

Flowers Images Classification with Deep Learning: A Review

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Abstract

Significant progress has been made in the field of digital image processing in recent years through the utilization of machine learning and deep learning, surpassing previous methods by a large margin. Deep learning methods allow devices such as computers and mobile to automatically understand pattern characteristics. This review paper highlights challenges and issues in machine-deep learning applied to the domain of flower classification. In addition, the datasets were extracted that were found in the literature. The review offered in this article can encourage researchers in the domain of agriculture inspired techniques research society to further enhance the efficacy of the AI methods and to use the different AI techniques in other fields for solving complicated real-life challenges. In addition, the article provides an overview of the artificial intelligence techniques employed in the field of flower recognition, detection, segmentation, and other applications, delivering the most delinquent and recent literature for solving issues for researchers in the area of flowers.

Keywords: Machine Learning, Deep Learning, Flower Images, Data Acquisition, Methods, Evaluation Metrics.

1. Introduction

Flowers and the ability to identify them have fascinated mankind for centuries[1]. Flowers, as a botanical species, play a crucial role in maintaining ecological balance. Flowers have the ability to provide sustenance to various forms of life[2] by feeding practically all insect species on the planet [3], and are employed in a variety of helpful applications in relation to humans [2] such as pharmaceutical applications [4]. Plants have a crucial role in the advancement of society, the preservation of the environment, and the progress of agriculture[5]. Distinguishing flowers remains challenging for most people[2].

The primary reason for this is that Several flowers of various kinds have similar color, appearance, and shape, Furthermore, photographs of various flowers typically include similar surrounding items such as grass, leaves, and so on .There are around 250,000 identified flowering plant species categorized into approximately 350 families[6]. Recognizing and classifying these entities takes significant time and effort[7]. The process of manual classification is laborious and prone to mistakes that can accumulate over time[8]. As a result, developing a computer-aided approach for fast and accurate flower classification is an imperative step[9]. Flower classification is an important study in botany. Traditional flower classification systems have a difficult time limiting, the impact of flowers backdrop. This results in matter of an unsatisfying classification impact. Deep

learning has gained significant popularity as a study field in image classification issues due to the rise of huge data and the quick progress of Internet technology[10] .

The flower classification was Executed with machine learning and deep learning techniques. Machine learning is an AI approach used to identify patterns in data[11]Major brief of machine learning is information evaluation. Numerous algorithms present for system classification like decision trees (DT), Neural Network, Navie Bayes, SVM[12]. Deep learning is a particular type of machine learning[13],such as ResNet50, MobileNet, DenseNet169, InceptionV3 and VGG16[14],that enables computers to extract data automatically[15].

Readers can quickly understand the concepts of data preparation, model selection, and improvement in recent papers, enabling them to solve more complex problems by building upon past research.

The paper is structured as follows: Section 2 presents a comprehensive summary of the application types in literature review current methodologies and approaches that have been reviewed in the literature. Section 3 offers Challenge solved using machine learning in this literature. Section 4 offers Challenge solved using deep learning in this literature. Section 5 offers Challenge solved using Hybrid models in this literature. section 6 presents a summary for AI techniques used through the literature and the dataset mentioned through the literature. finally, Section 6 the Conclusion of this study.

2. Application Types in literature review

A result of examining the various literature, the authors highlight the different applications that exist in the literature such as classification, detection, segmentation, recognition, identification, and lastly localization. Table 1. summarizes the application types used in the literature review of flower images in this study. In addition, the frequency of each application determined in the literature was demonstrated in Figure 1. This indicate that classification is the most frequent application however identification and localization were the least frequent application.

Table 1. the application types used in the literature review.

Reference	Applications
[20],[21],[22],[23],[24],[9],[6],[25],[3],[26],[27],[29],[31],[2],[32],[33],[34],[37],[16],[17],[18],[4],[40],[41],[43],[19],[44],[42],[10]	Classification
[21],[11],[23],[25],[28],[32]	Detection
[6],[32]	Segmentation
[30],[35],[38],[39],[40],[10]	Recognition
[36]	Identification
[21]	Localization

