Flower Image Classification: A Review

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***Abstract*- The categorization of flower images is a difficult subject in computer vision since there are so many different types of flowers and the visual qualities of flowers are so much more complicated than other things. Convolutional neural networks (CNNs), in particular, have developed as effective tools for handling this job in recent years. Deep learning methods have also emerged as useful tools. The purpose of this paper is to offer an overview of several strategies and methodologies that are currently being used in floral picture categorization via the use of deep learning.**

Index Terms: **Image classification, Deep learning, Flower classification, Transfer learning, Neural network.**

I. INTRODUCTION

The categorization of flower images is an important process that is used in a variety of fields, including agriculture, botany, and environmental monitoring. Traditional methods of flower categorization often depended on handmade features and shallow learning algorithms, both of which failed to capture the subtle intricacies and variances that are present in floral photographs. This discipline has been completely transformed by the introduction of deep learning, which has made it possible to automatically extract features and build hierarchical structures from raw pixel data.

The categorization of flowers using transfer learning is an application of transfer learning in which a deep learning model that has been pre-trained is used to categorize photographs of flowers into several categories. After been trained on a large dataset of generic photos, such as ImageNet, the pre-trained model is often fine-tuned using a smaller collection of flower photographs. ImageNet is an example of such a dataset. The objective of flower classification via the use of transfer learning is to create a model that is both accurate and efficient, and that is capable of classifying flowers into the species or categories that are appropriate for them. Several other areas, including botany, agriculture, and horticulture, might benefit from this at some point.

Using transfer learning, there are a number of different deep learning architectures that may be used for flower classification. Some examples of these models are VGGNet, ResNet, and Inception. A smaller dataset of flower photos, such as the Oxford Flowers 17 and Oxford Flowers 102 dataset. In Oxford Flowers 102 dataset, comprises photographs of 102 distinct flower species, is generally used to fine-tune the pre-trained model. As part of the process of fine-tuning, the last layer of the pre-trained model is replaced with a new layer that generates the required number of categories or classes. Following this, the model is trained on the flower dataset by using transfer learning methods. Through the use of this strategy, the model is able to make use of the information that it has acquired from the general dataset during the pre-training phase, which ultimately results in a model that is more accurate and efficient for flower classification.

II. LITERATURE SURVEY

The biodiversity that exists on earth is very varied. Within the ecology of the planet, there are around 360000 creatures that work together to form a healthy biome. It is possible that several of them have similar physical qualities, such as shape, size, and color. Because of this, successfully identifying any species might be difficult. Setosa, Versicolor, and Virginica are the three subspecies that make up the Iris flower species. Both of these subspecies consist of the same flower. After careful consideration, Shukla et al. [1] decided to use the Iris dataset for the implementation of the classification application since it is simple to access. There are three categories in the Iris flower dataset, and each category includes fifty occurrences. Through the use of machine learning, the Iris dataset identifies subclasses of the Iris flower. The study that is being conducted focuses on this strategy, which is how Machine Learning algorithms can automatically identify the class of flower with a high level of accuracy as opposed to trying to approximate it. There are three phases involved in the implementation of this technique: segmentation, feature extraction, and validation processes.

The applications of deep learning techniques to plant species are becoming more common. In one of the research, Tog acaar et al. [2] presents a hybrid approach that operates in combination with feature selection techniques and Convolutional Neural Network (CNN) models. This hybrid strategy is used to get the desired results. Feature extraction in this model is accomplished by the use of CNN models. The characteristics of these models are combined, and feature selection strategies are used in order to choose the most effective characteristics. In this case, they want to exclude and classify characteristics that overlap with one another that were gathered via the use of feature selection techniques. When the results of the experiments are compared, the impact of the intersection of the features that were created by the various feature selection procedures on classification performance is taken into consideration.

Deep neural networks are very effective systems for recognizing patterns in images, and they have found widespread use in the field of computer vision. Object detection in computer vision may be used for a variety of purposes, including the identification of faces and vehicles, the detection of plant leaves, and video surveillance. Because of the similarities that exist within classes and the intraclass variation, it is still challenging to implement an automatic ownership identification system across categories. As a result, the deep learning model requires data that is of higher quality and more properly labeled. The research conducted by Abbas et al. [3] makes use of an optimized and generalized deep convolutional neural network that is equipped with a Faster-Recurrent Convolutional Neural Network (Faster-RCNN) and a Single Short Detector (SSD) in order to recognize, localize, and classify lower objects. In order to train pretrained models such as ResNet 50, ResNet 101, Inception V2, and Mobile Net, they created a total of two thousand photographs.

