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A Comprehensive Review of Flower Classification Techniques Using Deep learning

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Abstract*—This paper analyzes deep learning techniques for categorizing flowers, covering new advances, issues, and advancements in this emerging field. As the significance of automated flower identification continues to grow across many domains, deep learning algorithms have emerged as powerful tools for attaining accurate and effective categorization. By combining a variety of papers, methods, and datasets, this study offers a structured overview of the state-of-the-art in deep learning-based flower categorization. The main concepts, architectures, pre-processing techniques, transfer learning methodology, and performance evaluations employed in diverse research are covered in the article. By examining the benefits, drawbacks, and contrasting assessments of different methods, this research provides helpful insights for academics, practitioners, and enthusiasts interested in employing deep learning for flower categorization.

Keywords: Deep learning, flower classification, Convolutional neural networks, transfer learning, image recognition, machine learning, computer vision.

I. Introduction

Deep learning techniques have revolutionized the way we see, interpret, and categorize visual data, making significant strides in the field of computer vision. The classification of flowers, which is significant in fields like botany, ecology, agriculture, and horticulture, is one fascinating and varied area in computer vision. Botanists and flower enthusiasts have historically identified flower species manually because it is a laborious, time-consuming, and error-prone process[1]. The application of deep learning to the classification of flowers not only expedites the procedure but also improves accuracy and productivity.A complex investigation of numerous visual characteristics, including as petal color, shape, texture, and arrangement, as well as the general structure of the plant, is required to identify different flower species. Traditional image analysis techniques face substantial difficulties because of the complexity and diversity of these features[2]. Deep learning, a kind of machine learning, has shown its power in extracting and comprehending complex patterns from unprocessed images. Deep learning is characterized by its capacity to autonomously create hierarchical representations from data.

This review paper seeks to explore the deep learning landscape as it relates to flower classification. The purpose of this study is to offer a structured review of the state-of-the-art methodology, problems, and future directions in this field by synthesizing existing research, methodologies, and achievements. This paper attempts to shed light on the developments that have altered flower classification, improving its accuracy and application, through a thorough exploration of several deep learning architectures, pre-processing methodologies, and assessment measures.We will explore the various approaches used to tap the potential of deep learning for flower categorization in the next sections of this research. We will explore the subtleties of data pre-processing, a crucial step in ensuring the best model performance. We will also look at well-known datasets that are used to train and test deep learning models on classification of flowers. The important performance indicators used to judge these models' efficacy will also be included in this examination. This work provide a review of the existing research to undertake a comparison analysis of a few deep learning algorithms, highlighting their advantages and disadvantages in addressing the complexity of flower categorization. We will open the door for future research directions by identifying gaps and difficulties, which could improve and broaden the use of deep learning in this field.

II. Methodologies

The effective application of deep learning techniques to the classification of flowers has resulted in the introduction of a wide range of methodologies, each of which advances the reliability and accuracy of automated flower identification. This section of the study explores the various approaches and

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architectures used to maximize the effectiveness of deep learning for the goal of classifying flower species.

A. ***Convolutional Neural Networks (CNNs):*** Convolutional Neural Networks (CNNs), at the cutting edge of deep learning approaches for image analysis, have become a pillar in the classification of flowers. By utilizing Convolutional and pooling layers, CNNs are created to automatically learn hierarchical representations of images, allowing them to capture subtle visual characteristics that are essential for differentiating between various flower species[12].
B. ***Recurrent Neural Networks (RNNs) for Temporal Features:*** While Recurrent Neural Networks (RNNs) add temporal context to the flower classification landscape, CNNs excel at extracting spatial characteristics from photos. RNNs are useful tools for jobs involving time-series data, such as determining the stages of flower growth since they are well-suited to capture sequential patterns and include memory cells[13].
C. ***Hybrid Architectures for Multimodal Insights:*** Hybrid deep learning architectures have been developed as a result of the combination of various modalities, such as visual and textual data. These models enhance classification accuracy and resilience by combining the advantages of different neural network types to offer thorough insights into flower characteristics[19].
D. ***Transfer Learning Strategies*:** Transfer learning algorithms have become popular due to the dearth of labeled data and the computing requirements of training deep neural networks[20]. Researchers have shortened the training process and enhanced the performance of floral classification models by utilizing pre-trained models on large-scale datasets.
E. ***Attention Mechanisms and Interpretability:*** Because there is a lack of labeled data and training deep neural networks requires a lot of compute, transfer learning methods have grown in popularity[20]. By using pre-trained models on extensive datasets, researchers have sped up the training process and improved the performance of floral classification models.