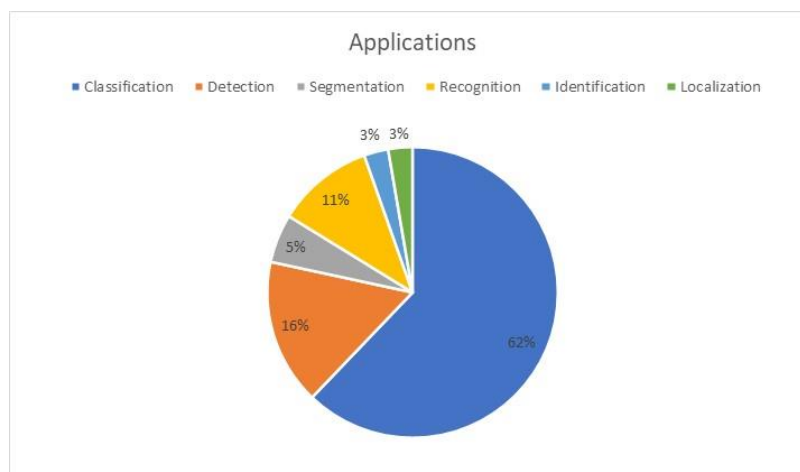


Figure 1. number of applications utilized in literature review

3. Challenge solved using ML

There are some limitations of this work. The effect of training and testing data splitting can be checked[11]. This research proposes a flower image classification approach. It uses a pre-trained CNN (Convolutional Neural Network) AlexNet as a tool to extract features. The approach relies on certain deep features and Multiclass SVM[16]. The problem statement in the first source is related to the classification of generating sunflower images by employing a feature extraction approach based on first-order methods and the Multiclass SVM identification algorithm. The aim is to distinguish between different types of sunflowers, which can be challenging due to their similar shape. The study focuses on using mean, skewness, variance, kurtosis, and entropy as input features for classification, and the model achieved an average accuracy of 79%[17]. The focus of the paper is on comparing the performance of SVM and LAF. Regarding the precision in identifying support vectors, with SVM demonstrating superior performance / The researchers employ both the Innovative Support Vector Machine technique and the logistic activation function technique to evaluate the iris dataset[18]. The study aims to explore the effectiveness of utilizing Local Binary Pattern (LBP) and Speeded-Up Robust Features (SURF) as feature descriptors for flower classification[19]. Figure 2. Highlight the number of challenges solved using ML based on each application

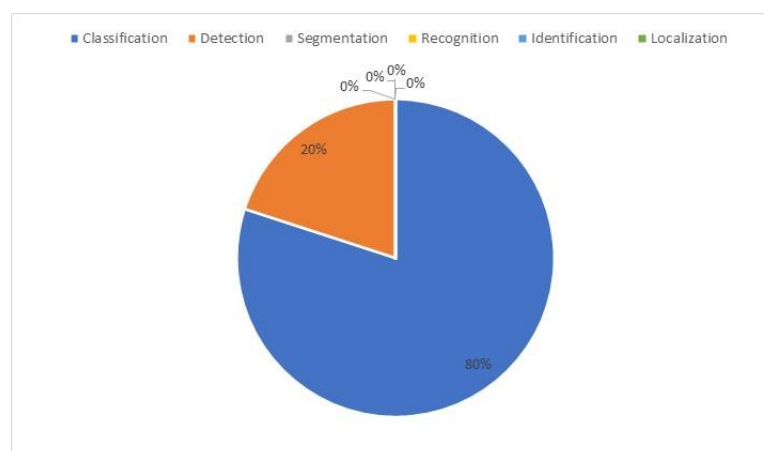


Figure 2. number of applications utilized machine learning in literature review

4. Challenge solved using DL

The sample size used in the experiments is relatively small, with 5120 training images and 1280 test images. This may limit the generalizability of the results. The paper does not discuss the potential impact or implications of the proposed approach beyond its application in local flower classification. / The issue has been tackled and a method has been suggested to identify the indigenous flowers of Bangladesh[20]. Efficiently performing flower image analysis involving the detection, location, and classification of multiple flower classes, collection is a challenging task in the realm of agriculture[21]. The study focuses on a specific set of deep learning models (MobileNet, DenseNet, Inception, and ResNet) and optimizers (Adam and SGD), without exploring the potential benefits of other models or optimization techniques./ The researchers aim to develop an application that can accurately identify different flower species based on their images[22]. However, keeping the number of epochs fixed, increasing the depth and complexity of a network substantially increases the computing time for training the network[23]. The paper acknowledges the limitations of flower classification, Examples of challenges in floral picture analysis include inter-class similarity, significant intra-class variance, non-rigid deformation, changes in illumination, variations in viewpoint, occlusions, and scale, The background of the images also poses a challenge in flower classification [24]. Training deep neural networks can be computationally expensive and time-consuming, especially when starting from scratch, fine-tuning a pre-trained model may not always guarantee improved performance, as it depends on the quality and relevance of the pre-trained model to the specific task /. Hence, this approach presents an intriguing opportunity to address the issue of floral categorization. The pre-trained model has undergone training and testing using the 102-oxford flowers dataset, resulting in a superior accuracy of 98.6% when compared to other methods. We utilize the Pytorch framework. PyTorch is largely developed by Facebook's AI Research (FAIR) team and serves as a deep learning research framework that offers exceptional flexibility and speed[9]. Limited accuracy compared to other approaches: The accuracy reported on flower classification using the proposed method is limited compared to other published works, such as Complexity for handling certain tasks: Deeper models like ResNet are generally too complex to handle the flower classification task due to the large number of parameters, making them less suitable for this specific application / Flower classification is a formidable challenge due to the vast array of flower species that exhibit comparable characteristics in terms of shape, look, and their surroundings, such as leaves and grass[6]. The YOLOv5 model used in the research, although effective, may have a complex architecture that requires careful implementation and understanding/ The project aims to accomplish precise picture categorization of flowers by taking into account the similarities between different classes and the differences within the same class in floral photos. The objective is to employ the YOLOv5 object identification algorithm to create a profound learning technique that can accurately recognize and classify five distinct categories of flowers within the dataset. The research aims to address the challenges of overlap and occlusion in flower images and enhance the detection of blocked objects[25]. The presence of a wide variety of flower species poses a significant challenge in their classification, particularly when they exhibit striking similarities. The traditional method of segmenting and selecting flower images for classification is considered primitive and less accurate compared to the use of deep CNN and machine learning algorithms/ Nevertheless, it is an undeniable fact that numerous plants found in the wild can be successfully farmed. Furthermore, enhancing the

