Knowledge Extraction through Floweret Recognition using ML and DS: A Sustainable Approach for 21st century Agriculture and Smart Cities

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Abstract--Recognizing flowers presents a formidable challenge due to the considerable similarity among various species in terms of size, shape, color, and the presence of surrounding elements like leaves, grass, petals, sepals,and stems. In this study, the authors propose an innovative two-stage deep learning classifier aimed at distinguishing between various species of flowers. Initially, an automated blossom segmentation process is employed to isolate the flower region, facilitating the creation of a minimal bounding box around it. This segmentation step is integral for narrowing the focus to the relevant flower area and minimizing the impact of extraneous visual information. Subsequently, the authors develop a robust convolutional neural network (CNN) classifier tailored for different types of flowers. The CNN is designed to effectively capture and differentiate the diverse characteristics of various flower species. The combination of these two stages—segmentation and classification—provides a comprehensive approach to enhance the accuracy of flower recognition, particularly in cases where species exhibit similarities in size, shape, and color.To better define flower recognition, our team first applied CNN (Convolutional Neural Network) with one, three and four convolutional layer and then ResNet50 pre-trained model in which we found fixed and best accuracy in comparison to others. From CNN with four-convolution layer we attain the accuracy of 97.1%

MOTIVATION

Flower identification techniques are used in agriculture to monitor crop health, optimize pollination, and determine what effects plants have can be used to detect various diseases or pests. This could drastically increase crop yields and promote more sustainable agricultural practices and also Flower identification apps and other tools can empower citizen scientists and nature lovers to contribute to scientific research by collecting data on plant species. This crowdsourced data could prove to be excellent for broader ecological and botanical studies. Flower recognition can make learning in the fields of botany and plant diversity much more engaging and accessible to students and the public. It can be used as an educational tool to promote environmental awareness and appreciation of nature.

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SCOPE of the STUDY

First, we will decide on the types of flowers whether we will focus on recognizing a specific type of flower (for example, roses, daisies, orchids) or a wide range of flower species. The more specific our focus is, the easier it will be to collect and process data.We will then specify the methods and techniques we will use to identify flowers. This may involve computer vision, machine learning, or deep learning algorithms. We will also clarify whether we will be working with images or other data types (e.g., leaf shape, petal color).

TOPIC ORGANIZATIONS

This study, gives a general idea of flower identification today. The author described the flower identification activity that has been carried out since ancient times. The author conducted a literature survey and reviewed ten research papers on related topics etc. This literature survey provides in-depth information about flower identification and various flower identification experiments.The author has described the methodology he used to represent the study. This study used DS (Data Science) based critical analysis of data where data collected from Oxford 102 analyzed. Furthermore, the paper discusses the arrangement of collecting data which is presented in a logical sequence resulting in an unbiased result.The manuscript also presents all data in graphical and tabular form. The novelty section refers to elements that are new in the research. Finally, the findings section represents the final evaluation and describes the overall findings of the study.

I. INTRODUCTION

In this project, a novel flower recognition system leveraging image processing techniques has been created. The system employs edge and color features extracted from flower images to facilitate accurate flower classification. The application of the seven-moment algorithm contributes to the extraction of edge features, while characteristics such as red, green, blue, hue, and saturation are derived from the image histogram. Recognizing that flowers serve as the most visually captivating and distinctive aspects of plants, the system aims to enhance plant knowledge through accurate flower identification. By focusing on the fundamental characteristics of color and shape, the model is trained to successfully identify unknown flowers, thereby advancing its recognition capabilities.

A. Agriculture of Food and Flower Plants in South Asian Continent

A significant portion of Asia faces challenges in terms of arability, primarily attributable to adverse climate and soil conditions. Conversely, regions boasting optimal yields exhibit exceptionally intensive farming practices, facilitated by the irrigation of fertile alluvial soils in major river deltas and valleys. Predominant crops in Central Asia, such as rice, sugarcane, and sugar beans, particularly thrive in environments with abundant water resources. While rice necessitates extensive irrigation, other crops and grains can be cultivated using only natural rainfall. A noteworthy advancement in Asian agriculture involves the adoption of high-yield varieties of grains, contributing to increased productivity per acre. This agricultural transformation, witnessed since the late 1960s, is credited to the widespread adoption of new technologies, marking a collaborative effort in enhancing crop yields across many Asian countries.**(11)**.

Food security persists as a significant concern in the subcontinent. Government policies continue to prioritize grain self-sufficiency, leading to a substantial allocation of land for grain cultivation. While nations such as Bangladesh, India, and Sri Lanka have attained national food security, the emphasis remains on augmenting the production of rice and wheat. Conversely, countries facing deficits in food grain production, such as Bhutan, Nepal, and Pakistan, are earnestly working towards enhancing their agricultural output.**(12).**

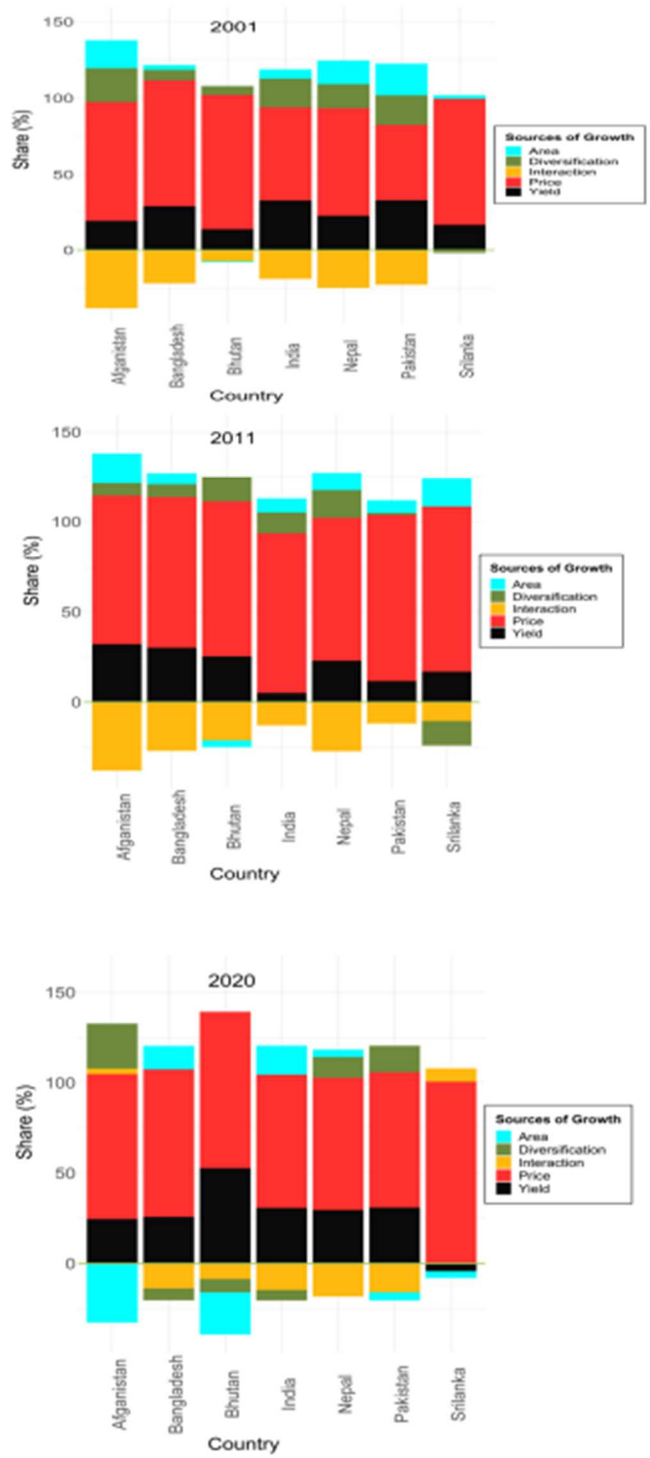

Figure 1. Sources of agricultural growth in different countries of South Asia (2001, 2011, and 2020)
Image URL- https://www.mdpi.com/2071-1050/14/15/9363

