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Flower Identification and Quality Assessment using ML and CNN

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***Abstract*— The floricultural assiduity of India is huge and diversified. Other diligence similar to herbal assiduity, drugs, scents, spices, cosmetics, skincare, and medicinal diligence is dependent on the floricultural diligence directly or laterally. That is why it's important to check the quality of the flowers before they're applied to other diligence to maintain thickness in the quality of the flowers and to meet client satisfaction. still, delicate floricultural products are veritably perishable and vulnerable to the external terrain. therefore, exposing them to the external terrain for a long time for quality checking can reduce their overall life. Statistics show that the post-harvest processing loss for fresh-cut flowers can be as high as 31.88, of which the grading loss makes up 21.74. So, it's important to make a system for quality checking and health classification of flowers through image scanning grounded on their appearance. So that, only healthy, fresh, non-infected flowers can be named, and dead, infected flowers can be barred from the process. Because of this force will be reduced for homemade checking and effectiveness will be bettered.**

***Index Terms*— Quality assessment, Quality detection, Healthiness, Flower classification, Machine learning, CNN, Transfer learning**

I. INTRODUCTION

India is rich in its husbandry field. Also, the floriculture assiduity in India is huge. India has significantly advanced in its floriculture sector, flower creation, and import. colorful flowers are used for botany studies. They're used for enduing purposes as well. Most of the time they're used for decoration purposes. Flowers have medicinal properties because of which they're used in herbal products and remedies. Some flowers are comestible and used in different food particulars. Essential canvases are uprooted from flowers which has a vast request. They're a natural source of making scents, spices, and scented canvases which is a wide assiduity. There's a huge request where flowers to be used for skin care, facial products, and hair products. Flowers are important in Indian Ayurveda for their mending purposes and health benefits. Indeed dried flowers are used for making casting and art systems for their visual appeal. They can be used as tea composites for herbal teas. In general, the Cosmetics and Skincare Industry, Pharmaceutical and Herbal Medicine Industry, Perfume and Fragrance Industry, Aromatherapy assiduity, and decoration diligence are dependent on floriculture assiduity directly or laterally.

The floriculture sector is an evergreen sector and its Significance is increasing day by day According to some coffers, loss after post-harvesting was 20- 30 which impacts delicate and sensitive floricultural products. It's important to check the quality of the product. still, the traditional styles of checking flower quality are force-

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ferocious, trouble-ferocious, and time-consuming. This system is total and also it depends on the experience of the people who are checking that. Homemade testing and quality checking of the flowers aren't suitable to meet the request competitiveness of lately cut flowers and standardized products. Due to homemade quality checking, elegant flowers suffer handling damage. They may be touched, or picked, which can beget petal damage, and stem breaking. numerous flowers are largely perishable, and the time spent on quality can largely reduce the time to stay in optimal condition. In the Homemade examination, We've to remove flowers from their ideal storehouse which exposes them to temperature and reduces their lifetime. Also the labor cost increases, and the overall distribution cost of the flowers in the request increases.
Thus, robotization in flower quality discovery processes is needed to increase the effectiveness of this assiduity. Machine learning- a grounded system that will fete and classify the flowers, and describe their quality and vitality grounded on their current structure, shape, texture, appearance, color, tone viscosity, and other parameters by surveying the images through the system. The system can classify flowers according to their dead flowers, infected flowers, non-infected flowers, and healthy flowers and will grade flowers on a scale among one of the classified orders. So that healthy flowers can be used and infected or dead flowers can be barred from the process. This system of Image scanning provides an objective and harmonious way to assess the quality of flowers. Automated systems can increase effectiveness over homemade examinations. This can lead to an accurate vaticination by considering minute details that can be made by humans. This system will give harmonious products while supplying requests with strict quality norms. This technology can be integrated into sorting and grading processes, allowing flowers to be distributed grounded on quality attributes automatically. By directly relating flowers that don't meet quality norms, the system can help reduce waste by ensuring that only high-quality flowers are transferred to request. This helps optimize pricing and distribution grounded on quality situations. Delivering constantly high-quality flowers to consumers enhances their satisfaction and fidelity, encouraging reprise business. The data collected through image scanning can be used to identify trends and areas for enhancement in flower products, leading to inventions in civilization. Overall, this system can increase delicacy and effectiveness. thickness in Quality assessment and therefore encouraging consumer satisfaction.