discernment ability of various indigenous plant species, such as *elecampane* and *verbascum thapsus*, which are restricted to a certain region and cultivated exclusively under specified weather conditions, would bolster the advancement of the pharmaceutical sector [3]. Classifying various varieties of flowers is a highly challenging task due to multiple factors. There is a significant amount of diversity in the colors exhibited by flowers within a single class, although there is also a notable resemblance between multiple classes. Even experienced botanists and gardeners may struggle to reliably identify certain plants. However, pre-trained models that have been trained on ImageNet for picture classification can be utilized for other image datasets with minimal data, without the risk of overfitting[26]. The inclusion of diverse elements is a crucial determinant in enhancing the efficacy of ensemble models. Our future work will focus on generating a more diversified network for integration. Nevertheless, there exist certain constraints when it comes to choosing suitable network architectures, parameters, and algorithms, as well as the need for extensive training durations to achieve optimal recognition performance in practical scenarios[27]. The conventional computer visual techniques are inefficient and imprecise. Thus, our study incorporated SSD deep learning technology into the domain of flowers detection and identification[28]. Flower classification is achieved by utilizing Convolutional Neural Networks (CNN) and employing transfer learning within the CNN framework requires a large amount of labeled data for training the models, which can be time-consuming and require expertise in the field. The use of deep learning methods like CNN and transfer learning may require significant computational resources and processing power, which can be a limitation for some applications, especially in resource-constrained environments./ The challenge lies in accurately classifying flowers based on their visual characteristics[29]. Flower recognition is a significant challenge due to the vast number of flower species that exist worldwide. The task is quite tough and requires a significant amount of time. It has primarily been undertaken by botanists./ Inter-class similarities between different species and the intra-class variation among the same species pose a significant challenge in flower recognition[30]. The efficacy of the suggested approach in enhancing performance relative to alternative data fusion methods may vary based on the unique dataset and classification objective., and may not always achieve superior results ,The proposed algorithm does not address the potential issue of class confusion in flower classification, which could affect the accuracy and reliability of the classification system / The study aims to address the problem of flower classification using both image and text data for improved performance[31]. The learning accuracy of MDCNN depends on factors Examples of the information include the learning rates, batch loss values, and the specific sorts of photos utilized to train the model. The performance characteristics of the MDCNN model are compared with those of pre-trained convolutional neural networks (VggNet-16, GoogleNet, AlexNet, and ResNet-50) demonstrating its superiority[32]. The paper does not provide a detailed analysis of the limitations or potential drawbacks of the proposed transfer learning-based method for flower image classification. The specific choices made in fine-tuning the AlexNet model, such as the number of layers replaced and the specific layers retained, are not explicitly justified or discussed in the paper. /The problem addressed in the paper is the classification of flower images using deep learning techniques. The paper aims to improve the classification accuracy of flower images by leveraging transfer learning and a pre-trained AlexNet model[33]. Classifying flowers can be a tough task due to various reasons, including the presence of blurry, noisy, and low-quality photographs, as well as obstructions such as

plant leaves, stems, and insects. The field of object identification, particularly recognizing flowers, poses challenges. Because of the extensive range of flower species exhibiting diverse colors, styles, and sizes, along with their accompanying foliage, shrubs, and other objects./ The field of object identification faces challenges in recognizing flowers due to their diverse colors, forms, sizes, and surroundings. Flower classification has benefited from the use of machine learning techniques and deep neural networks, which have replaced traditional manual ways of extracting characteristics[34].The problem addressed in the paper is the need for an improved flower image recognition method that has higher accuracy, better generalization, and a shorter recognition process[35].The accuracy of the identification may be affected by variations in lighting conditions, camera angles, and other environmental factors, leading to potential recognition failures/The problem addressed in the provided sources is the accurate identification of flower species using deep learning techniques. The existing methods for flower recognition often require extensive manual examination of botanical guides, which can be time-consuming and challenging for non-experts. The goal is to develop a mobile application that can automatically identify flower species based on images captured in a natural environment setting. The application utilizes deep learning models, such as ResNet50V2, InceptionV3, and MobileNetV2, that have been fine-tuned on a custom dataset named FlowerNet. The accuracy of the models is evaluated using a test dataset, and the best performing model achieves an accuracy of 99.74% with a prediction period of 0.09 seconds. The developed mobile application, The inclusion of the dataset and deep learning models can facilitate future study in the field of flower recognition[36].Performs slightly worse in terms of FLOPs (floating point operations) compared to the baseline model (AlexNet)[37]. However, the presence of several diverse flower species is a significant obstacle and adds complexity to the task of accurately detecting and classifying them. Furthermore, the conventional CNN model and other pre-trained models such as VGG16, VGG19, Xception, and MobileNet-V2 were unable to achieve a high level of validation accuracy[38]. Identifying flower species is a difficult undertaking because of the differences in shape, size, , and color among various flower types [39]. Nevertheless, the research recognizes the difficulties encountered by current technologies in the classification of flowers, including issues like overfitting, computational complexity, restricted accuracy, and parameter adjustment./ The goal is to surpass the performance of the most advanced techniques in the classification of flowers and highlight The significance of appropriate data preprocessing and augmentation strategies in attaining optimal performance [40].The research paper addresses the challenge of image classification, Pretrained models have been effectively employed in a notable domain of deep learning. [41].The research paper focuses on the challenges faced in flower category recognition, a fine-grained image recognition task, including insufficient Instances used for training, similarity within the same class, and a lack of precision in recognizing different flower categories[42].The research paper addresses the issue that traditional flower classification methods and standard convolutional neural networks struggle to mitigate the impact of the flower background, leading to suboptimal classification results[10]. [19]. Figure 2. Highlight the number of challenges solved using DL based on each application