This section examines different procedures in an effort to reveal the various approaches taken by researchers to the challenging task of deep learning flower classification. The fundamental ideas and advantages of each strategy can be understood, then gain a better understanding of the methods and strategies that support precise and effective automated flower identification.

III. PRE-PROCESSING TECHNIQUES

The ability of deep learning architectures, as well as the caliber and applicability of the input data, are key factors in the accurate classification of floral species. Preprocessing methods are essential for improving the efficiency, generalization, and robustness of deep learning models for classifying flowers. This section explores a variety of preprocessing methods used by researchers to clean up and prepare flower photos for efficient analysis.

A. Data Augmentation: A key component of preprocessing is data augmentation, which includes creating various training samples from existing data by using a range of transformations. Rotation, scaling, cropping, and flipping are a few examples of transformations that add variability to the training set and allow the model to draw lessons from a wider variety of floral forms. This section investigates the use of data augmentation in the categorization of flowers, highlighting its contribution to lowering over-fitting and improving model performance.

***B. Image Normalization**:* Standardizing pixel values across images is the goal of normalization approaches, which improve model convergence and stability during training. Neural networks are better able to identify relevant features and patterns in the data when pixel intensities are scaled to a common range. The significance of picture normalization is covered in this part, which also elaborates on well-known methods including mean subtraction, standardization, and min-max scaling.

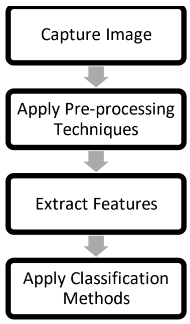

Fig.1. Basic Steps of Flower Classification

***C. Feature Extraction**:* Deep learning algorithms must be able to extract significant features from floral photos in order to recognize distinctive traits. Edge detection, texture analysis, and form representation are just a few examples of the techniques used in feature extraction.

D. Noise Reduction and Image Enhancement: Noise, artifacts, or poor lighting can all degrade the quality of input photos. To address these issues and enhance the overall clarity and quality of floral photographs, noise reduction and enhancement techniques are used. In-depth discussion of denoising algorithms, histogram equalization, and other methods of improvement that help to improve the quality of the input data for deep learning models is provided in this section.

E. Dimensionality Reduction: Computational difficulties and the dimensionality curse can be brought on by high-dimensional image data. Images are converted into lower-dimensional spaces using dimensionality reduction techniques like Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE), which speeds up processing and may also reveal latent features in the data.

These preprocessing methods play in enhancing the input data for deep learning models through the exploration of these preprocessing methods. Researchers can use these methods to improve the performance and resilience of flower classification models by grasping the nuances and advantages of data augmentation, normalization, feature extraction, noise reduction, and dimensionality reduction.

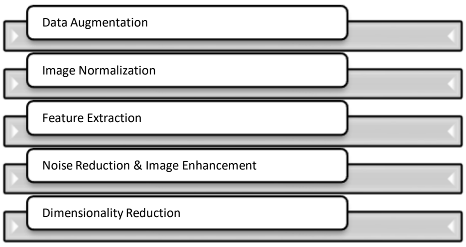

Fig.2. Preprocessing techniques

IV. Datasets

The foundation upon which deep learning models for flower categorization are formed is robust and diversified datasets. The models may be trained, validated, and tested using these datasets, which give them the opportunity to understand complex patterns and apply those patterns to real-world situations. This part of the paper examines significant flower datasets that have advanced the field of deep learning-based classification of floral species.

A. Oxford Flower 17 Dataset: An established standard for classifying flowers is the Oxford Flower 17 dataset. This dataset presents a condensed yet varied array of floral species and includes 17 flower types. Each category has a finite amount of samples, which makes it appropriate for investigating model performance in the face of data scarcity. 80 photos per class are included in the 17 category flower dataset. The flowers selected are several that are popular in the UK. There are classes with many variations of photographs within the class and close similarities to other classes, as well as vast variances in scale, attitude, and light in the images.

