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Flower Classification using CNN

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ABSTRACT

In contemporary applications, deep learning methodologies have become indispensable for intricate tasks include semantic classification, picture segmentation, and feature extraction. Particularly in the domain of flower species classification, deep learning methods have exhibited considerable efficacy in recent years. This paper presents an endeavor to classify 102 flower species utilizing a robust Convolutional Neural Network (CNN) model with ResNet architecture. Leveraging datasets sourced from TensorFlow, we employ Algorithm 1 for data collection, preparation, and model training. To make it easier to evaluate the model, the dataset is divided into testing, validation, and training sets.The convolutional, pooling, and fully linked layers that make up our carefully crafted CNN architecturealso referred to as CNN flower. Training involves iteratively optimizing model parameters via backpropagation and an optimization algorithm to minimize the loss function. Fine-tuning is conducted to achieve higher accuracy, resulting in a notable 84% accuracy for the dandelion class, surpassing previous benchmarks for the same dataset.

Keywords— Trained Datasets , Test Datasets and CNN.

INTRODUCTION

Flowers are essential to the food chain and provide habitat for a variety of insect pollinators, making their accurate identification essential to the conservation of biodiversity and ecosystem management.However, manual identification of the vast array of flower species across different regions poses a daunting challenge, even for seasoned botanists. Because many flower kinds share similarities in their forms, colors, and petal arrangements, automation of flower categorization has advanced significantly since the development of computer vision technology.

In order to extract handmade elements like color, form, and texture from raw photos, most machine learning approaches require preprocessing processes. However, by absorbing raw pictures directly without requiring significant preprocessing, deep learning techniques—in particular, Convolutional Neural Networks (CNNs)—have shown impressive efficiency.CNNs excel in learning hierarchical features automatically, making them well-suited for image recognition tasks.

In this context, we leverage the power classifying different species of flowers automatically using a CNN-based model and botanical Traditransfer learning.Theeffectiveness of our network is improved via transfer learning techniquesparticularly when dealing with limited datasets. The foundation of our suggested model is therefinement of a trained machine learning construction, namely the ResNet-50 model.ResNet-50 has gained prominence in image classification tasks owing to its superior accuracy and ease of training, facilitated by direct connections between layers. We train and evaluate our model using the TensorFlow Flowers dataset, achieving a commendable accuracy of 84%, outperforming other existing models..

LITERATURE SURVEY

In addressing the challenge of flower classification, researchers have proposed various algorithms, spanning from traditional methods utilizing handcrafted features to modern deep learning approaches. With a maximum precision of 84% across 35 different flower types, Guru et al. [6] presented a textural feature-based approach for classifying floral photos. Comparable outcomes were obtained in [7], where color and texture data were applied to eighteen flower classes. Multilayer Perceptron (MLP) was used for classification, while gray-level occurrence matrix (GLCM) was used to extract texture features.

Additionally, newer algorithms have surfaced that use logarithmic plus local binary patterns (LBP) features to classify images, leading to better accuracy—91 percent for 8x8 images, for example [8]. The usefulness of feature combinations in classification tasks was demonstrated by Lodh and Patekh's [9] approach for flower recognition, which combined color and GIST characteristics.

The areas of image processing and visual analysis fields have witnessed a notable surge in interest in deep neural networks, especially Convolutional Neural Network (CNNs), which have become the preferred method over conventional deep learning techniques. Xia et al. [10] used a trained Inception v3 model to produce a precision of 94 percent using the Oxford 102-flower dataset, demonstrating the effectiveness of transfer learning techniques. Furthermore, [11] studied the performance of pre-trained networks, including LeNet and AlexNet, on flower datasets gathered from multiple sources. Adapted LeNet versions demonstrated significant accuracy improvements. In their investigation of flower classification accuracy, Mete and Ensari [12] used a variety of classifiers, with the highest accuracies shown by SVM and MLP. Other classifiers included KNN, Random Forest (RF), and Support Vector Machine (SVM).

METHODOLOGY

A. Image Pre-processing

Before inputting the images into our network, we perform pre-processing to enhance the effectiveness of our method. As our dataset comprises images of varying sizes and dimensions, we standardize them by resizing and normalizing. This pre-processing step ensures consistency in the input data, thereby facilitating better training outcomes. Subsequently, these processed images are utilized to train our optimized model.

B. ResNet ,A model

Currently, we are using transfer learning to refine a trained ResNet-50, which model for the classification of flowers. Transfer learning avoids the need to create new models to the ground up, which can be laborious and expensive, particularly when working with data sets that have small sample sizes. ResNet-50, our selected pretrained model, was first trained using the ImageNet dataset, which includes millions of images in 1000 different classes.