In the figure we have shown the country wise source of growth % share for the years 2001, 2011 and 2020. In this we have found out how much source of growth has happened in which country with each year's update or how much in the last few years**(as per Figure 1).**

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B. Flowers have Herbal and Medicinal Properties

Dried flowers and plant parts find utility in teas and extracts, known for both relaxation and medicinal advantages. Various flowers, including chamomile, lavender, rose, hibiscus, marigold, chrysanthemum, and jasmine, are commonly incorporated into teas. The aromatic oils present in flowers contribute to their distinctive scents and possess pain-relieving properties. Extracted essential oils from flowers play a crucial role in stimulating the body's natural healing processes by restoring normal biochemical and physiological functions. These oils, rich in minerals and vitamins, are concentrated and used to treat various diseases. Essential oils, typically derived through steam extraction from volatile oils in flowers, are easily absorbed by the skin, making them central to aromatherapy. Aroma therapeutic practices often involve the application of these oils in soothing massages, with scents like rose, jasmine, and lavender being favored choices. Chamomile, with a history of herbal medicinal use, remains popular due to its array of bioactive phytochemicals, suggesting enduring therapeutic potential **(13).**

C. Global Importance of Floweret Recognition in Health and Mental Fitness

Receiving flowers is universally cherished, and beyond aesthetic appeal, it offers unexpected health benefits. Plants, including flowers, enhance air quality and uplift the ambiance at home. As a florist, you play a role in positively impacting people's mental well-being by providing them with beautiful bouquets. Whether gifted to spread joy or purchased for personal solace, flowers have the potential to brighten someone's day. Recent studies reveal that the presence of flowers contributes to improved mood, reduced stress-related depression, and elevated positive energy levels. Aesthetically pleasing environments, enriched by flowers, promote productivity and happiness. Just as being surrounded by nature's beauty outdoors is uplifting, incorporating floral elements into indoor spaces, whether at home or work, proves to be a therapeutic remedy, especially during challenging times **(14).**

D. Knowledge Extraction through Project Data Collection

To extract knowledge through flower identification project data collection, we have to follow a structured process. This process will typically include collecting, cleaning, and analyzing data. Here we have given the steps that should be followed.

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Define the Project Scope-Here we will clearly define the goals and objectives of our flower identification project. Through this knowledge extraction process we want to achieve:

Data Collection- Here we will collect a diverse dataset of flower images. This can use a variety of sources such as online image stores, botanical gardens, or your own photos. This allows us to ensure that the dataset represents different flower species, colors and variations. We will organize our data in a structured format preferably separating it into training and testing datasets.

Data Cleaning-In this process, we aim to eliminate undesired entries in our dataset, which may encompass duplicates or irrelevant observations. Duplicate data is a common occurrence, arising from various sources such as combining datasets from multiple locations, scraping data, or receiving information from clients or diverse departments. The amalgamation of data from these varied sources often results in the inadvertent inclusion of duplicate observations, necessitating their identification and removal for data integrity and accuracy.

Knowledge Extraction-In this we will analyze the predictions and errors of the model, Identify patterns and insights from the model's predictions. For example, which flower species are most accurately identified, and which are more challenging. Understand the importance of various characteristics (e.g., petal shape, color) in the model's decision-making process **(15).**

E. Scientific Data Analysis and Strategy and Decision Making

The vast scale of big data renders traditional data analysis tools impractical. Scientists harness this extensive data landscape to extract valuable insights, enabling data-driven decision-making in the face of an escalating focus on performance excellence. The generation of knowledge from data has become pivotal for evidence-based decisions, supporting key strategic and policy considerations. Core competencies and work systems are shaped by these decisions to enhance overall organizational performance. To effectively address strategic challenges, organizations must leverage data science techniques to identify patterns and formulate strategies based on customer, market, and operational data. The utilization of data visualization tools ensures seamless communication of knowledge to stakeholders, facilitating a comprehensive understanding of consequences and guiding appropriate actions. In the contemporary digital environment, diverse devices like mobile phones, desktops, laptops, wearables, and those connected to the Internet of Things generate, capture, and store a myriad of data types.**(16).**

F. Applying Scientific Temperament in Flower Scent and Herbs Industry

Flavor and aroma play a crucial role in the beverage and food industries, and obtaining these essential compounds involves biosynthesis or extraction methods. Due to the vast array of chemical structures associated with flavor and aroma, the discovery of new compounds poses a significant challenge for both academic and industrial research. This overview aims to present the current state of biotechnology in beverage aroma, incorporating recent advancements in sensing, sensor methods, and statistical techniques for data analysis. It encompasses the latest findings in food fragrance biotechnology, exploring fragrances derived from natural sources through extraction processes (utilizing plants as a primary flavor source) or enzymatic precursors (involving hydrolytic enzymes). Additionally, it covers compounds obtained through de novo synthesis, such as microbial respiration or fermentation of substrates like glucose and sucrose, with applications in both beverage aroma manufacturing and product development. The overview extends to sensory and sensor methods developed for the quality assessment of fragrances **(17).**

G. Global Usage of Analysis Based Strategies in Floweret Agriculture and Their Impacts

Agriculture and climate change share intricate connections, with climate change serving as a primary cause of both biotic and abiotic stress, thereby adversely affecting the agriculture of a given area. The impact ofclimate change on land and agriculture is multi-faceted, involving variations in annual rainfall, average temperature, heat waves, and modifications in weeds, insects, microorganisms, atmospheric CO2, ozone levels, and sea level fluctuations. These variations pose a significant threat to global crop production, raising concerns about food security on a global scale. Forecast reports highlight agriculture as one of the most endangered activities due to climate change. As a result, the focus has intensified on issues related to food security and ecosystem resilience worldwide. To mitigate the adverse effects of climate change, climate-smart agriculture has emerged as the key approach. Emphasizing the need for proactive crop adaptation, climate-smart agriculture aims to address the challenges before they significantly impact global crop production**(18).**