B. Flower-102 Dataset: The Flower-102 dataset adds to the Oxford Flower 17 dataset by increasing the number of flower types to 102, giving researchers a more complex and extensive dataset. Since this dataset includes a wider variety of species, it more accurately captures the diversity that can be found in situations involving flower identification in the real world.

C. Large-Scale Flower Datasets: Several large-scale flower datasets have appeared, offering hundreds to millions of floral photos in various categories, in recognition of the significance of scaling up dataset size. These datasets, including the TACoS-MD dataset and the flower subset of the ImageNet dataset, make it easier to train deep learning models with a large amount of data, which increases their ability to generalize to a greater variety of flower species.

D. ***Domain-Specific Datasets:*** Domain-specific datasets are tailored to specialized flower identification tasks in addition to general flower datasets, such as crop categorization, wildflower recognition, or uncommon species identification. These datasets fill the gap left by the lack of specialized training data, allowing models to perform well in certain settings.

E. Challenges and Considerations: While datasets are essential for both training and assessing deep learning models, they also present problems such class imbalance, the need for data augmentation, and dataset bias. Through this section researchers find a thorough grasp of the crucial role that high-quality data plays in furthering the field of deep learning-based flower categorization by examining these datasets and their individual characteristics, difficulties, and contributions. A thorough understanding of dataset nuances becomes more important in fostering creativity and enhancing model performance as researchers continue to explore new datasets and push the limits of automated flower recognition.

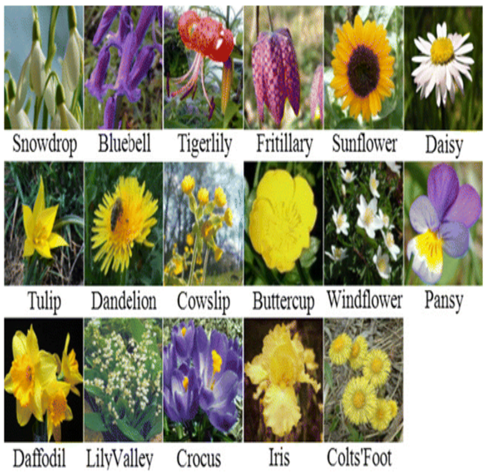

Fig.3. Flower-17 Dataset

Table.1. Comparing of various deep learning approaches on different dataset for flower classification

Approach	Model Architecture	Preprocessing Techniques	Dataset Used	Accuracy
CNN	ResNet-50	Data Augmentation	Flower 17	0.85
CNN with Attention	VGG-16 with Attention	Image Normalization	Flower-102	0.88
RNN	LSTM	Feature Extraction	Flower 17	0.78
Hybrid Model	CNN+LSTM	Data Augmentation	Flower 102	0.87
Transfer Learning	Inception V3	Noise Reduction	Large sale flower set	0.92
Mutimodal Integration	CNN+BERT	Image Textual	Domain specific dataset	0.89

A. **Precision, Recall, and F1-score:** When working with imbalanced datasets, metrics like precision, recall, and the F1-score offer a more nuanced understanding of model performance. Recall (sensitivity) indicates the percentage of true positive forecasts among all actual positives, whereas precision represents the proportion of true positive predictions across all positive predictions. The F1-score balances precision and recall by taking both false positives and false negatives into account.

B. **Confusion Matrix**: A thorough visual representation of a model's performance across various classes is provided by the confusion matrix. It allows for a more thorough understanding of the model's advantages and disadvantages by segmenting predictions into true positives, true negatives, false positives, and false negatives.

C. **Receiver Operating Characteristic Curve(ROC) and Area Under the Curve(AUC)**: The ROC curve, which is frequently used in binary classification problems, illustrates how the true positive rate (recall) and the false positive rate trade off as the decision threshold changes. The model's capacity to distinguish between classes is indicated by the AUC, which condenses the performance of the ROC curve into a single scalar value.

D. **Mean Average Precision (mAP):** A statistic used extensively in object detection and image segmentation applications is mean average precision. It evaluates the trade-off between precision and recall at various confidence levels, giving a comprehensive view of model performance.