To adapt the model for our task, we retrain the final layer for our specific 102 flower classes through fine-tuning. This involves keeping the parameters of the earlier layers fixed while updating the classifier layer. The ResNet-50 architecture, characterized by its 24 layers with interconnections between them, facilitates efficient feature extraction. Each layer in ResNet-50 employs a non-linear transformation to compute its output based on the concatenated outputs of the preceding layers. This design minimizes parameter redundancy while ensuring effective information flow during training. Fig. 2 illustrates the structure of the ResNet-50 model.

Our utilization of ResNet-50 offers several advantages, including its streamlined architecture with fewer parameters compared to traditional CNNs, as well as its efficient gradient flow, enabling effective training without issues related to information propagation. These attributes contribute to the model's effectiveness in flower classification tasks .

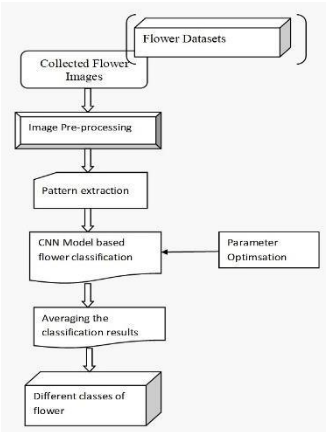

Fig1: Flow Chart

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RESULTS

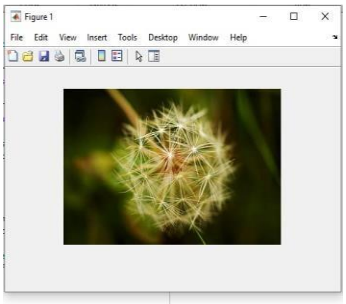

Fig 2. Input Image

TEST LABEL : DANDELION
PREDICTED LABEL: DANDELION

Fig 2 shows an example Dandelions are herbs that first grew in Eurasia. Where plants first grow is often referred to as their native location. Europeans brought dandelions with them as they traveled and colonized the world and dandelions now grow in many temperate regions. A temperate region is an area with a mild climate. Dandelions belong to the Asteraceae family, the same family as lettuce, artichokes, daisies, and chamomile. A plant family is a group of plants that are related to each other. What do Asteraceae family plant shave in common? Plants in this family have compound flowers. A compound flower has clusters of tiny florets that look like one larger flower. A dandelion can contain up to 200 florets on a single flower head.

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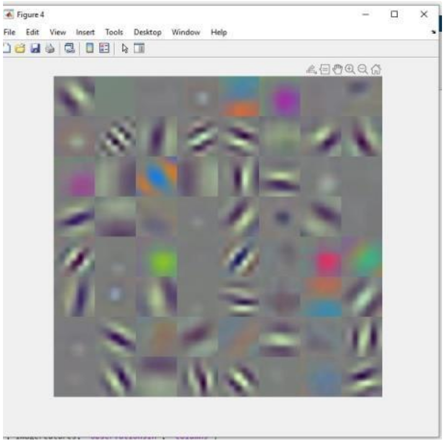

Fig 3. Feature extracted

Visualizing Feature Maps:
CNNs process images through convolutional layers that learn filters to detect specific patterns or edges. These filters are applied across the image, generating feature maps that highlight the presence of those patterns in different regions of the image. The image you described, with colored squares arranged in a grid, could be a representation of these feature maps.
Understanding the Feature Maps:
While the specific details of the colors and squares' arrangement might be specific to the implementation, the general idea is that each square or grid cell corresponds to a specific feature or pattern learned by a filter in a convolutional layer. The activation level of each square (represented by color intensity or value) might indicate the strength or certainty of the corresponding feature being present in that particular image region.
Feature Extraction:
Feature extraction is a fundamental process in Convolutional Neural Networks (CNNs) where the network learns to extract relevant features from input images. This is achieved through convolutional layers that employ filters or kernels to convolve across the input image, capturing various features at different spatial scales. As the image traverses through the network, these features become increasingly abstract, representing complex patterns and structures inherent in the input data. Feature Extracted View:
The feature extracted view refers to the representation of learned features within the CNN model, specifically pertaining to dandelion flowers in this context. By visualizing these features extracted at different layers of the network, researchers gain insights into the distinguishing attributes that the CNN has learned to recognize as characteristic of dandelion flowers. This visualization enables the identification of patterns, textures, and shapes that contribute to the model's classification decisions, providing valuable information for understanding how the CNN perceives and distinguishes dandelion flowers from other classes.
Interpretation and Analysis:
Through the feature extracted views, researchers can interpret the CNN model's inner workings and analyze which visual cues are most influential in distinguishing dandelion flowers. This analysis involves identifying key discriminative features such as petal shape, color distribution, texture variations, or other unique characteristics specific to dandelion flowers. By understanding these learned features, researchers can validate the model's performance and gain valuable insights into the features' ability to discriminate for precise classification.

```
confMat =

    0.8143    0.0571    0.0571    0.0286    0.0429
    0.0286    0.8714    0.0286    0.0571    0.0143
         0         0    0.9143    0.0286    0.0571
    0.0143    0.1143    0.0286    0.7857    0.0571
         0    0.0143    0.2000    0.0429    0.7429


ans =

    0.8257
```