II. Machine Learning

As humans, we can learn from our former guests and make opinions in the present. In the case of machines, at an introductory position, we've to program an introductory way in them for making some specific task. But to make them work as mortal smarts similar to recognition, classification, and vaticination, we've to feed some data into them and train them on that data using some specific algorithm, this is called Machine learning. In general, it enables computers to learn from their former gets and to make opinions.
Machine learning is like tutoring computers to learn from exemplifications. rather than telling them exactly what to do, we show them lots of data and let them figure out patterns and form opinions on their own. The delicacy of Machines depends on the combinations of algorithms used and the data trained on them. Machine learning encompasses three abecedarian types grounded on the learning style and data characteristics:
Supervised learning: Supervised learning uses a labelled dataset. The primary end is to enable the algorithm to establish a mapping from input to affair, allowing it to make accurate prognostications or groups for new, unseen data. This approach finds common operations in tasks similar to image Classification, spam dispatch discovery, and prognosticating casing prices. Unsupervised learning.
Unsupervised learning: It revolves around training algorithms using unlabelled data, where predefined affair markers are absent. The core idea is to uncover patterns, structures, or connections within the data. Typical tasks include data clustering, dimensionality reduction, and anomaly discovery. exemplifications of this approach include grouping analogous newspapers or reducing data confines for visualization.
Reinforcement learning: Reinforcement learning entails an agent interacting with the terrain and learning to make sequences of opinions to maximize accretive prices.

III. Related Work

Devesh Kumar Shrivastava, Dharmendra Narayan Jha Ref. [1], This paper aims to give a judgment of the health of flowers and identify contagious flowers. In computer networks, customized CNN-grounded simple Direct iterative clustering (SLIC) super pixel segmentation algorithm is used. SLIC super pixel segmentation adapts Kmeans. Features of the scene are taken with the help of a network and colluded average super pixel segmentation. After trimming and dimensionality reduction, features are submitted to a pre-trained classifier which will return a threshold value with which results can be concluded. The perfection rate is 80.

Anuradha Sharma, Abhilash Sonker Ref. [2], K- means were used for segmentation and image preprocessing. By using GLCM, features are removed, and data is then saved in a database for support vector machines (SVM). Then, using a mobile camera, the database is constructed by dropping imperfect (rotten) and faulty (fresh) rose blooms. Using MATLAB interpretation13.0, these methods were made to appear to be real.

YEQI FEI 1,2, ZHENYE LI2, TINGTING ZHU2, AND CHAO NI2 Ref. [3], The goal is to categorise RGB photos of freshly cut rose blooms. statistics about the depths of 434 rose blooms. A stereo binocular depth camera is employed. Under the constraint of small samples, a set of data confabulation outcomes were created in conjunction with the factual product line categorization terrain. The armature was created and improved. To categorise flowers of five specifications, transfer learning was carried out and an appropriate attention medium was used, both of which were based on the ShuffleNet V2 network backbone unit. a class of delicacy Three (RGB) channels RGB and depth channels for the flower dataset categorization time per flower for the 99.915 flower datasets was 0.020 seconds.

*Kanwarpartap Singh Gill, Avinash Sharma *, Rupesh Gupta, Rupesh Gupta Ref. [4],* Deep learning flower classifier that is reliable and effective is built on transfer learning and the most cutting-edge convolutional neural networks. 104 flower species were categorised in the study using images from five public sources. While some classes have many sub-types, others only have one. Images with uncommon backdrops and interesting compositions can be found in the dataset. 12,753 training photos, 3,712 confirmation images, and 7,382 test images make up the dataset. ResNet-50 (48 convolutional layers) is a 50-subcaste convolutional neural network. The proposed ResNet50 model classifies flowers (one MaxPool subcaste and one average pool subcaste) using the Adam optimizer with a time of value 30. Residual neural networks (RNNs) are ANNs that construct networks from residual blocks.

Jiahao Huo, Qicong Qian, Sijie Qiao, Jiaxi Yang Ref. [5], They aimed to produce a cost-effective, largely accurate flower recognition model. Their result introduced a featherlight yet exceptionally precise flower recognition network, using MobileNetV2 as its foundation. To further boost the model's performance, they incorporated an attention medium to punctuate pivotal image features. The attention medium achieved a maximum delicacy of 95.88, while the model lacking this medium reached a maximum delicacy of 93.53. This demonstrates the significance of the attention medium in their model's success (2022).