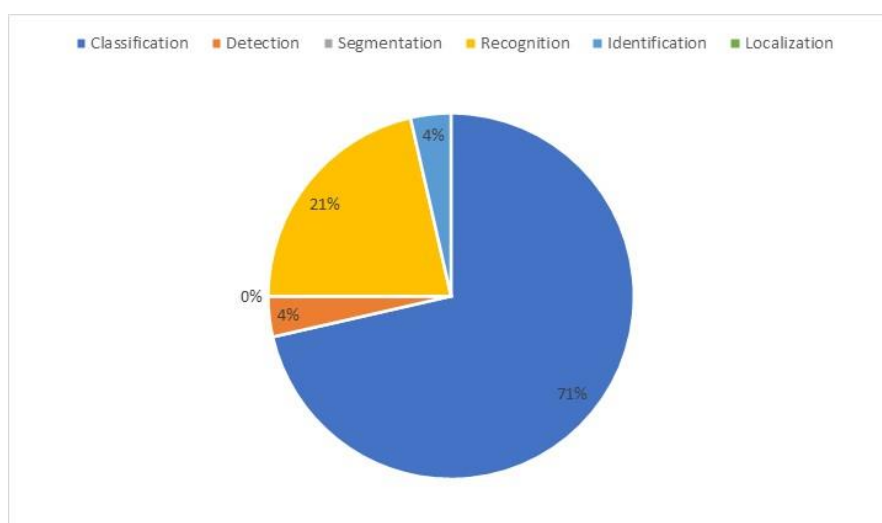


Figure 3. number of applications utilized deep learning in literature review

5. Challenge solved using Hybrid models

Currently, differentiating flowers in image processing systems remains a challenging endeavor. The primary factor contributing to this phenomenon is the shared resemblance in shape and color among many flower species, including grass and leaves, which poses challenges in differentiation[2]. While advancements in deep neural networks and computer vision have improved the accuracy of flower classification, there is still a need for further improvement/ The paper addresses the problem of accurate classification of flowers, which is a challenging task because of the significant diversity of flowers types and species [4]. Manual classification can be subjective and prone to human error, leading to inconsistencies in the results. This manual process is not scalable and may not always yield accurate or reliable classifications[43]. The research paper addresses the challenge of flower classification in the presence of high intra-class variation within the Oxford 102 Flowers dataset[44].

6. AI methods and datasets used in the literature

Different AI techniques and algorithms have been developed and presented throughout the years and various researchers worldwide implemented and enhanced these methods in different applications. Moreover, each AI method required a dataset that was employed to train and improve the results of these techniques. Table 2. Summarizes the machine learning and deep learning methodologies, as well as the metrics utilized for evaluating these techniques, aims of these techniques must be classification-detection- -segmentation- Recognition-Identification-Localization with the metrics used to measure the performance.

Table 2. ML - DL methods in the literature

Ref	DL - ML technique	Metrics Used	Aim
[20]	DL(CNN)	the F1-score average= 0.85, Precision average= 0.85, and Recall average= 0.85. The performance of this model is quite good with 85% accuracy	classification
[21]	DL (NAS-FPN R-CNN)	The maximum average precision (mAP) score achieved was 87.6% on a dataset consisting of 102 flower classes, and	classification, localization,