Fig 4. Confusion Matrix

A confusion matrix constitutes a the table that is used to compare the predicted labels produced by the CNN model with the actual labeling for the blossoms in the test set in order to assess how well a classification model performs. This is done for the purpose of classifying flowers. The examples of the true class are represented by each row in the matrix, and the instances that are part for a predicted class are represented by each column. This illustrates the use of a confusion matrix in the classification of flowers.
Actual flower labels are shown in the confusion matrix's rows, while the anticipated flower labels are shown in its columns. As an illustration, the top departed cell (0.8143) displays that 81.43% of Daisy blossoms were correctly classified as daisies by the model.
The model's performance for each class is displayed on the confusion matrix's diagonal. With an accuracy of 82.57% (bottom right corner, 0.8257), it appears that the model worked well in this instance on all flowers. The real class of flowers is represented by each row.
The anticipated class of flowers is represented by each column.
The figures in the cells of the matrix represent the count of instances where flowers of a certain actual

class were predicted to belong to a certain predicted class.

For example, the cell in row "Sunflower" and column "Dandelion" has a value of 8, indicating that 8 instances of sunflowers were misclassified as dandelions. From top-left to bottom-right, the diagonal elements show how many instances of each class were correctly classified.

V. CONCLUSION

Convolutional neural networks, or CNNs, are used for flower classification has showcased remarkable effectiveness and potential in automating the task of identifying and categorizing diverse floral species. CNNs have demonstrated robustness in handling variations in scale, orientation, and illumination, common challenges in flower image classification. By employing convolutional layers and pooling operations, CNNs effectively extract hierarchical features from input images, enabling accurate discrimination between different flower species. Furthermore, the interpretability of CNNs, facilitated by techniques like gradient-based visualization and activation maximization, aids in understanding model behaviour and fosters trust in CNN-based flower classification systems

Despite the advancements made, certain challenges remain, including the need for more diverse and balanced datasets, mitigation of biases in training data, and optimization of model architectures for efficiency and scalability. It will be essential to solve these issues if CNN accuracy and dependability are to be increased for flower classification tasks. Regarding the field of agriculture,CNN-based flower classification systems can be integrated into farming practices for crop management and biodiversity conservation. Moreover, in botanical gardens and research institutions, CNNs can assist botanists and researchers in cataloging and studying diverse floral species, contributing to our understanding of plant biodiversity and ecosystem dynamics.

Future work in CNN-based flower classification holds immense potential across various sectors such as agriculture, ecology, and horticulture. Advancements in technology may lead to the emergence of portable CNN-powered devices for real-time flower recognition and habitat assessment, facilitating on-the-ground conservation efforts and ecosystem monitoring. Additionally, integration with Botanical education could undergo arevolution thanks to new technologies like augmented reality (AR) and virtual reality (VR),making it more engaging and accessible to students and enthusiasts worldwide. By fostering collaboration and knowledge sharing through online platforms and databases powered by CNNs, we can harness the collective expertise of individuals across the globe to further advance our understanding of floral biodiversity and conservation needs.

REFERENCES

[1] Hanafiah, M., Adnan, M. A., Abdul-Rahman, S., Mutalib, S., Malik, A. M. A., and Shamsuddin, M. R., “Flower Classification using Deep Convolutional Neural Networks”, in IOP Conference Series: Earth and Environmental Science, 2022, vol. 1019, no. 1. doi:10.1088/17551315/1019/1/012021.

[2] Ferhat Bozkurt, "A Study on CNN Based Transfer Learning for Classification of Flower Species," European Journal of Science and Technology, Special Issue 32, pp. 883-890, 2021. Crossref, https://doi.org/10.31590/ejosat.1039632.

[3] Deepak Mane, [2] Dr Sirbi Kotrappa , ” A Survey on Deep Learning Approaches For Flower Detection”, International Journal of Engineering Research in Computer Science and Engineering (IJERCSE) , Vol 8, Issue 2, February 2021.

[4] Parvathy S N, N Vrinda Rao, Shahistha Bai S, Naeema Nazer, Prof. Anju J, “Flower classification System Using CNN”, International Research Journal of Engineering and Technology (IRJET) , Volume: 07 Issue: 06 | June 2020.

[5] I. J. R. P. R. “Flower classification Using Deep Learning”, International Journal of Research Publication and Reviews, 2020 .