Ramazan KURSUN, Ilkay CINAR, Y. Selim TASPINAR, Murat KOKLU Ref. [6], In this model, they employed a dataset containing 4,317 images of five different types of flowers. The exploration was conducted in three phases first, deep features were uprooted from the images using the SqueezeNet deep learning armature in a transfer learning approach. In the alternate phase, 1,000 uprooted features were classified using Neural Network and Logistic Retrogression ways from the machine learning. In the third phase, the deep features were optimized using the flyspeck mass Optimization Algorithm (PSO), performing in 488 features, which were also classified again using machine learning ways. The styles employed included Neural Networks, Logistic Retrogression, Transfer learning with CNN, cross-validation, Confusion Matrix, SqueezeNet, and PSO. especially, the study set up that used PSO to reduce the number of features bettered delicacy and reduced classification times, leading to faster results (2022).

Faeze Sadati, Behrooz Rezaie Ref. [7], In this study, the authors introduced a new approach for classifying flowers using Convolutional Neural Networks (CNNs) as point extractors. Unlike traditional styles, CNNs can directly prize useful features from the input data, which are also classified using Support Vector Machine (SVM) machine learning. They conducted trials on two datasets and set up that CNN models with Global Average Pooling (GAP) produced effective features for classifications, achieving advanced delicacy compared to former styles. specially, they employed four prominent CNN models ResNet101, InceptionV3, DenseNet121, and MobileNet. The results demonstrated that their system outperformed recent models, achieving the loftiest average delicacy of 97.64 for the flower dataset" 17" and 96.47 for the flower dataset" 102." (2021).

*Mingzhi He, Huasheng Zhu *, Yongjian Li, Shuyin Tang, Zhaxin Sun Ref. [8],* They offer a novel method called MSDRNet in this research that combines the advantages of ResNet and DenseNet. Instead of using huge complications in the original layers, it uses a complication group with colourful scales of minor complications to reduce parameter complexity. The technique additionally adds thick connections between residual blocks to improve point application, widens residual blocks to collect additional features, and eventually increases delicacy. The suggested technique for classifying floral images, which is based on this conception and ResNet- 50, overcomes block range and scale constraints while exhibiting quick convergence and sophisticated delicacy in comparison to ResNet- 50, VGG- 19, Inceptionv3, and DenseNet- 121. It displays a commitment to categorise vibrant stores and creatures, considerably advancing image classification research (2021).