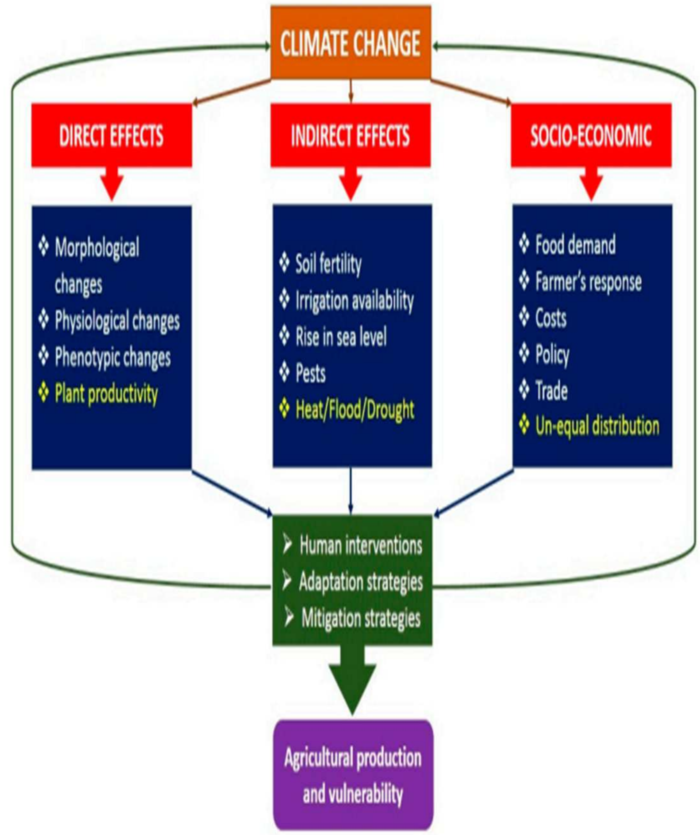

Figure 2. Direct, Indirect and Socio-Economic Effects of Climate Change on Agricultural Production Part.
Image URL:
www.ncbi.nlm.nih.gov/pmc/articles/PMC6409995/pdf/plants-08-00034.pdf

This figure tells us about the negative impact of climate change on agricultural production and vulnerability, first direct effect, second indirect effect and last socio economic with the help of Human interventions,Adaptation strategies and Mitigation strategies **(as per Figure 2).**

H. Knowledge Tree and Knowledge Dimensions for Different Walks of Life

A "knowledge Tree" and "Knowledge Dimensions" are a way to visualize and classify knowledge in different fields and areas of life. Here, I will provide a high-level overview of what a knowledge tree might look like and the dimensions of knowledge that can be applied to different areas. Keep in mind that this is a simplified representation and knowledge is often interconnected, so these categories may overlap or be mixed in reality.

Knowledge Tree-A knowledge tree is a structure that categorizes knowledge into different branches or domains. It can be thought of as a tree with the trunk representing the basic knowledge and the branches representing subfields or specialized areas

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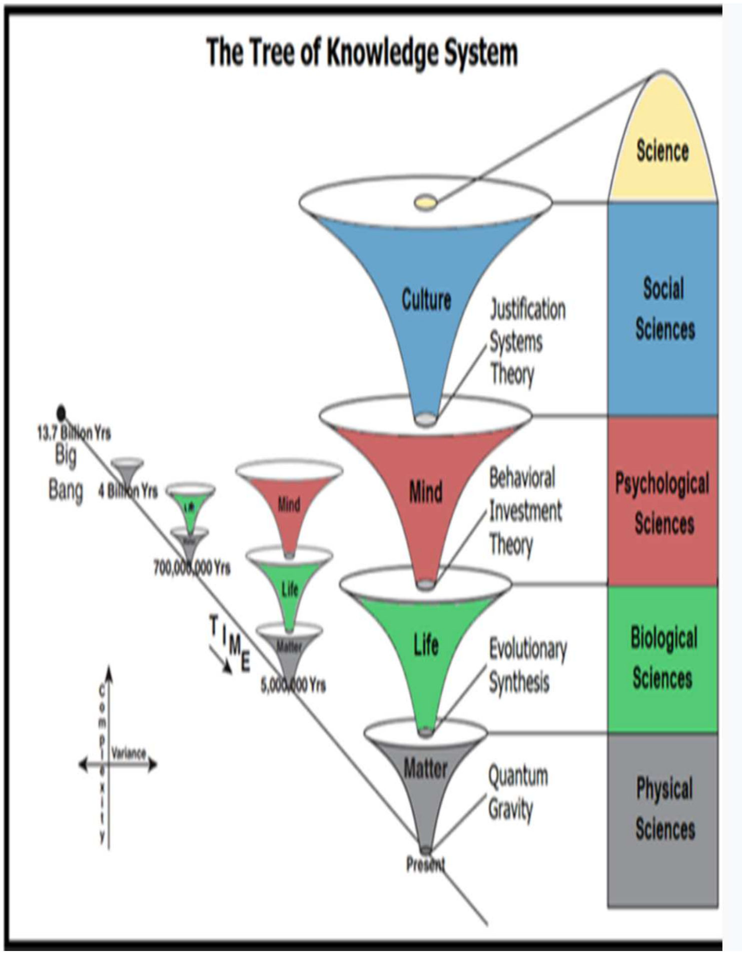

Figure 3. The Tree of Knowledge System
Image URL:https://arxiv.org/pdf/2002.00388.pdf
The Tree of Knowledge (TOK) system presents a novel framework for Big History, mapping the evolution of the cosmos across four distinct levels of existence: matter, life, mind, and culture. These levels correspond to the physical, biological, psychological, and social domains, respectively.**(As per Figure 3).**

Knowledge Dimensions-The analysis of knowledge involves examining its various dimensions and characteristics to better understand its nature and application. These dimensions are applicable across diverse areas of knowledge. The knowledge dimension is categorized into four types, spanning from concrete knowledge to abstract knowledge. These categories play a crucial role in shaping decisions related to what to teach and how to teach it, influencing instructional content and the selection of instructional methods and activities **(19).**

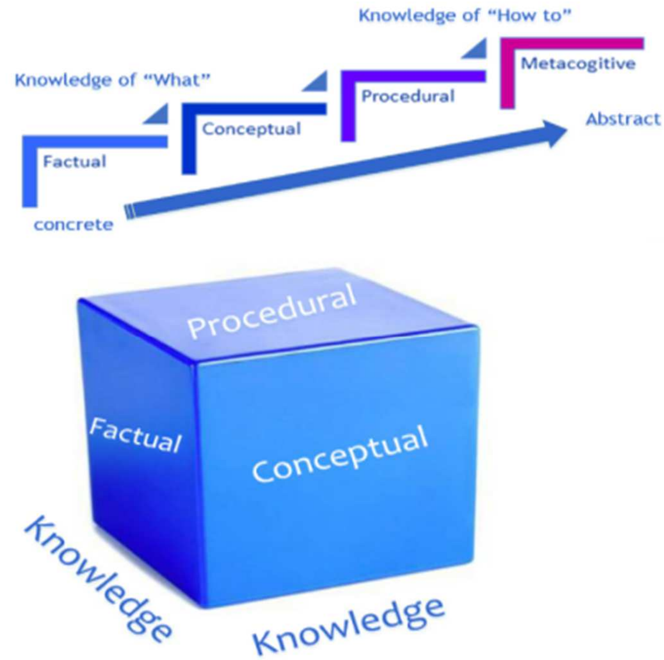

Figure 4. The Dimensions of Knowledge System
Image URL-https://arxiv.org/pdf/2002.00388.pdf
Factual Knowledge refers to the fundamental elements essential for learners to be familiar with a discipline or address problems. Conceptual Knowledge involves understanding the interrelationships among these basic elements within a larger structure, facilitating their cohesive functioning. Procedural Knowledge pertains to the practical understanding of how to perform specific tasks, encompassing methods of inquiry and criteria for skill application. Metacognitive Knowledge encompasses a broader awareness of cognition in general, including an individual's self-awareness and understanding of their own cognitive processes.**(As per Figure 4).**

II. BACKGROUND STUDY

Hiary, H.et al, (2018) In their research paper, the task of flower identification and classification is acknowledged as challenging due to the shared characteristics among a wide range of flower classes, such as similar color, shape, and appearance. Additionally, images of different flowers often include analogous surrounding objects like leaves and grass. With over 250,000 known species of flowering plants divided into about 350 families, the paper proposes a two-step approach to address the flower classification problem. The initial step involves localizing the flower by determining the minimum bounding box around it, achieved through flower region segmentation using the FCN method. Subsequently, a CNN in the second stage is trained to accurately classify diverse flower classes. The research incorporates the FCN algorithm and three datasets: Oxford 102, Oxford 17, and Jo-Nagi. The findings indicate an average improvement of 7.5% in segmentation accuracy and 4.1% in detection accuracy,

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presenting a deep learning-based method for the division, detection, and classification of flower images.**[1]**.

