNet dataset and fine-tunes these models using the Oxford flower dataset. Transfer learning involves transferring knowledge gained from ImageNet to improve flower recognition. The key idea is that these pre-trained models can automatically extract relevant features for flower classification.

Results: The paper demonstrates that transfer learning with CNN models significantly enhances the accuracy, robustness, and generalization ability of flower recognition compared to traditional methods. Results indicate substantial improvements in flower classification on the Oxford flower dataset, validating the effectiveness of their approach.

Strengths: The paper addresses a real-world problem of flower classification, showing the practical application of deep learning and transfer learning in image recognition. It offers a systematic comparison of different CNN architectures, demonstrating how transfer learning can mitigate issues like overfitting. The methodology is well-documented and includes key details on model training and experimental setup.

Weaknesses: The paper does not provide detailed numerical results or performance metrics, making it challenging to quantify the extent of improvement. While it discusses the effectiveness of transfer learning, it doesn't delve deeply into the limitations or potential challenges of this approach. The paper is somewhat dated, and more recent advancements in CNN models and techniques may have emerged since its publication.

Flower image classification based on improved convolutional neural network

Link: https://ieeexplore.ieee.org/document/10086258

Methodology: The paper leverages deep learning, specifically CNNs, for flower image classification. The authors use a dataset consisting of real flower images, which is divided into training, test, and result test sets. Various preprocessing techniques, including color optimization, filtering algorithms, color-space optimization, and binarization optimization, are applied to enhance the dataset. The CNN model is based on the ResNet architecture, with adjustments to improve its performance. Batch Normalization layers are added before convolutional layers to speed up training, reduce overfitting, and mitigate gradient vanishing issues. The network also utilizes the ReLU activation function and overlapping maximum pooling for feature richness.

Results: The paper reports significant improvements in flower image classification accuracy. After a series of optimizations to the dataset and network structure, the final model achieves an accuracy rate exceeding 91.61%, demonstrating the effectiveness of the proposed approach.

Strengths: The paper addresses the practical application of deep learning and CNNs in flower image classification, a real-world problem. The authors conduct thorough data preprocessing and optimization, enhancing the quality of the dataset and improving model performance. The utilization of the ResNet architecture and Batch Normalization layers reflects a sophisticated approach to model design.

Weaknesses: The paper does not delve into the specifics of performance metrics or numerical results, making it challenging to quantify the extent of improvement. While the paper discusses model improvements, it could benefit from more detailed explanations of specific optimizations and their impact. The dataset used is not thoroughly described, and details about data collection and sources are missing.

Multispecies Fruit Flower Detection Using a Refined Semantic Segmentation Network

Link: https://ieeexplore.ieee.org/abstract/document/8392727

Methodology Overview: The paper addresses the need for accurate and automated flower identification to estimate bloom intensity in orchards. Traditional methods relying on human visual inspection are time-consuming and error-prone. Existing computer vision systems for flower identification are limited in their applicability, as they often rely on hand-engineered features and controlled environments. The proposed approach employs deep learning and a fully convolutional network (FCN) fine-tuned for pixel-wise flower segmentation. A unique refinement method is used to distinguish individual flower instances. The study also presents an annotated dataset with pixel-accurate labels for flower segmentation.

Results: The method proves robust and effective for flower segmentation across various species, including apple, peach, and pear flowers. It generalizes well to different lighting conditions, backgrounds, and image resolutions, with segmentation results obtained in under 50 seconds for high-resolution images.

Strengths: The paper introduces an automated and robust method for flower identification, addressing a critical need in precision agriculture. Deep learning and FCNs are employed, resulting in superior segmentation accuracy compared to traditional methods. The proposed approach generalizes across flower species and uncontrolled environments, demonstrating its applicability.

Weaknesses: While the paper emphasizes generalizability, the evaluation of different species is primarily limited to fruits (apple, peach, pear). Evaluation across a broader range of plant species would be beneficial. The paper does not provide a detailed comparison with other state-of-the-art flower identification methods, making it challenging to assess the uniqueness of the proposed approach. There is limited discussion of real-world deployment challenges and potential sources of error.