*Neda Alipour *, Omid Tarkhaneh, Mohammad Awrangjeb, Hongda Tian Ref. [9],* In this study, they employed the DenseNet121 armature and transfer learning to classify 102 different flower species from the Oxford- 102 dataset. After homogenizing and resizing the images, they fine-tuned the pre-trained model, achieving a motional 98.6 delicacy over 50 ages, surpassing other deep-learning styles. their approach involved image pre-processing, algorithm training, verification, and testing. As an unborn work, they also aim to enhance our classifier and extend its connection to colorful classification tasks.
Xudong Wei , Hongyu Zhang, Changkai Shi, Xinyue Yang , Huan han Ref. [10], This paper focuses on classifying lightweight flowers using MobileNetv3 and an enhanced KD method, resulting in improved classification accuracy. Specifically, the model achieves an impressive 98.76% accuracy for smaller-sized flowers. Overall, this study demonstrates significant advancements in lightweight flower classification[2022].
Mrs. Akshata Patil, Mrs.Rama Bansidhar Dan, Mrs.Priya N Ref. [11], This paper introduces a system for classifying distinctive Malaysian flowers through Neural Networks and image processing. Additionally, the paper suggests a technique that combines a* b* color attributes and rare fractional-based texture features for classification of flower, utilizing shape modeling and Neural Networks with KNN for classification, resulting in strong accuracy outcomes[2022].
Muhammed Yildirim , Ahmet Cinar , Emine Cengil Ref. [12], This paper introduces a method for identifying various types of flowers, designed to assist non-experts in flower recognition using mobile phone images. The approach leverages pre-trained deep classification models to extract feature maps from the image dataset. The research employs a Subspace Discriminant classifier, achieving a notably high accuracy rate. The paper provides a clear overview of the methods, classifiers, optimization techniques, and the achieved results[2021].
Dr. Shantala giraddi, Dr. shivanand seeri, Dr. P.s. hiremath, Dr. jayalakshmi g.n Ref. [13], This paper delves into the various attributes of flowers, including their medicinal, culinary, and visual appeal qualities. It places particular emphasis on the rarity of flowers, which proves valuable for botanists, campers, and medical practitioners. The paper introduces a system capable of extending its applications to image searches, making use of photos for flower identification. This innovation holds great potential in fields like floriculture and the development of harvesting robots. Despite challenges related to variations in color, class similarities, and external factors, the creation of an automated flower recognition system is stressed as essential for saving time, assisting newcomers in the field, and supporting commercial ventures such as floriculture. The methodology involves implementing transfer learning through the VGG16 architecture for the classification of flowers, encompassing model setup, compilation, fitting, evaluation, and prediction[2020].
R. Murugeswari, Kumbham Bhanu Sai Teja, Kasi Vishwanath Nila, Kurivelu Venkata Prabhas, V. Raja Dhananjeyan Ref. [14], This study employs Convolutional Neural Networks (CNNs) and transfers classification to recognize flowers, vital for botanical and medicinal research. Using a dataset of 3670 flower images categorized into 26 classes, the CNN architecture includes convolutional layers, max-pooling, and a SoftMax output for classification. The methodology covers dataset prep, CNN training, and validation with data augmentation and transfer learning. Results show the model's superior accuracy over regular CNNs, AlexNet, and GoogLeNet. In summary, CNNs and transfer learning enhance flower recognition, improving accuracy in identifying flower species and addressing real-world challenges like flower identification.
Rongxin Lv1, Zhongzhi Li2, Jiankai Zuo3, Jing Liu2 Ref. [15],* This study tackles the difficulty of flower classification amid background interference using deep classification, specifically Convolutional Neural Networks (CNNs). It introduces a method for extracting saliency areas in images through spectral residual analysis and Gaussian blur. The efficient VGG-16 model is chosen for classification, optimized using stochastic gradient descent and dropout to prevent overfitting and transfer learning from ImageNet. Experiments on the Oxfordflower-102 dataset yield rapid training and validation improvements, achieving over 85% accuracy in 25 iterations and outperforming traditional methods with a 91.9% accuracy. In conclusion, this approach effectively handles flower image classification challenges, making it suitable for flower identification tasks.
Shital Pawar, Wagisha Raj, Suruchi Bibikar, Bhakti Patil, Shubhangi Kumari, Anjana Patil Ref. [16], This project employs Convolutional Neural Networks (CNNs) and TensorFlow for precise flower species identification. It underscores the need for a specialized system due to the challenges in flower recognition. The literature review highlights prior work, especially with CNNs and transfer learning, identifying research gaps. The project's scope covers the identification of five flower species and their diverse user benefits, driven by a personal interest in flower recognition. The methodology outlines steps, including data processing and CNN models, and introduces Gradio for user-friendly interaction. Impressive results show approximately 98.68% accuracy with the Keras model. In summary, this project effectively uses CNNs, notably the Keras model, for precise flower classification, offering room for improvements and a user-friendly interface through Gradio.