Shidnekoppa,R. et al, (2020) in their research paper,aims to provide an automated systemwhich detects and identifies flower species."Automatic Flower Recognition" helps to identifyImage of a flower to find out more about themCommon Name, Scientific Name, Kingdom, Its Uses and Methods to cultivate it. This proposed software includes color, shape andTextures are used to extract features to feed to models.Neural network classifier, KNN (K-Nearest Neighbour Algorithm) and database in thisBloom Pictures is taken from the world and contains 4242 images labeled flowers.The paintings are divided into five sections: Chamomile, Tulip,rose, sunflower, dandelion. There are around for each class800 photos.Finally, the result from this research paper was that how can we divide the flowers using the app **[2].**

Jiantao, Z. et al, (2021) In the research paper, additional advantages of Convolutional Neural Networks (CNN) are discussed, highlighting its intricate network structure with more hidden layers. The CNN is noted for its robust capability in both feature learning and feature expression. The paper delves into specific components, such as the Point Convolutional Layer, Poinisation Layer, Activation Function, Full Connection Layer, and Softmax Classifier. To enhance the dataset, four types of flowers - tulip, dandelion, sunflower, and rose - are introduced, and the CNN algorithm is applied. The research addresses various flower image classification challenges through convolutional training, exploring differences in learning rates and data to compare results achieved by neural networks during growth.**[3].**

Patel,I.etal,(2019) In their research paper, the identification of flowers traditionally falls under the purview of taxonomists or botanists. The paper introduces an innovative approach known as multi-label classification using MKL-SVM. Employing the multi-label, specifically label powerset, transforms the problem into a multi-class one. Subsequently, a multi-class classifier is trained on distinct label groupings within the training dataset. The research employs MKL (Multiple Kernel Learning), ANN (Artificial Neural Network), KNN (K-Nearest Neighbors), and SVM (Support Vector Machine) algorithms with the Oxford flower dataset. The paper thoroughly documents the experimental process conducted on the flower image dataset, encompassing details and analysis of results. Notably, it includes comprehensive comparisons between the classifications algorithms considered in the experiment. The culmination is the creation of a prediction model utilizing SVM integrated with MKL and multi-labeling techniques.**[4].**

Abbas,T. et al, (2022) In this particular research paper, the focus revolves around the utilization of smartphone applications, such as LeafSnap, PL@NTNET, and Microsoft Garage's Flower Recognition app, which have undergone extensive research and development to swiftly identify flowers. The primary objective of the paper is to present a proposed framework that incorporates classification with localization. This framework enables the recognition of numerous flowers in a digital image by establishing a bounding box around the identified flower along with a corresponding label. The research employs the Fast-RCNN and Deep Convolution Neural Network (DCNN) algorithms, utilizing pre-trained models from the COCO dataset. Three object detection models are featured in the paper, with experiments involving the training of SSD and Faster-RCNN on images of ten flower classes. Performance analysis is conducted on these trained object detection models, employing transfer learning approaches on various backbones, including Inception v2, ResNet50, ResNet 101, and MobileNet v2 **[5].**

Cao, S. et al, (2021)n this research paper, a novel flower recognition method based on the attention mechanism, termed Visual Attention-Driven DCNN (VA-DCNN), has been proposed for accurate identification of flower species. The model is segmented into four main stages. Firstly, to ensure robust performance, especially in deep learning methods requiring extensive training data, data augmentation techniques are employed to augment samples. This involves rotating the images clockwise and combining them with the original samples in the training set for experimentation, utilizing the Deep Convolutional Neural Network (DCNNs) algorithm with the publicly available Flowers 17 dataset. Secondly, a Visual Attentional Learning (VAL) block is constructed to enhance discriminative learning capabilities, specifically designed for vanilla DCNNs (with ResNet14 and ResNet50 used as baselines in this paper). Third, the model's layer weights are compared with VGGNet, GoogLeNet, and Inception V3, highlighting the high accuracy achieved by the proposed method. Specifically, VA-ResNet14 and VA-ResNet50 exhibit improvements in accuracy by 1.7% and 3.6%, respectively. The paper conducts experiments to validate the feasibility and effectiveness of the proposed methods using the Flower 17 Dataset, demonstrating an achieved accuracy of 85.**[6].**

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Shi, L. et al (2018) In their research, the authors implement an expedited method for retraining CNN networks based on Inception-v3 and smaller datasets, achieving enhanced accuracy compared to alternative feature extraction approaches. They amalgamate datasets from Oxford-102 and Oxford-17, creating the FLOWERS32 dataset with 32 flower species. The primary architectural framework of the flower recognition system comprises four stages: data labeling, training, validation, and testing. FLOWERS32 encompasses a total of 2560 images, with 80 images allocated for each of the 32 categories. This dataset is utilized to train a flower classification model using the CNN algorithm, yielding an impressive accuracy of nearly 100% for training data and approximately 95% for test data. The cross-entropy values between training and test data exhibit marginal differences of 0.01 and 0.07, respectively.**[7].**

Rao,V. et al, (2020)in this research paper, develop an efficient model Flower Image Classification Using Convolutional Neural network. Pre-collected images of multiple people Flowers and their associated labels have been used Train the model. Once trained, the model takes as input, Predicts the image and common name of a flower also the family name of the flower. It also displays the major use of the plant thus identified is increasing. A subset of the Oxford 102 flower dataset is used for training CNN model, The original dataset contains 102.The result was that training loss, validation loss, training accuracy and How to check validation accuracy for each epoch, In this way this system has become more useful. Forward model a web tool was installed **[8].**

Bhutada,S.et al, (2021) In this research paper, the project has been developed to provide detailed information about flowers using an existing dataset. The paper presents both advantages and disadvantages to enhance effectiveness. The experiment utilizes the Iris dataset, consisting of three different species with around 150 samples. Machine learning, particularly the K-Nearest Neighbors (KNN) algorithm, plays a significant role in classification, achieving an accuracy of over 80%. Additionally, the Random Forest algorithm is employed to extract features from text data. The Iris Flower Data Set, introduced by Ronald Fisher, comprises 50 samples for each of the three iris species, focusing on four characteristics: length and width of sepals and petals. The project employs two algorithms, KNN and Random Forest, for classification, with the KNN algorithm demonstrating notably higher accuracy compared to the Random Forest algorithm.**[9].**