E. **Cross-Validation and Generalization:** By repeatedly dividing the dataset into training and validation sets, cross-validation approaches, such k-fold cross-validation, can evaluate a model's generalization performance. This method offers a more reliable estimate of a model's actual performance when applied to unobserved data. The use of cross-validation to increase the accuracy of performance measures techniques.

This section gives researchers the means to thoroughly assess the capabilities of deep learning models in the field of flower classification by digging into these performance indicators, their computations, and their importance. Each indicator provides a new viewpoint on model performance, allowing researchers to compare various strategies, make educated decisions, and tweak models to get the best flower species identification accuracy.

V. Comparative Analysis

For academics and practitioners to choose the best methodology, a thorough grasp of the advantages and disadvantages of various deep learning approaches for flower categorization is necessary. This section compares a few deep learning models to give light on their performance, effectiveness, interpretability, and flexibility when used to identify different flower species.

Convolutional Neural Networks (CNNs) vs. Recurrent Neural Networks (RNNs): RNNs bring time context to the table, but CNNs are excellent at extracting spatial characteristics from flower photos. The investigation considers variables like dataset size, diversity, and the existence of sequential information [10] as well as circumstances in which each design excels.

Transfer Learning vs. Fine-Tuning: While fine-tuning enables these models to be tailored to particular flower classification tasks, transfer learning makes use of pre-trained models on huge datasets. The investigation evaluates their effectiveness, rate of convergence, and performance across various datasets and types of flowers[15].

Hybrid Architectures vs. Single-Modal Models: The advantages and challenges of hybrid architectures that combine multiple modalities (e.g., visual and textual) are juxtaposed with single-modal models that rely solely on image data. The comparative analysis delves into the benefits of multimodal insights, model complexity, and the interpretability trade-offs associated with these two approaches.

Attention Mechanisms vs. Conventional Architectures: The contributions to interpretability and classification accuracy of models including attention mechanisms and traditional deep learning architectures are compared. By concentrating on prominent flower traits and the consequences for model transparency, the analysis assesses how attention processes improve model performance.

Generalization and Robustness: Deep learning models' flexibility in real-world situations is demonstrated by comparing their generalization and resilience across diverse datasets and flower species. The analysis predicts about model which has the best generalization abilities while taking into account overfitting, class imbalance, and the capacity to handle uncommon or unknown flower species.

Interpretability and Explainability: The interpretability and explainability of models are compared, with a focus on the ways in which various architectural configurations make categorization decisions more understandable. The analysis explores the usage of interpretability techniques, how they affect user confidence, and whether they have the potential to reveal information regarding floral traits.

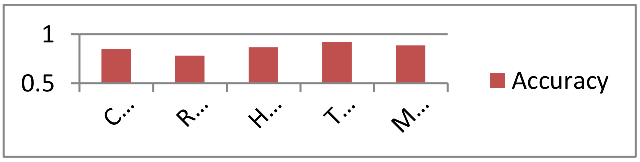

Fig.4. Classification accuracy for different dataset using feature extraction

Through this comparative analysis, readers gain a nuanced understanding of the trade-offs, benefits, and challenges associated with various deep learning approaches for specific goals, resources, and requirements for accurate and efficient flower species identification.

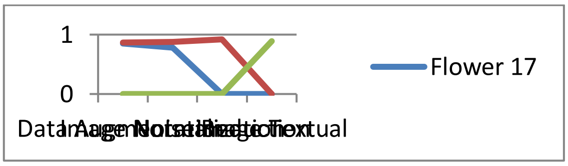

Fig.5. Comparison between various deep learning methods

VI. Challenges and Future Directions

Despite the fact that deep learning for flower categorization has advanced quickly, there are still many obstacles to overcome and possibilities to seize. The current state of automated flower species identification is examined, ongoing problems are noted, and suggested directions for future research and innovation are presented in this section of the paper.

Limited Data and Data Augmentation: The lack of labeled data, particularly for uncommon or recently found flower species, is one of the persistent problems in deep learning. In order to solve this problem, it is necessary to investigate cutting-edge data augmentation methods, generative models, and domain adaption tactics. This will enrich training datasets and improve model generalization.

Class Imbalance: Biased models that favor the majority class and struggle with the minority one can result from unbalanced class distributions. Ensuring balanced representation and accurate classification for all flower species requires the design of specific loss functions, oversampling and undersampling strategies, and ensemble approaches.