Flower provides a large amount of scientific and application value, in addition to being of immense significance in our lives. Traditional methods of flower classification are mostly centered on characteristics such as shape, color, or texture. This approach needs humans to choose characteristics for the purpose of flower categorization, which results in a low level of classification accuracy. An other technique that was published by Wu et al. [4] is an effective flower classification strategy that makes use of a convolution neural network in conjunction with transfer learning. The VGG-16, VGG-19, Inception-v3, and ResNet50 models were used in order to provide a comparison between the network initialization model and the transfer learning model. According to the results, transfer learning has the potential to effectively eliminate problems related to local optimum and over-fitting as they pertain to deep convolution networks.

The use of pretrained models in problem solving is brought to the attention of the reader by a research that was presented by CENGİL et al. [5]. The technique known as transfer learning is used for the purpose of picture categorization. This technique makes use of deep learning models that have been pretrained and are regularly used, such as Alexnet, Googlenet, VGG16, DenseNet, and ResNet. The significance of the transfer learning technique is underlined throughout the course of this research. Beginning the classification process using pretrained networks rather than random weights is favorable in terms of time and accuracy performance requirements. This is because pretrained networks are more likely to provide accurate results. The findings indicate that the models that were used do, in fact, reach satisfactory levels of performance, with the VGG16 model achieving the maximum possible level of performance.

The categorization of flowers is a challenging task since there are a great number of flowering plant species that are comparable to one another in terms of their shape, color, and overall look. There are many different applications that may be found for a flower classification, such as field monitoring, plant identification, medicinal plants, the floriculture industry, and study on plant taxonomy. The most recent developments in deep learning techniques, such as CNN and transfer learning in CNN, have been presented and analyzed by Narvekar et al. [6]. Using a flower dataset that is available to the general public, a prototype CNN model architecture and transfer learning approach were presented and evaluated on VGG16, MobileNet2, and Resnet50 architectures for the purpose of flower classification.

The use of deep learning techniques is becoming more significant in the context of complicated tasks such as the extraction of images, segmentation, and semantic classification. Over the course of the last several years, these techniques have had a significant influence on the classification of different types of flowers. An investigation was presented by Alipour et al. [7], in which the authors tried to classify 102 different kinds of flowers by using a powerful deep learning algorithm. In addition to this, they classified a number of different kinds of flowers that were included in the Oxford-102 dataset by using a transfer learning strategy that was based on the DenseNet121 architecture. There was an effort made by them to enhance the accuracy of our model in comparison to other methods.Prior to sending the photographs to our fine-tuned pretrained model, they preprocessed the photographs by changing their size and normalizing them. The accuracy that they attained throughout 50 epochs was 98.6%, which is greater than the accuracy that was achieved by earlier deep-learning-based systems.

In the fields of botany, agriculture, and the pharmaceutical industry, there is a requirement for an algorithm that can classify flowers based on the photographs of those flowers. With regard to this particular scenario, Desai et al. [8] proposed a flower classification technique that was based on a convolutional neural network. In order to categorize flowers, they made use of a transfer learning method and extracted features from a VGG19 convolution neural network architecture. In order to classify flowers into 17 separate categories, they used 17 neurons in the last dense layer of the VGG19 convolution neural network design. The activation function that they used was softmax. We were able to classify flowers with a validation accuracy of 91.1% and a training accuracy of 100%, as shown by the findings.

The classification of flowers is a challenging endeavor since there are a great number of flower species that are comparable in terms of their forms, looks, or the objects that surround them, such as grass and leaves. As part of their research, Hiary et al. [9] proposed a novel two-step deep learning classifier for the purpose of identifying flowers belonging to a variety of species. At the outset, the floral area is automatically divided in order to facilitate the identification of the smallest bounding box that surrounds it. inside the framework of the approach, a floral segmentation strategy is expressed as a binary classifier that operates inside a fully convolutional network architecture. In addition to this, they develop a powerful convolutional neural network classifier that can differentiate between different types of flowers. They provide one-of-a-kind training processes in order to obtain robust, accurate, and real-time classification via their suggestions.

III. DATASETS

This text presents a thorough examination of floral picture datasets that are accessible to the public. It includes well-known datasets such as Oxford floral-17 [10], Oxford Flower-102, and TACoS. These datasets range in terms of the number of categories, picture resolutions, and variety of flower species, making it easier to evaluate and compare alternative classification techniques.