Janne, A. et al, (2020) In this research paper, it has been shown to have low accuracy on benchmark datasets with using CNN (Conventional Neural Network) algorithm. Although some Feature extraction techniques combining both global and local can give a reasonable amount of accuracy in feature classification flowers, still we need proper and efficient system when they automatically recognize flower species, There are large quantities. No image has color attributes Sufficient to determine the quantity of flowers in multi-species Depending on the environment, two or more species may have the same color. As An example would be a rose and a tulip having the same color. An overview on flower species is presented in this paper **[10].**

Table I. The Summary of Literature review

Title and Author's Name	**Introduction**	**Methodology**	**Data Set and Algorithms**	**Gap Analysis**
Flower classification using deep convolutional neural networks Hiary, H. et. al, (2018)(1)	In this research paper, Flower identification and classification is a challenging task because the wide range of flower classes share similar characteristic	Research on availability of two method first is localizes the flower by finding the minimum bounding and second is CNN learns to accurately	FCN algorithm and three datasets are used, Oxford 102, Oxford 17, Jo-Nagi.	Old algorithm used
Automated Flower Species Detection and Recognition using Neural Network Shidnekoppa,R. et. al, (2020)(2)	In this research paper, aims to provide an automated system Which detects and identifies flower species	This proposed software includes color,shape and Textures are used to extract features to feed to models	Neural network classifier, KNN(K-Nearest Neighbour Algorithm) and database in this Bloom Pictures	Small dataset used
Research on Flower Image Classification Algorithm Based on Convolutional Neural Network Jiantao,Z. et. al, (2021)(3)	More advantages of CNN: It has more hidden layers and complex network structure	Explained in this paper on Point Convolutional Layer, Poinisation Layer, Activation Function, Full Connection Layer, Softmax Classifier.	CNN algorithm and Four types of flowers have been added to the dataset - tulip, dandelion, sunflower and rose	Accuracy is low

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Flower Identification and Classification using Computer Vision and Machine Learning Techniques Patel,I. et. al, (2019) (4)	Flowers are identified by taxonomists or botanists	An innovative approach called multi-label classification using MKL-SVM is proposed	MKL,ANN, KNN and SVM algorithm used with Oxford flower dataset	Very high and complex technology
Deep Neural Networks for Automatic Flower Species Localization and Recognition Abbas,T. et. al, (2022) (5)	The proposed framework classifies with localization, allowing to recognize countless flowers in a digital image by placing a bounding box around the identified flower with a label	Three object detection models have been used. During the experiment	Fast-RCNN and Deep Convolution Neural Network (DCNN) algorithm was used using pre-trained models of COCO dataset	Only about specific area
Visual attentional-driven deep learning method for flower recognition Cao,S. et. al, (2021) (6)	novel has been proposed which Flower recognition method based on attention mechanism (Visual Attention-Driven DCNN, VA-DCNN)	Firstly, due to deep learning method guarantee always requires large scale training data performance, including data augmentation techniques to increase samples Have been adopted	It applies Deep Convolutional Neural Network algorithm with public Flowers 17 dataset It applies Deep Convolutional Neural Network (DCNNs) algorithm with public Flowers 17 dataset	Very small Data set
A Flower Auto-Recognition System Based on Deep Learning Shi,L. et. al, (2018) (7)	Implements a fast way to retrain CNN networks based on Inception-v3	construction process is described Flower recognition system, which consists of four stages: data labeling, training process, validation Process and test procedure	Used FLOWERS32 for training the flower classification model with CNN (Conventional Neural Network) algorithm	Accuracy is low
FLOWER RECOGNITION SYSTEM USING CNN Rao,V. et. al, (2020) (8)	Once trained, the model takes as input, Predicts the image and common name of a flower Also the family name of the flower	Their associated labels have been used Train the model.	A subset of the Oxford 102 flower dataset is used for training CNN model, The original dataset contains 102	Result are not satisfied the all image of dataset
FLOWER RECOGNITION USING MACHINE LEARNING Bhutada, S. et. al, (2021) (9)	The project of this paper has been developed in such a way that If you want to know all the details of a flower then All are displayed with the help of existing dataset	The experiment is done using Iris dataset,It contains three different species with about 150.	KNN algorithm and Random forest algorithm with Iris dataset	Data set are small size
Flower Species Recognition System Janne,A. et. al, (2020) (10)	It has been shown to have low accuracy on benchmark datasets with using CNN (Conventional Neural Network) algorithm	When they automatically recognize flower species, There are large quantities. No image has coloured attributes Sufficient to determine the quantity of flowers in multi-species	Benchmark datasets with using CNN (Conventional Neural Network) algorithm.	Only one algorithm used

III. METHODOLOGY AND SETUP OF EXPERIMENT

A two-stage strategy has been suggested for addressing the flower recognition problem. In the initial stage, the flower is localized by determining the minimum bounding box around it, achieved through segmentation of the flower region using the FCN method. Subsequently, in the second stage, a CNN is trained to precisely classify various flower classes. The segmentation FCN is initialized by the VGG-16 model, and the classification CNN is initialized by the segmentation FCN.

A. Experimental Setup

Based on this, the team identified the problem and then created problem statement, survey, data set, sampling, image capture, preprocessing, feature extraction training, ML model, testing etc. Creating a survey for flower recognition can help

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gather data about people's knowledge and interest in identifying different types of flowers. The goal of sampling is to collect a diverse and representative dataset that covers a wide range of variations in flower appearance, such as different species, colors, sizes, and lighting conditions.

B. Steps of Execution

- **Problem Identification-** Developing a robust flower recognition system for automated identification of various flower species from images.
- **Problem Statement-**Developing a flower recognition system for accurate species classification based on image analysis.
- **Survey-** Survey of different Flowers in farming land.
- **Dataset-** Oxford 102
- **Sampling-** Sample a diverse dataset of flower images.
- **Capture Image-** Capturing high-quality images of flowers for accurate species recognition and classification.
- **Image Preprocessing-** Image preprocessing techniques to enhance the quality and extract relevant features
- **Feature Extraction-** Extracting discriminative features from flower images to enable accurate species recognition.
- **Feature Selection-** Select the most relevant features for flower recognition using a suitable machine learning algorithm.
- **Training Data-** Collect and prepare a diverse dataset of labeled flower images
- **Machine Learning Model-** Train a convolutional neural network (CNN) for flower recognition using the prepared dataset
- **Recognition Algorithm-** Implement a deep learning-based convolutional neural network (CNN) for flower recognition using a pre-trained model.
- **Testing-** Evaluate the flower recognition model's performance on a separate testing dataset to assess its accuracy and generalization.
- **Post Processing-** Apply post-processing techniques like thresholding or filtering to refine and improve the accuracy.
- **Result-** Obtain the final flower recognition output, typically a label or class prediction for a given input image.
- **Comparison in Different Algorithm-** Compare the performance of various flower recognition algorithms using metrics such as accuracy, precision, recall, and F1-score to determine the most effective approach.
-

C. Methodology

The methodology for flower recognition involves several key steps. First, collect a diverse dataset of flower images, ensuring it includes multiple species, colors, and variations in lighting and backgrounds. Preprocess the data by resizing, cropping, and normalizing the images, and apply data augmentation techniques to enhance dataset diversity. Next, select an appropriate computer vision model, often a Convolutional Neural Network (CNN), and train it on the labeled dataset, reserving a portion for validation to fine-tune hyper parameters. After training, evaluate the model's performance on a separate testing dataset, using metrics.