Detecting Tomato Flowers in Greenhouses Using Computer Vision

Link:
https://www.researchgate.net/publication/313404418_Detecting_Tomato_Flowers_in_Greenhouses_Using_Computer_Vision

Methodology: The paper focuses on developing a real-time and computationally simple algorithm for detecting yellow tomato flowers in greenhouse conditions. The algorithm aims to work efficiently on a drone's processor. The methodology involves image acquisition using different angles and lighting conditions, adaptation to varying illumination conditions, color-based segmentation using the HSV color space, morphological operations for noise removal, and size-based classification.

Results: The algorithm was tested on 1,069 images captured in greenhouse conditions, considering different angles of acquisition and times of acquisition. The analysis indicates that the front view angle provides the best results. Moreover, images acquired in the afternoon generally yield better results than other times of the day. The algorithm achieved a precision and recall of 74% and 75%, which improved to 80% when using the optimal parameters.

Strengths: The paper addresses the challenge of detecting tomato flowers in greenhouse conditions, which is crucial for tasks like pollination. It presents an algorithm that performs well, with an emphasis on real-time processing suitable for drone deployment. The study provides insights into optimal parameters for detecting tomato flowers.

Weaknesses: The algorithm's performance is affected by varying lighting conditions, which may still pose challenges in certain real-world scenarios. The paper primarily focuses on the detection of tomato flowers and doesn't offer extensive comparisons with other methods or broader applications. Future work is mentioned to improve the algorithm further, particularly in the context of machine learning, but these enhancements are not included in this paper.

Flower Image Classification Using Deep Convolutional Neural Network

Link:
https://www.researchgate.net/publication/352093979_Flower_Image_Classification_Using_Deep_Convolutional_Neural_Network

Methodology: The paper focuses on the classification of 102 different flower species using a deep learning method. They employ a transfer learning approach, using the DenseNet121 architecture, to fine-tune a pre-trained model for flower classification. Image preprocessing is carried out, including resizing and normalizing images, and the dataset is divided into train, validation, and test sets. The pre-trained model is fine-tuned for 102 flower classes using PyTorch.

Results: The authors achieve an accuracy of 98.6% for 50 training epochs, which outperforms other deep learning-based methods for the same dataset.

Strengths: The paper addresses the important task of flower species classification, which has applications in biodiversity protection. The use of transfer learning with DenseNet121, a powerful pre-trained model, is an effective approach to achieve high accuracy with a relatively small dataset. The fine-tuning of the model for 102 flower classes demonstrates its flexibility and adaptability to specific tasks.

Weaknesses: The paper does not specify the publication venue and date, which makes it challenging to locate the full paper for detailed information. While the paper mentions the use of the Oxford 102-flower dataset, it lacks details on the dataset's source and composition. More information about the experimental setup, such as hyperparameters and data augmentation techniques, would provide a clearer understanding of the approach.

1. Flower Image Classification Using Deep Convolutional Neural Network – (May 2021) https://www.researchgate.net/publication/352093979_Flower_Image_Classification_Using_Deep_Convolutional_Neural_Network
2. Detecting Tomato Flowers in Greenhouses Using Computer Vision - https://www.researchgate.net/profile/Dor�Oppenheim/publication/313404418_Detecting_Tomato_Flowers_in_Greenhouses_Using _Computer_Vision/links/5899a3dcaca2721f0db0c9cf/Detecting-Tomato-Flowers-in�Greenhouses-Using-Computer-Vision.pdf
3. Multispecies Fruit Flower Detection Using a Refined Semantic Segmentation Network – https://ieeexplore.ieee.org/abstract/document/8392727
4. Flower image classification based on improved convolutional neural network https://ieeexplore.ieee.org/document/10086258
5. Convolution Neural Network based Transfer Learning for Classification of Flowers https://ieeexplore.ieee.org/document/8600536
6. Detection and classification of opened and closed flowers in grape inflorescences using Mask R-CNN. https://ieeexplore.ieee.org/document/9290720
7. Flower Identification System Using Vision Based Technique. https://ieeexplore.ieee.org/document/9760663
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9. SMARTFLORA Mobile Flower Recognition Application Using Machine Learning Tools. https://ieeexplore.ieee.org/document/9781961
10. Four-Dimension Deep Learning Method for Flower Quality Grading with Depth Information. https://www.mdpi.com/2079-9292/10/19/2353
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15. A vision-based hybrid approach for identification of Anthurium flower cultivars https://www.sciencedirect.com/science/article/abs/pii/S0168169918309232?via%3Dihub