Mattapally Sai Nithin, Ayesha Shaik Balasundaram, Kovvuri Uday Surya Deveswar Reddy, Lakshmi Sai Ram Kakarla, Selvakumar A. Ref. [17], This paper explores deep classification using VGG19 and EfficientNetV2L architectures for flower classification, achieving notable accuracies of 88.21% and 96.28%, respectively. It highlights the complexity of distinguishing similar flowers and underlines the importance of CNNs and transfer learning. The related works section surveys prior research using various architectures like DenseNet121 and ResNet, showcasing datasets and results. The proposed methodology explains CNN components, preprocessing, and dataset details, including 15,740 images from Kaggle. Image resizing to 224x224 is discussed for efficiency. The paper introduces VGG19 and EfficientNetV2L architectures, their fine-tuning, and the use of ImageDataGenerator. Experimental results compare their performance, emphasizing their superiority. In conclusion, the paper acknowledges the flower classification challenges and celebrates the success of deep classification, hinting at further advancements in the field.
Mingzhi He, Huasheng Zhu, Yongjian Li Ref. [18], This work describes the classification of floral images using multi-scale dense residuals. ResNet-50 forms the basis of the algorithm. Four components make up the algorithm utilised in this study: the stem, the dense layer, the transition layer, and the linear layer. This study tests four trained models—ResNet-50, VGG-19, Inceptionv3, and DenseNet-121—against 3670 picture samples of five different kinds of flowers. The public database tf-flowers from Tensorflow is used in this paper for model training. The five types of flowers in the database are tulips, roses, daisies, and dandelion.
Mingyu Qiao, Xiao Liang, Minjie Chen, Ying Guo Ref. [19], In order to create a novel algorithm to enhance the classification of flowers, this work combines GAN with ResNet. Images can be produced using GAN to expand the data set and produce better data while classifying smaller datasets. Deep convolution generative adversarial networks are an efficient unsupervised training model that is extensively used. It is more stable than GAN, easier to scale, and has good quality. This paper first generates images of five different flower varieties using the DCGAN model. To categorise the short batches of images produced by DCGAN, it use VGG19. Then, it generates photos that are accurately categorised using the M4 model with the best classification effect.
Mingzhi He, Huasheng Zhu, Yongjian Li, Shuyin Tang, Zhanxin Sun Ref. [20], They employed a transfer learning methodology to differentiate flowers and created a flower classification method based on a CNN. For the extraction of features, they used the VGG19 CNN architecture. They divided flowers into 17 different classes, therefore using the softmax activation function, we employed 17 neurons in the final dense layer of the VGG19 convolution neural network design. The supplied dataset is divided 80:20 across training and testing halves. Each of the 17 flower categories in the Oxflower 17 data set has 80 photos. 1360 photos with labels and a size of 224x224x3 are included in the dataset. The classification of flowers has accuracy of 91.1%, according to the results.
Shital Pawar, Wagisha Raj, Suruchi Bibikar, Bhakti Patil, Shubhangi Kumari, Anjana Patil Ref. [21], By creating a CNN, a highly effective model for image classification, the proposed flower detecting method is put into practise. The system employs CNN and Tensorflow to recognise images. Classifying flowers is done using CNN and Deep Classification, despite the fact that they constructed a web application. Alxmamaev's dataset from Kaggle, which included roughly 3400 floral photos, was used. Image scaling, noise filtering, and RGB to Grayscale conversion are the first steps in the preparation of images. Using the Otsu thresholding method, the image segmentation is complete.Both ResNet50 and ResNet18 were applied.With scores of 73% and 83.48%, respectively, the value accuracy we used to transfer learning (resnet50) and ResNet18 outperformed regular CNN.
Boda Venkata Nikith1, Masabattula Teja Nikhil1, Mutyala Sai Siddhartha1, Murali K2 Ref. [22], There are 4326 flower photos in the dataset used to train the CNN network. Each image has a 320x240 pixel resolution. The primary focus of this research is on how LIME interacts with image data. The model's input image is converted into superpixels by Lime, which then produces various visual perturbations before making predictions for each sample. The super-pixels of each sample will be given equal weights based on the predictions. Four convolution layers, four max-pooling layers, and dense layers with RELU activation make up the CNN model.
Xu Xianchong, Gao Yuanyuan Ref. [23],* The dataset for this paper design includes 4242 pictures of flowers. Google Image data is used to obtain data based on Flickr photographs. The dataset is taken from the Internet, and the popularity of photographs, so the trained model gives better results, as compared to the traditional Oxford-17 flower dataset in 2006. It is discovered through comparison that CNN performs classification better than the conventional shallow classification method. The accuracy is 97% at 100 iterations. The model exhibits overfitting, and the test set's accuracy is only about 68%.
Saiful Islam, Md. Ferdouse Ahmed Foysal, Nusrat Jahan Ref. [24], Although they have only worked on a small number of image sets at this time, they have developed a method in this research for categorising native flowers from Bangladesh using their image collection. Their current model was trained using CNN to increase model accuracy after they first worked to construct their own dataset using local flowers, including (chapa, Kadam, Kath

golap, Shiuli, Shapla,Rongon, Radahachura, and Rojonigondha). This CNN model exhibited test accuracy of about 85%.

Dr. Shantala Giraddi, Dr. Shivanand Seeri, Dr. P. S. Hiremath, Dr. Jayalaxmi G.N Ref. [25], With a variety of deep-classification models, the author investigated flower classification. They used the Kaggle dataset, which includes 5 kinds of floral photos. The five processes in this methodology are data splitting, processing, training, fine-tuning VGG16, validating the model, and testing the model on the test dataset.