IV. EVALUATION METRICS

The article examines prevalent assessment measures used to gauge the efficacy of floral picture classification models, including accuracy, precision, recall, F1-score, and confusion matrices. The text emphasizes the need of taking into account the imbalance in class distribution and the special issues of the domain throughout the assessment process.

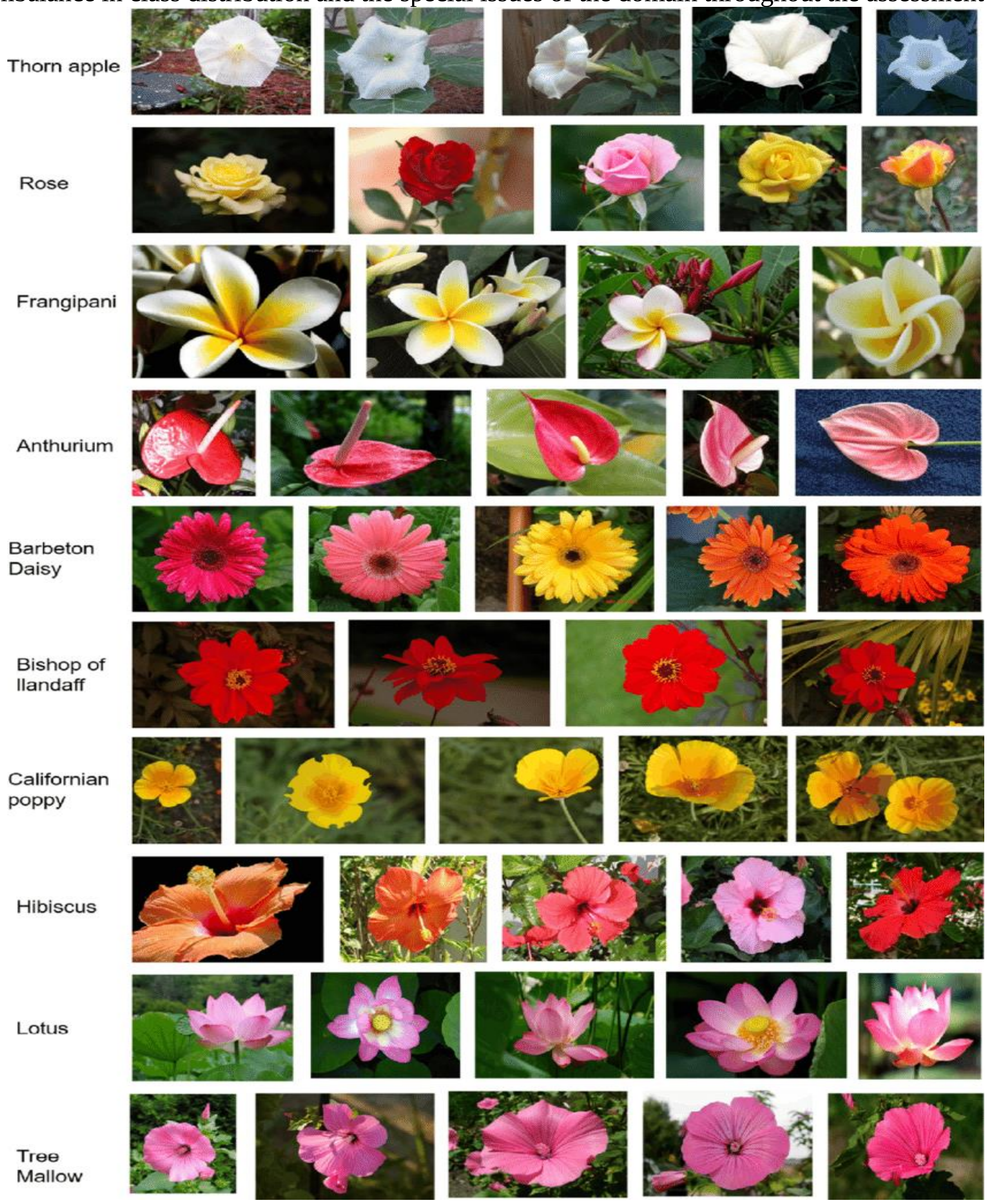

Figure 1: Illustrative flower dataset from Oxford University[10]

V. CONCLUSION

The availability of large-scale datasets, strong computing resources, and creative model designs have all contributed to the extraordinary gains that have been made in flower picture categorization via the use of deep learning. The purpose of this study is to give insights into the present state-of-the-art approaches, problems, and future prospects in this interesting topic. These findings have implications for a wide range of applications, including biodiversity conservation, horticulture, and other areas.

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