		96.2% on a dataset consisting of 30 flower classes.	detection,
[22]	DL (MobileNet, DenseNet, Inception, and ResNet)	null	classification
[11]	ML (KNN Random Forest Decision Tree)	System achieves the accuracy of 94.8 %.	detection
[23]	DL (Light CNN)	null	Classification detection
[24]	DL(CNN)	Our approach achieves 76.54% classification accuracy	Classification
[9]	DL(DenseNet121)	achieve the accuracy of 98.6%	Classification
[6]	DL (FCN CNN)	Accuracy: 97% on all datasets	Segmentation Classification
[25]	DL (YOLOv5)	Precision reaching 0.942, Recall reaching 0.933, and mAP reaching 0.959.	detection Classification
[3]	DL (Deep CNN)	Consequently, we achieved a superior level of accuracy of 98.5% for the Oxford 102-Flowers dataset by employing the (SVM) Classifier. The Oxford 17-Flowers Dataset achieved a remarkable accuracy of 99.8% using the MLP Classifier.	Classification
[26]	DL (fine-tuned VGG16 model)	The model attained a classification accuracy of 97.67% for the validation set and 95.00% for the testing dataset.	Classification
[27]	DL(MobileNet)	null	Classification
[28]	SSD	According to the experimental data, the average accuracy is 87.4% using the evaluation standard of Pascal VOC2012, and 83.64% using the evaluation standard of Pascal VOC2007.	detection
[29]	DL(CNN) and transfer learning in CNN VGG16, MobileNet2, and Resnet50	null	Classification
[30]	DL(CNN)	null	Recognition
[31]	DL(CNN)	Accuracy 93.69	Classification
[2]	DL(CNN) and ML(SVM)	The Support Vector Machine (SVM) approach produced a classification success rate of 98.91%.	Classification
[32]	DL (Modified Deep-Convolution Neural Network Model (MDCNN).	accuracy up to 98%,	classification, detection, segmentation
[33]	DL (AlexNet model)	null	classification
[34]	DL(ResNet50)	The accuracy achieved by the Adam optimizer while using the ResNet50 model is 93 percent.	classification
[35]	DL(MobileNetV3)	Higher accuracy: The improved MobileNetV3 achieved recognition accuracy exceeding 99%	Recognition
[36]	DL(MobileNetV2)	got the maximum classification accuracy of 95.90%.	Identification
[37]	DL (Alex Net)	With Oxford 17 achieved accuracy 89.3, With Oxford 102 achieved accuracy 81.5, With China 5 Flower data set achieved accuracy 93.3.	classification
[16]	ML (Multiclass SVM)	The KL University Flower (KLUF) dataset achieves a classification accuracy of 98.3%, while the Flower 17 dataset has a classification accuracy of 97.7%.	classification
[17]	ML (Multiclass SVM)	The model achieved an average accuracy of 79%	classification

[18]	ML (Support Vector Machines (SVM) and Logistic Activation Function (LAF))	The accuracy rates of the two methods are compared, with the Novel (SVM) algorithms achieving a better accuracy of 98.64% compared to the (LAF) algorithm's accuracy of 97.86%.	classification
[4]	(e.g., Random Forest, k Nearest Neighbors, and Support Vector Machine) and deep neural networks (e.g., Resnet, Inception, AlexNet, and DenseNet)	null	classification
[38]	DL We renamed (DenseNet-201 and EfficientNet-B7) as "FlowerConvNet".	95% validation accuracy.	Recognition
[39]	DL (combination of DenseNet201 and MLP)	The model achieves impressive classification results on multiple datasets, including 79.13% on Oxford102, 94.47% accuracy on Kaggle, and 98.23% and 97.35% on Oxford17 for two different protocols.	Recognition
[40]	DL(Xception)	70.03%	classification
[41]	DL(AlexNet, Google net, VGG16, DenseNet, and ResNet)	AlexNet: 86.28% ResNet18: 91.29% Google Net: 89.75% DenseNet201: 93.06% VGG16: 93.52%	classification
[43]	DL+ML (CNN and SVM)	CNN achieved an accuracy of 91.6% in flower image classification	classification
[19]	ML (LBP and SURF as features and SVM as a classifier).	accuracy, accounting for 70% of the evaluation criteria weight.	classification
[42]	DL (novel attention-driven)	achieves the recognition accuracy of 85.7%.	recognition
[44]	ML+DL (Random Forest)	achieving an accuracy of 88.74%	Classification
[10]	DL(VGG-16)	achieved accuracy of 91.9%	Classification Recognition

As for datasets, Table 3. The chosen studies employed diverse types of datasets and different size and types of flowers. Datasets are a crucial component of the object recognition process. Our review of the academic literature identified that researchers utilized self-constructed datasets, publicly available datasets, or a combination of both[45]. That may be available or not.

Table 3. Dataset in the literature

Ref	Dataset size	Types of Flowers	Public/Private
[20]	Every flower has 800 sample images and total of 6400 samples later applying augmentation techniques	(Shiuli, Shapla, Rongon, Radhachura, Rojonigondha, Chapa, Kadam, Kath Golap).	Private
[21]	1)which has a 102-flower kind and a total number 18200 images. 2) One more dataset 6 has a total 30 flowers and a total number 1479 images.	(8189) of Flower102 dataset (3500) of Kaggle's Flower dataset (5) (1360) of Flower17 dataset (5157) of Dataset Accumulated (20)	Public Public Public private