Eisuke FUKUYAMA, Tomotaka KIMURA, Nobuhiko ITOH and Takefumi HIRAGURI Ref. [26], This research explores the use of machine learning and drones for tomato flower pollination in smart agriculture. Drones are used to identify and pollinate flowers, and machine learning is employed to classify flower shapes and stages. The study focuses on the challenges of low-resolution drone cameras and the need for data size reduction. It also presents results of classification accuracy and discusses the potential for further improvement. The research is supported by grants from relevant institutions.

Pheeraphat Sarikabuta, Siriporn Supratid Ref. [27], This paper examines the impact of layer sizes in ResNets on flower image classification using the Oxford-102 dataset with 10, 50, and 102 classes. Three ResNet models (ResNet50, ResNet35, ResNet17) are compared via 10-fold cross-validation. While ResNet35 slightly outperforms the others, the difference is less than 0.71% in accuracy. Considering ResNet35's 33% more parameters, ResNet17 is recommended for its comparable performance with fewer resources.

IV. OBSERVATION TABLE

TABLE I. OBSERVATION TABLE

Sr.No.	Year, Dataset Used:	Methods Used	Performance Metrics	Challenges
1.	2022, primary dataset for hibiscus flower	CNN, simple linear iterative clustering (SLIC) super Pixel algorithm	97.2% Accuracy	Other CNN Deep learning models can also be taken into consideration to judge and compare their accuracy.
2.	2019, Several types of Rose flowers are collected	SVM, DIP(digital image processing)	Accuracy 70%	No valid (or we say customized training and testing) dataset is available because no work done till now regarding detection of defected rose and healthy rose hence we cannot cross-validate our work and compare the result of our work.
3.	2023, data of 434 rose flowers	ShuffleNet V2 network backbone unit, transfer learning was performed	Accuracy:98.891%	They plan to expand this approach to more types of flowers in the future
4.	2023, Sample image of (a) Common Dandelion (b) Morning Glory (c)Wild Rose (d) Spear Thistle (e) Sweet William (f) Iris (g) Thorn Apple (h) Common Dandelion (i) Bolero Deep Blue (j) Hippeastrum (k) Toad Lily (l) Pink Yellow Dahilia (m) Tree Poppy (n) Sunflower (o) Camelia (p) Mangolia	ResNet-50 Artificial neural networks	Accuracy:93%	-
5.	2022, Oxflower 17 data set contains 17 category flowers with 80 images	Transfer Learning VGG16 VGG19	Accuracy:91%	-
6.	2022, Kaggle flower dataset	CNN ResNet50 ResNet18 KERAS	Accuracy: ResNet50: 73% ResNet18: 83%	-
7.	2022, google images, and yandex images	CNN	Accuracy:92%	-
8.	2022, Kaggle website. A total of 15,740 flower images had been collected which consists of 16 different	Transfer Learning VGG19 EfficientNetV2L	Accuracy: 96.28%	Lower Model Speed