D. Diagrams and their Description

Block Diagram

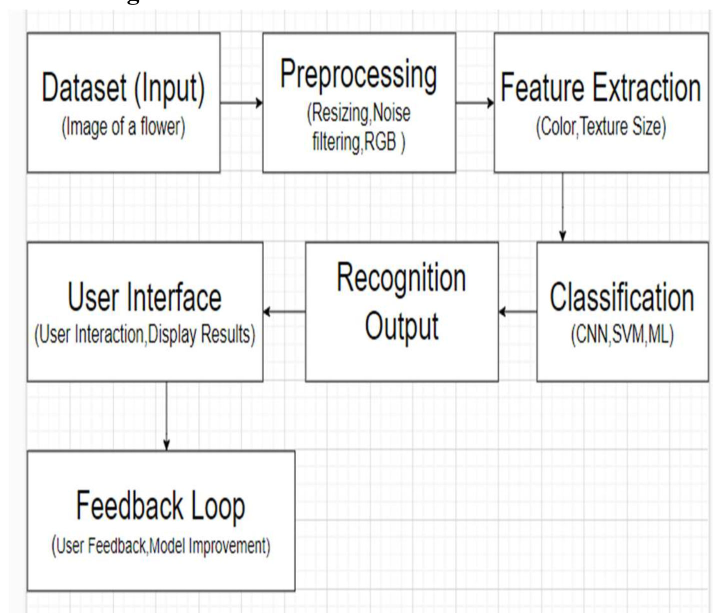

Figure 5. Block Diagram of Floweret Recognition

The block diagram of a flower recognition system includes "input data", which includes all types of flowers. Images are included. These images are subject to "preprocessing" to enhance and standardize their quality. The next step is "Feature Extraction", where important features such as color, texture, and shape are isolated. In the “model selection” step, an appropriate machine learning or deep learning model, such as Convolutional Neural Network (CNN), is chosen for classification. The selected model is "trained" using labeled flower images, then "tested" to assess its performance. The “recognition” phase applies the trained model to classify flower species. The final "output" displays the recognized flower species or relevant information, potentially accompanied by a confidence score. To maintain accuracy, a "feedback loop" continuously updates the model with new data. This 10-line diagram shows the main steps of a flower recognition system, from input to identification, ensuring accurate identification of flower species **(as per Figure 5).**

IV. Population, Sample and Drop Outs

A. Populations

The population for a flower recognition system includes a variety of elements. This includes users, hobbyists, botanists, and researchers who wish to identify different flower species.

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The system should cater to a wide collection of flower species, from common garden varieties to rare or exotic specimens, ensuring comprehensive coverage. Furthermore, the population spans huge datasets of flower images, each of which has unique features in terms of angle, lighting, shape, and color, to support accurate recognition. Recognition algorithms, which form a significant part of the population, involve various software and models employed for image processing and species recognition. Reference databases are also important, constituting populations of data containing information on different flower species, such as common and scientific names, descriptions and images. Finally, geographic regions must be considered within populations, as the effectiveness of the system may vary depending on the flora found in different parts of the world. An effective flower recognition system must be able to accommodate this diverse population to achieve accurate and reliable results in different use cases and regions.

B. Sample

Flower recognition involves the process of using an image of a flower to identify its species in a specimen. For example, imagine a user with a smartphone in a botanical garden who wants to identify a rare orchid. They capture a close-up image of an orchid blooming using a smartphone camera. The user then accesses the flower recognition app, uploads the image and begins the recognition process. Behind the scenes, the app's algorithms preprocess the image, extracting key features like petal size, color and shape. The system queries its flower database for a match, and after rigorous analysis, it confidently identifies the orchid species as "Cymbidium goeringii". The result is displayed on the user's screen, providing not only the common and scientific names but also additional information such as care tips and growth habits. In this sample, the flower recognition system shows its usefulness in helping users learn more about the botanical world and easily identify specific flowers, making it a valuable tool for enthusiasts, researchers, and nature lovers.

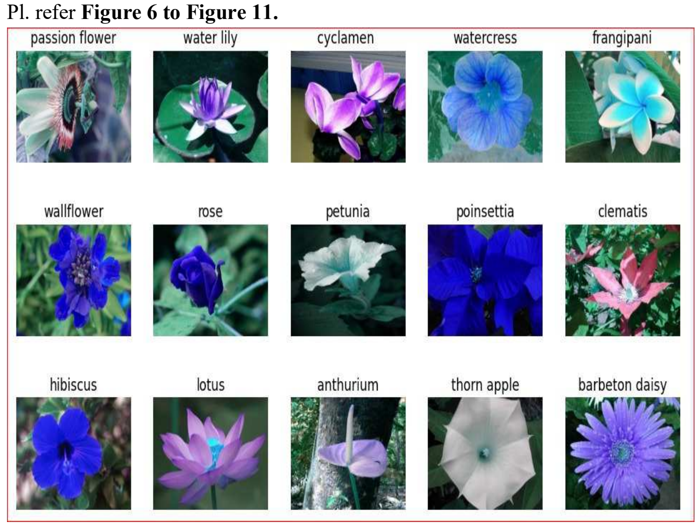
C. Sample Selection

Sample selection for flower recognition plays an important role in training and testing the accuracy of recognition algorithms. For example, let's consider a research project that aims to develop a robust recognition system for wild flowers in a specific area. Researchers begin by collecting a diverse set of flower samples from different locations, noting different species, colors, sizes, and lighting conditions. They carefully document the common and scientific names of flowers and take high quality photographs.This sample dataset becomes the basis for training the recognition system, enabling it to learn and distinguish between the distinctive features of each flower species. To assess the performance of the system, the researchers also create a separate test dataset, ensuring that the recognition system can accurately identify flowers that it has not encountered during the training phase. Sample selection in this scenario is crucial for building a reliable recognition model that can contribute to the conservation and study of wild flowers in the field, demonstrating the importance of careful and representative sampling in flower recognition research.

D. Category Wise Flower Images Data

Our dataset contains 102 categories of flowers. The flowers selected are those that are frequently found in the United Kingdom. There are between 40 and 258 pictures in each class.
Total number of images: 8189

Pl. refer **Figure 6 to Figure 11.**



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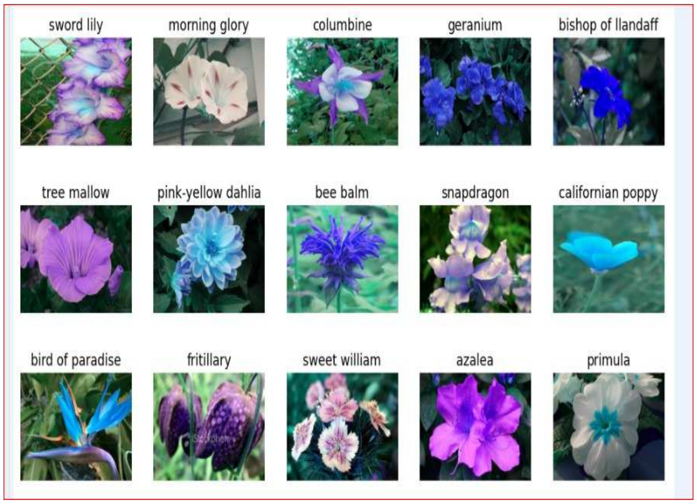