[22]	1)FlowersDataset (5) (3673) 2) Oxford-17 is a flower dataset with 17 different flowers categories and 80 images in each category	2)(daisy, tulip, rose, sunflower, and dandelion)	Public Public
[24]	which contains 79 different type of flowers and 52,775 images	null	private
[9]	Oxford 102-(consists of 40 to 258 images in each category).	null	Public
[6]	The Oxford102 dataset has 8189 images of flowers, divided into 102 categories. Each category has between 40 and 258 images, with varying image sizes. The Oxford 17 dataset involves of 1360 flower images, categorized into 17 different types.consisting of 80 images in each type with varying image sizes. And Zou–Nagy (consists of 612flowers images from 102 classes. Each class contains of six images and each image size are 300×240 pixels).	null null null	Public Public NA
[25]	five types of flowers contained in the dataset (The dataset consists of 400 images, each of different sizes).	daisy, dandelion, rose, sunflower and tulip.	Public
[3]	Oxford 102 Oxford 17	null	Public Public
[26]	five types of flowers contained in the dataset	daisy, dandelion, rose, sunflower and tulip.	Public
[27]	The database contains a total of 3670 flower images, which are categorized into five different species. These images were then split into two sets: a training set consisting of 3320 images and a test set consisting of 350 images. The another database had 1600 images of the identical flower species seen in the first database. The ILSVRC-2012-CLS image classification dataset was utilized as the sole classifiers for extracting features.	dandelion, daisy, rose, sunflower and tulip. sunflower, dandelion, rose, daisy and tulip. null	Public Public Public
[28]	selected 19 public flower images from the Oxford University.	Pink primrose, Balloon flower, Canterbury bells, Sweet pea, English marigold, Hard-leaved pocket orchid, Moon orchid, Bird of paradise, Monkshood, Tiger lily, Snapdragon, Colts foot, King protea, Globe thistle, Yellow iris, Globe-flower, Spear thistle, Purple coneflower, Peruvian lily.	Public

[29]	Kaggle flower dataset (Dataset size is 4323 images splited into training 3890 and testing 433.)	null	Public
[30]	Oxford-17 Oxford-102 FLOWERS32 dataset (32 classes of flower kind). The FLOWERS32 has 2560 images completely and 80 images for each kind.	null null null	Public Public NA
[31]	Oxford 102	null	Public
[2]	The five categories are sunflower, daisy, rose, dandelion, and tulip. The flower dataset comprises 734 images of sunflowers, 769 images of daisies, 784 images of roses, 1055 images of dandelions, and 984 images of tulips.	sunflower, daisy, rose, dandelion, and tulip.	Public
[32]	five categories of flowers	dandelion, daisy, sunflower, rose, and tulip.	Public
[33]	A dataset that covers 5 types and containing 3500 images of various flowers classes with nearly 700 images in each class.	rose, daisy, sunflower, dandelion, and tulip.	Public
[34]	The dataset consists of three distinct groups of images, namely 12,753 training images, 3,712 validation images, and 7,382 test images.	null	Public
[35]	Oxford 102	null	Public
[36]	Oxford 102	null	Public
[37]	Oxford-17 Oxford-102 China 5 Flower,	null null	Public Public Public
[16]	The datasets mentioned are the KL University Flower (KLUF) dataset and the Flower 17 dataset.	null null	NA Public
[17]	The dataset consists of 7 types of sunflowers,	Cherry Rose, Velvet Queen, Early Russian, Fiesta Del Sol, Teddy Bear, Sunny Smile, and Red Sun.	Public
[18]	Iris dataset	null	public
[4]	Kaggle-5, Oxford-17, Oxford-102, and Iris flower	null null null	Public Public public
[38]	The dataset has 4242 images of flowers, which are classified into five distinct categories. These images were obtained from the Kaggle flower recognition dataset.	null	public
[39]	Kaggle Oxford17 Oxford102.	null null null	Public Public public
[40]	The dataset has three data files, namely testing, training, and validation, each containing 16 files. A total of 104 unique flower species were identified.	null	public

	Classified with images sourced from five distinct public repositories.		
[41]	The dataset consists of five classes.	including chamomile, tulip, rose, sunflower and dandelion.	public,
[43]	The total dataset used is 1200, and was obtained randomly using Google image.	The data in the Rose category are 400, Tulip flowers are 400 and Aster flowers are 400.	public
[19]	Oxford17	null	public
[42]	The research paper utilizes the Flowers 17 dataset, which consists of 17 common flowers in the UK, including sunflowers, hyacinths, daffodils, and chrysanthemums, with each category having 80 images with variations in pose, size, and perspective	null	public
[44]	Oxford 102	null	public
[10]	Oxford 102	null	public

7. Conclusion

This paper provides a comprehensive summary of the most recent advancements in data, machine learning and deep learning algorithms are utilized for flowers image classification. It combines insights from over 40 studies published in the previous few years that have utilized machine learning and deep learning techniques to address this topic. The content presented in the whole document can be condensed as follows. Regarding data preparation, the initial step involves the selection of public datasets for training purposes. If the data in the public dataset is not enough, create a new dataset and carry out the required picture pre-processing and data improvement. Regarding model selection, based on the complexity of the problem to be resolved, therefore, based on these findings, we may deduce that the selection of a classification method is entirely contingent upon the specific problem domain and the research work's requirements. In the field of classification, it has been observed that numerous research papers have utilized many feature attributes, such as shape, color, and texture, in conjunction with various feature extraction methods. These studies have consistently demonstrated that using multiple features leads to improved performance compared to using a single feature alone. Deep learning possesses the capability to autonomously extract features and exhibits a robust ability to generalize, hence reducing the need for human intervention in the processing of floral images and significantly enhancing processing efficiency. By iteratively optimizing the model and improving the dataset, deep learning can be more capably utilized in practical applications related to flowers, thus making substantial contributions to human society.