	flower classes some of them are Astilbe, Bellflower, Sunflower, tulip, and waterlily			
9.	2022, Kaggle Dataset consist of total 3500 photos with 5 different classes	CNN Tensorflow	Accuracy:98.68%	Design of CNN needed to be improve.
10.	2022, 3670 photos of various flowers, Tensorflow flower Dataset	GoogleNet AlexNet Transfer Learning CNN	Accuracy:99.87%	Accuracy Level is low
11.	2021, Oxford flower 102	Transfer Learning VGG16	Accuracy:91.9%	-
12.	2021, Oxford-17 flower dataset	CNN VGG19 AlexNet SVM	Accuracy: 95.34%	Model Speed is low
13.	2022, Ocford 102 flowers images	ResNet17 ResNet35 ResNet50	Accuracy:0.706%	Low Accuracy
14.	2021, fine-tuned for the classification flowers into five categories, namely, Daisy, Dandelion, Sunflower, Rose and Tulip flowers	CNN(Convolution neural network), VGG16 Deep Learning Transfer Learning	Accuracy:97.67%	Very small dataset
15.	2022, Oxford-17 Category Flower Dataset, Oxford-102 Category Flower Dataset.	Improvements of VGG-16 Network , MobileNetV2, SENet, Transfer learning	Accuracy:95.88%	System can only identify one flower at a time in the picture, low accuracy
16.	2021, 5-class flower dataset consisting of chamomile, dandelion, rose, sunflower and tulip flowers	Neural Network , Logistic Regression , Convolutional Neural Networks , Transfer Learning, SqueezeNet ,Particle Swarm Optimization Algorithm	Acurracy:90.1%	Dataset used is small, time complexity is more
17.	2021, Oxford 17, Oxford 102	CNN models,(ResNet101, InceptionV3, DenseNet121, and MobileNet),SVM,	Accuracy:97.64% , 96.47%	Work can be expanded in more wider study related areas
18.	2021, The database includes 5 classes of flowers: daisy, dandelion, roses, sunflowers, tulips	Multi-scale dense residual network,ResNet-50, VGG-19, Inceptionv3, and DenseNet-121,MSDRNet	Accuracy:87.91%	Less accuracy, dataset can be extended for more vital species
19.	2020, 8 local flowers like Chapa, Kadam, Kath Golap, Shiuli, Shapla, Rongon, Radhachura, Rojonigondha	CNN with Adam optimizer	Accuracy:85%	Fresh counting approch for detecting freshness can be worked upon, can go for larger size of dataset
20.	2021, Tomato Flower	CNN , Deep learning	Accuracy:96.9%	A lack of learning images and a change in brightness at the preprocessing stage.identification by other methods can be workes upon.
21.	2021,oxford 102	CNN,transfer learning employing DenseNet121,robust deep learning	Accuracy: 98.6%	For more accurate and effective deep network can be build for flower image classification and for expanding the work in other classification applications
22.	2022 Oxford 102 flower	MobileNetv3, Knowledge distillation	Accuracy:98.76%	-
23.	2022, Caltech-UCSD flower 200	Deep Convolution Neural Network	Accuracy: more than 80%	The dataset of flowers should be presorted.

		Feature extraction Unsupervised learning algorithm Tenser flow		
24.	2021, Kaggle dataset of 10 different types of flowers: Tulips, orchids, peonies, hydrangeas, lilies, gardenias, garden roses, daisies, hibiscus, bougainvillea	MobilenetV2 Alexnet architectures NCA size reduction methods	Accuracy: 94% Accuracy in pre trained deep learning architecture :84%	-
25.	2020, Kaggle dataset of five flowers: Daisy , dandelion , sunflower, rose, tulip	Convolution neural network Transfer learning Deep learning Fine-tuning VGG16 model	Accuracy: For validation:97.67% For testing dataset: 95%	The use of larger dataset is not implemented yet.
26.	2021, tf_flower dataset	ResNet 50 MSDRNet, DenseNet-121, Inceptionv3, VGG-19	Accuracy:87.91%	-
27.	2021, Tulip dataset	DCGAN, VGG19, ResNet model	Accuracy:-	-

V. PROPOSED SYSTEM

The system architecture consists of a Front End, Back End, and Database. The front end consists of image classifier, identification, detection, and recognizing properties while the back end consists of classification and its validation and information retrieval.