Figure 6. Sample Dataset-1

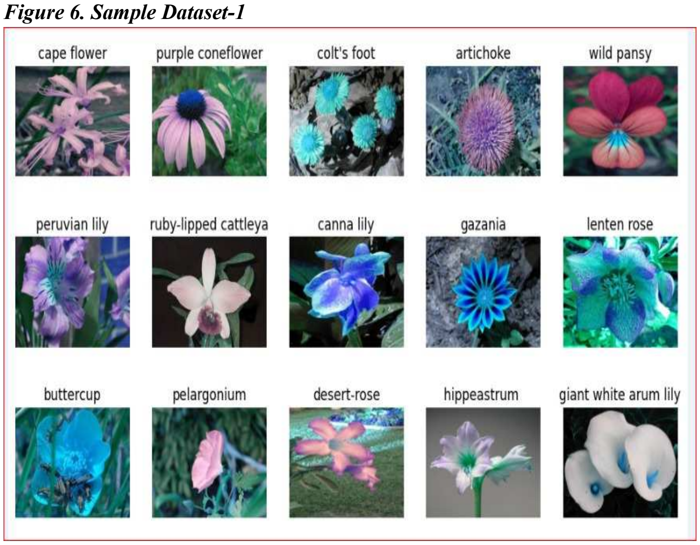

Figure 7. Sample Dataset-2

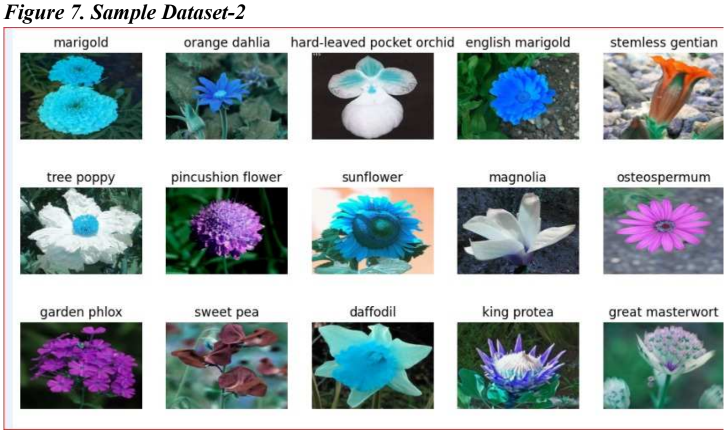

Figure 8. Sample Dataset-3

Figure 9. Sample Dataset-4

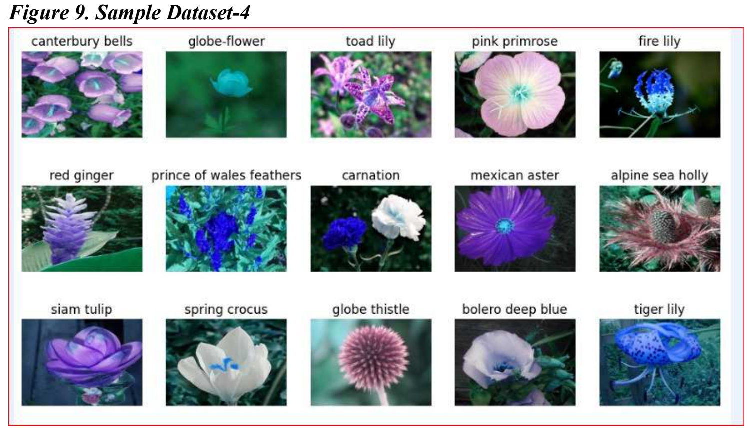

Figure 10. Sample Dataset-5

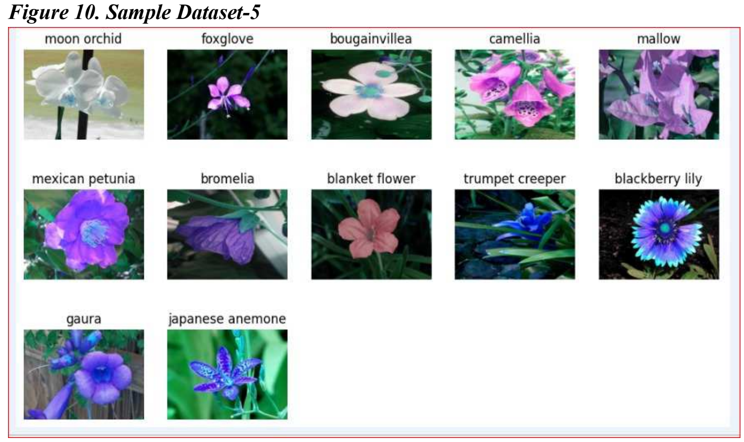

Figure 11. Sample Dataset-6

V. RESULTS and FINDINGS

A. Coding Snippets and Model Summary

Models Used for Flower Image Classification (Pl. refer Figure 19 to Figure 22).

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4.1.1: 1-Conv CNN: CNN with one Convolutional Layer

```
#  modelling starts using a CNN.
#  1-Conv CNN: 1 Convolutional Layer

model = Sequential()
model.add(Conv2D(filters=32, kernel_size=(3, 3), padding='same',
        activation='relu', input_shape=(224, 224, 3)))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Flatten())
model.add(Dense(128))
model.add(Activation('relu'))
model.add(Dense(102, activation="softmax"))
```

Figure 12. Coding Snippet-1

Model Summary

This model is designed as a Convolutional Neural Network (CNN) with a single convolutional layer, comprised of one pooling layer and one convolutional layer. The initial convolutional layer incorporates a rectified linear unit (ReLU) activation function, incorporating 32 filters with a 3x3 kernel size. Subsequent to the convolutional layer are pooling layers, with the first being a max-pooling layer of 2x2, reducing the spatial dimensions of the feature maps by half. The second pooling layer, also a max-pooling layer, has a pool size of 2x2.The final two layers of the model are fully connected. The first fully connected layer comprises 128 neurons, utilizing a ReLU activation function. The second fully connected layer involves 102 neurons and employs a softmax activation function to generate a probability distribution across 102 classes.

Input Shape

The input shape of the model is (224, 224, 3), which means that the model expects input images to be 224 pixels wide and 224 pixels tall, with 3 channels (red, green, and blue).

Output Shape

The output shape of the model is (102,), which means that the model outputs a probability distribution over 102 classes**(as per Figure 19)**.

4.1.2: 3-Conv CNN: CNN with three Convolutional Layer

```
#  modelling starts using a CNN.
#  3-Conv CNN: 3 Convolutional Layer
model = Sequential()
model.add(Conv2D(filters=64, kernel_size=(3, 3), padding='same',
         activation='relu', input_shape=(224, 224, 3)))
model.add(MaxPooling2D(pool_size=(2, 2)))


model.add(Conv2D(filters=64, kernel_size=(3, 3),
         padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))


model.add(Conv2D(filters=64, kernel_size=(3, 3),
         padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))


model.add(Flatten())
model.add(Dense(128))
model.add(Activation('relu'))
model.add(Dense(102, activation="softmax"))
```

Figure 13. Coding Snippet-2

Model Summary

This deep learning architecture, utilizing a convolutional neural network (CNN) for image classification tasks, consists of three convolutional layers, three pooling layers, and two fully connected layers. The initial convolutional layer incorporates 64 filters with a 3x3 kernel size, along with a rectified linear unit (ReLU) activation function. The subsequent convolutional layers maintain the same filter count and kernel size, also employing ReLU activation functions.Following the convolutional layers, there are three pooling layers. The first pooling layer is a max-pooling layer with a 2x2 pool size, halving the spatial dimensions of the feature maps. The second pooling layer is also a max-pooling layer with a 2x2 pool size but with a stride of 2, reducing the spatial dimensions by a quarter. The third pooling layer is a max-pooling layer with a 2x2 pool size and a stride of 2.The final two layers are fully connected layers. The first fully connected layer comprises 128 neurons, applying a ReLU activation function. The second fully connected layer involves 102 neurons and employs a softmax activation function, generating a probability distribution across 102 classes.