Cross-Domain and Cross-Species Generalization: As a result of the differences in flower species, growth stages, and environmental factors, achieving substantial cross-domain and cross-species generalization still poses a difficulty. Future studies could focus on transfer learning techniques that cut across species and settings and help models successfully adapt to novel situations.

Fine-Grained Classification and Hierarchical Models: Fine differences between closely related taxa are frequently used in flower categorization. By utilizing shared traits and relationships between flower species, hierarchical models and fine-grained categorization algorithms have the potential to improve accuracy in these situations.

VII. Conclusion

Our ability to recognize, classify, and appreciate the exquisite beauty of nature's botanical wonders has undergone a radical change as a result of the rapid advancement of deep learning technologies. An in-depth understanding of the dynamic interaction between contemporary artificial intelligence and the diverse world of flowers has been provided by this thorough review, which has negotiated the complex landscapes of methodologies, preprocessing techniques, datasets, performance metrics, challenges, and future directions.

REFERENCES

[1] Abbas, T. et al. (2022) “Deep Neural Networks for Automatic Flower Species Localization and Recognition,” Computational Intelligence and Neuroscience, 2022, pp. 1–9. Available at: https://doi.org/10.1155/2022/9359353.

[2] Toğaçar, M., Ergen, B. and Cömert, Z. (2020) “Classification of flower species by using features extracted from the intersection of feature selection methods in convolutional neural network models,” Measurement, 158, p. 107703. Available at: https://doi.org/10.1016/j.measurement.2020.107703.

[3] Çibuk, M. et al. (2019) “Efficient deep features selections and classification for flower species recognition,” Measurement, 137, pp.