REFERENCES

- [1] C. S. P. Rabindra Patel¹*, "A Review on Flower Image Recognition," . International journal of computer science and engineering 7(12), 206-216, 2019.
- [2] M. Toğaçar, B. Ergen, and Z. J. M. Cömert, "Classification of flower species by using features extracted from the intersection of feature selection methods in convolutional neural network models," vol. 158, p. 107703, 2020.
- [3] T. Ensari and B. R. METE, "Flower Classification with Deep CNN and Machine Learning Algorithms," 2019.

- [4] P. B. Hai, D. A. Tuan, and H. N. Nam, "Performance evaluation of the multiclass classification of flowers on diverse datasets," in *2023 3rd International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, 2023, pp. 1-6: IEEE.
- [5] Y. Chen *et al.*, "Plant image recognition with deep learning: A review," vol. 212, p. 108072, 2023.
- [6] H. Hiary, H. Saadeh, M. Saadeh, and M. J. I. C. V. Yaqub, "Flower classification using deep convolutional neural networks," vol. 12, no. 6, pp. 855-862, 2018.
- [7] C. Chen, Q. Yan, M. Li, and J. Tong, "Classification of blurred flowers using convolutional neural networks," in *Proceedings of the 2019 3rd International Conference on Deep Learning Technologies*, 2019, pp. 71-74.
- [8] I. Patel, S. J. I. J. o. E. Patel, and A. Technology, "Flower identification and classification using computer vision and machine learning techniques," vol. 8, no. 6, pp. 277-285, 2019.
- [9] N. Alipour, O. Tarkhaneh, M. Awrangjeb, and H. Tian, "Flower image classification using deep convolutional neural network," in *2021 7th International conference on web research (ICWR)*, 2021, pp. 1-4: IEEE.
- [10] R. Lv, Z. Li, J. Zuo, and J. Liu, "Flower classification and recognition based on significance test and transfer learning," in *2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE)*, 2021, pp. 649-652: IEEE.
- [11] V. Jain and A. Yadav, "Analysis of performance of machine learning algorithms in detection of flowers," in *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, 2021, pp. 706-709: IEEE.
- [12] R. Kaur, A. Jain, P. Saini, and S. J. E. T. Kumar, "A Review Analysis Techniques of Flower Classification Based on Machine Learning Algorithms," vol. 107, no. 1, p. 9609, 2022.
- [13] P. P. Shinde and S. Shah, "A review of machine learning and deep learning applications," in *2018 Fourth international conference on computing communication control and automation (ICCUBEA)*, 2018, pp. 1-6: IEEE.
- [14] R. Rani, S. Pundhir, A. Dev, A. J. I. J. o. C. I. Sharma, and Applications, "An optimized flower categorization using customized deep learning," vol. 21, no. 04, p. 2250029, 2022.
- [15] N. K. Chauhan and K. Singh, "A review on conventional machine learning vs deep learning," in *2018 International conference on computing, power and communication technologies (GUCON)*, 2018, pp. 347-352: IEEE.
- [16] M. Banwaskar, A. Rajurkar, and D. Guru, "Selected Deep Features and Multiclass SVM for Flower Image Classification," in *International Conference on Cognition and Recongnition*, 2021, pp. 352-365: Springer.
- [17] R. Nuraini, R. Destriana, D. Nurnaningsih, Y. Daniarti, and A. D. J. J. R. Alexander, "Sunflower Image Classification Using Multiclass Support Vector Machine Based on Histogram Characteristics," vol. 7, no. 1, pp. 146-152, 2023.
- [18] B. B. Sri, K. Anbazhagan, and S. Ramesh, "Iris Flower Species Identification Using Support Vector Machine over Logistic Activation Function," in *2023 Eighth International Conference on Science Technology Engineering and Mathematics (ICONSTEM)*, 2023, pp. 1-6: IEEE.
- [19] P. J. I. J. o. I. Dhar, Graphics and S. Processing, "A new flower classification system using LBP and SURF features," vol. 11, no. 5, pp. 13-20, 2019.
- [20] S. Islam, M. F. A. Foysal, and N. Jahan, "A computer vision approach to classify local flower using convolutional neural network," in *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*, 2020, pp. 1200-1204: IEEE.
- [21] I. Patel, S. J. I. J. o. S. Patel, and T. Research, "An optimized deep learning model for flower classification using nas-fpn and faster r-cnn," vol. 9, no. 03, pp. 5308-5318, 2020.
- [22] B. Duman, A. A. J. I. J. o. A. N. Süzen, and Applications, "A Study on Deep Learning Based Classification of Flower Images," vol. 14, no. 2, pp. 5385-5389, 2022.
- [23] J. Ärje *et al.*, "Automatic flower detection and classification system using a light-weight convolutional neural network," in *EUSIPCO Workshop on Signal Processing, Computer Vision and Deep Learning for Autonomous Systems*, 2019.