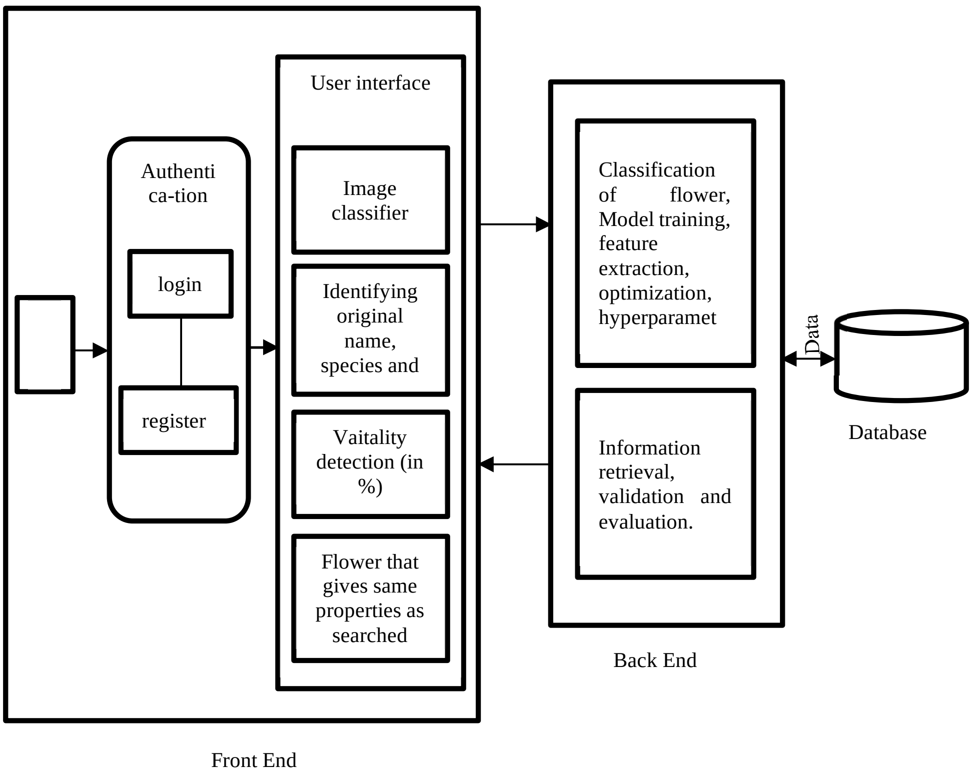

Figure 1. Proposed System

VI. METHODOLOGY

The diagram shows the basic flow of model building and how it will work. Involves feature extraction and steps to classify a flower. If the user wants to know more about the flower like its properties and rareness then it will further gives the percentage of its rareness and in which area it is available. Diagram will help to understand the basic flow and steps to be followed to achieve expected result.

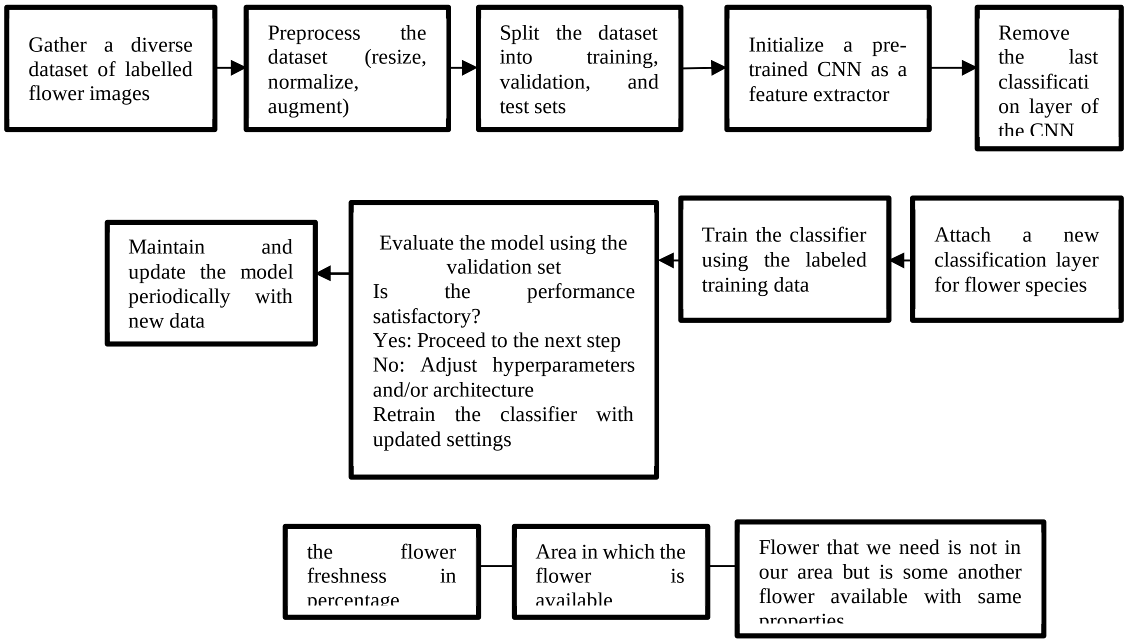

Figure 2. Methodology Sequence

VII. CONCLUSION

Output research focusing on the flower quality assessment. We have understood the need for the Development of a flower grading system that evaluates the quality and healthiness of flowers. The implementation of this system will significantly improve the efficiency of the floriculture industries. With this understanding, we are excited to contribute to this field and make advancements.

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