7–13. Available at: https://doi.org/10.1016/j.measurement.2019.01.041.
[4] Mann, H.M.R. et al. (2022) "Automatic flower detection and phenology monitoring using time-lapse cameras and deep learning," Remote Sensing in Ecology and Conservation, 8(6), pp. 765–777. Available at: https://doi.org/10.1002/rse2.275.
[5] Dias, P.A., Tabb, A. and Medeiros, H. (2018) "Apple flower detection using deep convolutional networks," Computers in Industry, 99, pp. 17–28. Available at: https://doi.org/10.1016/j.compind.2018.03.010.
[6] Seeland, M. et al. (2017) "Plant species classification using flower images—A comparative study of local feature representations," PLOS ONE, 12(2), p. e0170629. Available at: https://doi.org/10.1371/journal.pone.0170629.
[7] Tian, M., Chen, H. and Wang, Q. (2019) "Flower identification based on Deep Learning," Journal of Physics, 1237(2), p. 022060. Available at: https://doi.org/10.1088/1742-6596/1237/2/022060.
[8] Ghazi, M.M., Yanikoglu, B. and Aptoula, E. (2017) "Plant identification using deep neural networks via optimization of transfer learning parameters," Neurocomputing, 235, pp. 228–235. Available at: https://doi.org/10.1016/j.neucom.2017.01.018.
[9] Mohanty, A.K. and Bag, A. (2017) "Image Mining for Flower Classification by Genetic Association Rule Mining Using GLCM features," International Journal of Advanced Engineering, Management and Science, 3(5), pp. 516–521. Available at: https://doi.org/10.24001/ijaems.3.5.17.
[10] Nilsback, M. -e. and Zisserman, A. (2008) Automated Flower Classification over a Large Number of Classes. Available at: https://doi.org/10.1109/icvgip.2008.47.
[11] Wang, Z. et al. (2021) "Dynamic ensemble selection of convolutional neural networks and its application in flower classification," International Journal of Agricultural and Biological Engineering, 15(1), pp. 216–223. Available at: https://doi.org/10.25165/j.ijabe.20221501.6313.
[12] Hiary, H. et al. (2018) "Flower classification using deep convolutional neural networks," Iet Computer Vision, 12(6), pp. 855–862. Available at: https://doi.org/10.1049/iet-cvi.2017.0155.
[13] Alipour, N. et al. (2021) Flower Image Classification Using Deep Convolutional Neural Network. Available at: https://doi.org/10.1109/icwr51868.2021.9443129.
[14] Bae, K. et al. (2020) "Flower classification with modified multimodal convolutional neural networks," Expert Systems With Applications, 159, p. 113455. Available at: https://doi.org/10.1016/j.eswa.2020.113455.
[15] Anjani, I.A., Pratiwi, Y. and Nurhuda, S. (2021) "Implementation of Deep Learning Using Convolutional Neural Network Algorithm for Classification Rose Flower," Journal of Physics, 1842(1), p. 012002.
[16] Sarachai, W. et al. (2022) "Orchid classification using homogeneous ensemble of small deep convolutional neural network," Journal of Machine Vision and Applications, 33(1). Available at: https://doi.org/10.1007/s00138-021-01267-6.
[17] Andono, P.N. et al. (2021) "Orchid types classification using supervised learning algorithm based on feature and color extraction," Bulletin of Electrical Engineering and Informatics, 10(5), pp. 2530–2538. Available at: https://doi.org/10.11591/eei.v10i5.3118.
[18] Ghosh, S. et al. (2022) "SVM and KNN Based CNN Architectures for Plant Classification," Computers, Materials & Continua, 71(3), pp. 4257–4274. Available at: https://doi.org/10.32604/cmc.2022.023414.
[19] Guru, D.S., Kumar, Y.V.P. and Manjunath, S.S. (2011) "Textural features in flower classification," Mathematical and Computer Modelling, 54(3–4), pp. 1030–1036. Available at: https://doi.org/10.1016/j.mcm.2010.11.032.
[20] Alipour, N. et al. (2021b) Flower Image Classification Using Deep Convolutional Neural Network. Available at: https://doi.org/10.1109/icwr51868.2021.9443129.
[21] Dubey, A.K.; Chabert, G.L.; Carriero, A.; Pasche, A.; Danna, P.S.C.; Agarwal, S.; Mohanty, L.; Nillmani; Sharma, N.; Yadav, S.; et al. Ensemble Deep Learning Derived from Transfer Learning for Classification of COVID-19 Patients on Hybrid Deep-Learning-Based Lung Segmentation: A Data Augmentation and Balancing Framework. *Diagnostics* 2023, *13*, 1954. https://doi.org/10.3390/diagnostics13111954
[22] G. . Dubey, "A Hybrid Convolutional Network and Long Short-Term Memory (HBCNLS) model for Sentiment Analysis on Movie Reviews", IJRITCC, vol. 11, no. 4, pp. 341–348, May 2023.
[23] Kalpana, Chauhan, S.S., Singh, M.K., Bagoria, R. (2023). Novel Taxonomy for E-learning Recommender System Using Opinion Mining. In: Garg, D., Narayana, V.A., Suganthan, P.N., Anguera, J., Koppula, V.K., Gupta, S.K. (eds) Advanced Computing. IACC 2022. Communications in Computer and Information Science, vol 1782. Springer, Cham. https://doi.org/10.1007/978-3-031-35644-5_30
[24] . Gogul and V. S. Kumar, "Flower species recognition system using convolution neural networks and transfer learning," IEEE Fourth International Conference on Signal Processing, Communication and Networking (ICSCN), 2017, pp. 1-6, doi: 10.1109/ICSCN.2017.8085675
[25] Nilsback, M., Zisserman, A.: 'Automated flower classification over a large number of classes'. Proc. Sixth Indian Conf. Computer Vision, Graphics & Image Processing, Bhubaneswar, India, December 2008, pp. 722–729
[26] lbadarneh and Ashraf Ahmad, "Automated Flower Species Detection and Recognition from Digital Images",International Journal of Computer Science and Network Security, VOL.17 No.4, April 2017.
[27] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in The IEEE Conference on Computer Vision and Pattern Recognition (CVP), June 2016.
[28] M. He, "Research on face image digital processing and recognition based on data dimensionality reduction algorithm," Computational Intelligence and Neuroscience, vol. 2021, Article ID 3348225, 10 pages, 2021.
[29] Tazin, S. Sarker, P. Gupta et al., "A robust and novel approach for brain tumor classification using Convolutional neural network," Computational Intelligence and Neurosci-
ence, vol. 2021, Article ID 2392395, 11 pages, 2021.
[30] Das, R. Manmatha, and E. M. Riseman. Indexing flower patent images using domain knowledge. IEEE Intelligent Systems, 14(5):24–33, 1999.