- [24] Y. Liu, F. Tang, D. Zhou, Y. Meng, and W. Dong, "Flower classification via convolutional neural network," in *2016 IEEE International Conference on Functional-Structural Plant Growth Modeling, Simulation, Visualization and Applications (FSPMA)*, 2016, pp. 110-116: IEEE.
- [25] M. Tian and Z. Liao, "Research on Flower Image Classification Method Based on YOLOv5," in *Journal of Physics: Conference Series*, 2021, vol. 2024, no. 1, p. 012022: IOP Publishing.
- [26] S. Giraddi, S. Seeri, P. Hiremath, and G. Jayalaxmi, "Flower classification using deep learning models," in *2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE)*, 2020, pp. 130-133: IEEE.
- [27] Z. Wang, K. Wang, X. Wang, and S. Pan, "A convolutional neural network ensemble for flower image classification," in *Proceedings of the 2020 9th International Conference on Computing and Pattern Recognition*, 2020, pp. 225-230.
- [28] M. Tian, H. Chen, and Q. Wang, "Detection and recognition of flower image based on SSD network in video stream," in *Journal of Physics: Conference Series*, 2019, vol. 1237, no. 3, p. 032045: IOP Publishing.
- [29] C. Narvekar and M. Rao, "Flower classification using CNN and transfer learning in CNN-Agriculture Perspective," in *2020 3rd international conference on intelligent sustainable systems (ICISS)*, 2020, pp. 660-664: IEEE.
- [30] L. Shi, Z. Li, and D. Song, "A flower auto-recognition system based on deep learning," in *IOP Conference Series: Earth and Environmental Science*, 2019, vol. 234, no. 1, p. 012088: IOP Publishing.
- [31] K. I. Bae, J. Park, J. Lee, Y. Lee, and C. J. E. S. w. A. Lim, "Flower classification with modified multimodal convolutional neural networks," vol. 159, p. 113455, 2020.
- [32] V. Jaiswal, V. Sharma, D. J. M. T. Bisen, and Applications, "Modified Deep-Convolution Neural Network Model for Flower Images Segmentation and Predictions," vol. 83, no. 9, pp. 25713-25739, 2024.
- [33] R. Xiao and R. Wang, "Transfer Learning-Based Flower Image Classification: Leveraging The Pre-Trained Alexnet Model," in *2023 4th International Symposium on Computer Engineering and Intelligent Communications (ISCEIC)*, 2023, pp. 519-522: IEEE.
- [34] K. S. Gill, A. Sharma, V. Anand, and R. Gupta, "Flower Classification Utilisizing Tensor Processing Unit Mechanism," in *2023 2nd International Conference for Innovation in Technology (INOCON)*, 2023, pp. 1-5: IEEE.
- [35] R. Yanbiao *et al.*, "Flower Recognition Based on an Improved Convolutional Neural Network MobileNetV3," in *2023 8th International Conference on Image, Vision and Computing (ICIVC)*, 2023, pp. 688-692: IEEE.
- [36] G. Rajkomar, S. J. I. J. o. A. C. S. Pudaruth, and Applications, "A Mobile App for the Identification of Flowers Using Deep Learning," vol. 14, no. 5, 2023.
- [37] Z. Zeng, C. Huang, W. Zhu, Z. Wen, X. J. M. B. Yuan, and Engineering, "Flower image classification based on an improved lightweight neural network with multi-scale feature fusion and attention mechanism," vol. 20, no. 8, pp. 13900-13920, 2023.
- [38] M. F. Rabbi *et al.*, "An Ensemble-based Deep Learning Model for Multi-class Flower Recognition," in *2023 International Conference on Next-Generation Computing, IoT and Machine Learning (NCIM)*, 2023, pp. 1-6: IEEE.
- [39] J. X. Shee, K. M. Lim, C. P. Lee, and J. Y. Lim, "Flower Species Recognition using DenseNet201 and Multilayer Perceptron," in *2023 11th International Conference on Information and Communication Technology (ICoICT)*, 2023, pp. 307-312: IEEE.
- [40] P. Shourie, V. Anand, and S. Gupta, "Flower Classification using a Transfer-based Model," in *2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, 2023, pp. 1-6: IEEE.
- [41] E. Cengil and A. Çinar, "Multiple classification of flower images using transfer learning," in *2019 International Artificial Intelligence and Data Processing Symposium (IDAP)*, 2019, pp. 1-6: IEEE.
- [42] S. Cao, B. J. M. B. Song, and Engineering, "Visual attentional-driven deep learning method for flower recognition," vol. 18, no. 3, pp. 1981-1991, 2021.

- [43] A. Peryanto, A. Yudhana, and R. J. K. I. J. I. K. d. I. Umar, "Convolutional neural network and support vector machine in classification of flower images," vol. 8, no. 1, pp. 1-7, 2022.
- [44] F. R. Siregar and W. F. Al Maki, "Hybrid method for flower classification in high intra-class variation," in *2020 3rd International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, 2020, pp. 73-78: IEEE.
- [45] H. A. Hussein, M. Ahmed, M. B. Omar, and R. D. Ismael, "Taxonomy, Open Challenges, Motivations, and Recommendations in Augmented reality based on object recognition: Systematic."