[6] FatihahSahidan, Nurul & Juha, Ahmad & Mohammad, Norasiah & Ibrahim, Zaidah. “Flower and leaf classification for plant identification using convolutional neural network”. Indonesian Journal of Electrical Engineering and Computer Science. 16. 737. 10.11591/ijeecs.v16.i2.pp737-743. 2023.

[7] Almogdady, Huthaifa & Manaseer, Saher & Hiary, Hazem. “A Flower classification System Based On Image Processing And Neural Networks”. International Journal of Scientific and Technology Research. 7. 2018.

[8] Rabindra Patel, Chandra Sekhar Panda, “A Review on Flower Image classification,” International Journal of Computer Sciences and Engineering, Vol.7, Issue.10, pp.206-216, 2019.

[9] Hiary, Hazem & Saadeh, Heba & Saadeh, Maha & Yaqub,

Mohammad. “Flower Classification using Deep Convolutional Neural Networks”. IET Computer Vision. 12. 10.1049/iet-cvi.2017.0155, 2018.

[10] Gogul, I. & Kumar, Sathiesh. “Flower species classification system using convolution neural networks and transfer learning” ICSCN conference. 1-6., 2017.10.1109/ICSCN.2017.8085675

[11] Sabzi, , Sajad et al. "Flower Classification using Convolutional Neural Networks." IEEE Access 8 (2020): 44187-44199.

[12] Khan, Ahmad, and Salman Khan. "Flower classification using deep convolutional neural networks: A comprehensive review." Applied Soft Computing 105 (2021): 107261.

[13] Yu, Lei, and Chunjie Zhou. "Flower classification using convolutional neural networks with transfer learning from pre-trained models." Computers and Electronics in Agriculture 174 (2020): 105466.

[14] Ahmed, Abdul Jabbar, et al. "Deep learning-based flower classification system using convolutional neural network." SN Computer Science 1.5 (2020): 261.

[15] Jan, Kashif, and Waqar Hussain. "Deep learning approach for flower recognition using convolutional neural network." 2019 2nd International Conference on Communication, Computing and Digital Systems (C-CODE). IEEE, 2019.

[16] Singh, Bharti, and Kavita Thakur. "Flower classification using convolutional neural networks." 2019 International Conference on Communication, Computing and Internet of Things (IC3IoT). IEEE, 2019.

[17] Pandey, Anjali, et al. "Flower species recognition using convolutional neural network." 2018 2nd International Conference on Electronics, Materials Engineering & Nano-Technology (IEMENTech). IEEE, 2018.

[18] Singh, Gurjot, et al. "Flower species recognition using deep convolutional neural network." 2018 International Conference on Intelligent Computing and Control Systems (ICICCS). IEEE, 2018.

[19] Chhaya, Umang, et al. "Flower recognition using convolutional neural networks." 2017 International Conference on Intelligent Computing and Control (I2C2). IEEE, 2017.

[20] Nadeem, Ayesha, et al. "Flower classification using deep learning." 2017 3rd International Conference on Robotics and Artificial Intelligence (ICRAI). IEEE, 2017.

[21] Song, Zhihong, et al. "A novel deep learning method for flower classification using image patches." Neurocomputing 405 (2020): 6170.

[22] Xie, Xiangyu, et al. "A flower image recognition method based on deep convolutional neural network." Procedia Computer Science 143 (2018): 79-85.

[23] Vu, Thao Thi Phuong, et al. "Deep learning-based flower classification system using convolutional neural network." 2019 IEEE-RIVF International Conference on Computing and Communication Technologies (RIVF). IEEE, 2019.

[24] Hu, Zhiwei, et al. "A flower recognition method based on deep convolutional neural network." Procedia Computer Science 91 (2016): 116-121.

[25] Roy, Pradipta, and Rashmi Ranjan Rout. "Performance comparison of convolutional neural network architectures for flower classification." 2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN). IEEE, 2019.

[26] Paudel, Awanish, et al. "Flower species recognition using deep learning techniques." 2020 IEEE 10th International Conference on Electronics Information and Emergency Communication (ICEIEC). IEEE, 2020.

[27] 17. Nguwi, Yok-Yen, and Young Im Cho. "Automatic recognition of flower images." Multimedia Tools and Applications 78.18 (2019): 25321-25342.

[28] Gani, Abdullah, et al. "Flower classification using deep learning techniques: A comparative study." Journal of King Saud UniversityComputer and Information Sciences 33.4 (2021): 500-508.

[29] Nnolim, Nkemdilim G., et al. "A review of deep learning techniques for flower classification." Applied Sciences 11.10 (2021): 4744.

[30] 20. Milioto, A., et al. "Real-time flower detection and classification using deep learning for agricultural robots." Journal of Field Robotics 35.8 (2018): 1248-1262.