Input Shape The input shape of the model is (224, 224, 3), which means that the model expects input images to be 224 pixels wide and 224 pixels tall, with 3 channels (red, green, and blue).

Output Shape The output shape of the model is (102,), which means that the model outputs a probability distribution over 102 classes **(as per Figure 20)**.

4.1.3: 4-Conv CNN: CNN with four Convolutional Layer

```
#  modelling starts using a CNN.
#  4-Conv CNN: 4 Convolutional Layer
model = Sequential()
model.add(Conv2D(filters=64, kernel_size=(5, 5), padding='same',
        activation='relu', input_shape=(224, 224, 3)))
model.add(MaxPooling2D(pool_size=(2, 2)))


model.add(Conv2D(filters=64, kernel_size=(3, 3),
        padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))


model.add(Conv2D(filters=64, kernel_size=(3, 3),
        padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))

model.add(Conv2D(filters=64, kernel_size=(3, 3),
        padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))

model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dense(102, activation="softmax"))
```

Figure 14. Coding Snippet-3

Model Summary

This model comprises four convolutional layers, four pooling layers, and two fully connected layers:

- The first convolutional layer features 64 filters with a 5x5 kernel size.
- The second convolutional layer also includes 64 filters with a 3x3 kernel size.
- The third convolutional layer consists of 64 filters with a 3x3 kernel size.
- The fourth convolutional layer involves 64 filters with a 3x3 kernel size.

All convolutional layers apply a rectified linear unit (ReLU) activation function and utilize "same" padding. Following the convolutional layers, four pooling layers are introduced. The initial pooling layer uses a 2x2 max-pooling operation, effectively reducing the spatial dimensions of the feature maps by half. The second pooling layer employs the same 2x2 max-pooling operation but with a stride of two, skipping every other pixel and further decreasing the spatial dimensions by a factor of four. The third and fourth pooling layers also use 2x2 max-pooling operations with strides of two, further reducing the spatial dimensions. The final two layers consist of fully connected layers. The first fully connected layer comprises 512 neurons, applying a ReLU activation function. The second fully connected layer involves 102 neurons and applies a softmax activation function, producing a probability distribution across 102 classes.

Input shape: (224, 224, 3) This means that the model expects input images to be 224 pixels wide and 224 pixels tall, with three channels (red, green, and blue).

Output shape: (102,) This means that the model outputs a probability distribution over 102 classes**(as per Figure 21)**.

4.1.4: ResNet50

```
resnet = ResNet50(
    input_shape = [224,224,3], # Making the image into 3 Channel, so concating 3.
    weights = 'imagenet', # Default weights.
    include_top = False   #
)

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resne
ernels_notop.h5
94765736/94765736 [==============================] - 307s 3us/step
```

```
for layer in resnet.layers:
    layer.trainable = False
```

```
x = Flatten() (resnet.output)

prediction = Dense(len(folders), activation = 'softmax')(x)

model = Model(inputs = resnet.input, outputs = prediction)
```

Figure 15. Coding Snippet-4

Model Summary This convolutional neural network (CNN) model is based on a version of the ResNet50 architecture. It utilizes the original ResNet50 pre-trained model with its weights frozen, followed by a flattening layer and a fully connected layer with a softmax activation function .

Input Shape The input shape of the model is (224, 224, 3), which means that the model expects input images to be 224 pixels wide and 224 pixels tall, with 3 channels (red, green, and blue).

Output Shape The output shape of the model depends on the number of classes in the classification task. In the provided code, the 102 variable is used to determine the number of classes, so the output shape will be a vector of length 102**(as per Figure 22)**.

B. Research Visualizations: Learning Performance of Models

4.2.1: 1-Conv CNN: CNN with one Convolutional Layer**(as per Figure 23 and Figure 24).**

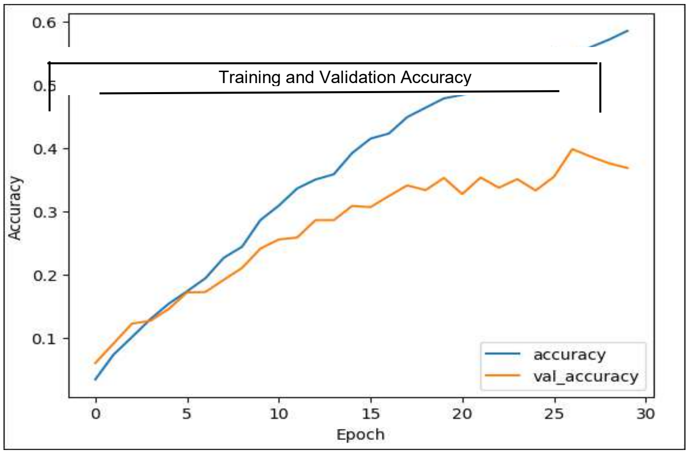

Figure 16. Inference for Training and Validation Accuracy Graphs of a 1-Conv CNN Model

- Training Accuracy: The training accuracy increases steadily over the training epochs.
- Validation Accuracy: The validation accuracy also increases but plateaus around epoch 15.

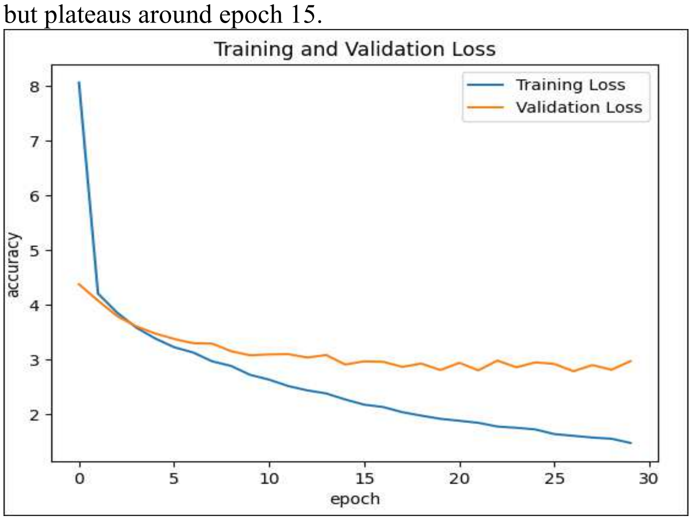

Figure 17. Inference for Training and Validation Loss Graphs of a 1-Conv CNN Model

- Training Loss: The training loss decreases rapidly in the initial epochs and then it steadily decreasing
- Validation Loss: The validation loss initially decreases but starts to diverge from the training loss around epoch 10.

4.2.2: 3-Conv CNN: CNN with three Convolutional Layer**(as per Figure 25 and Figure 26).**

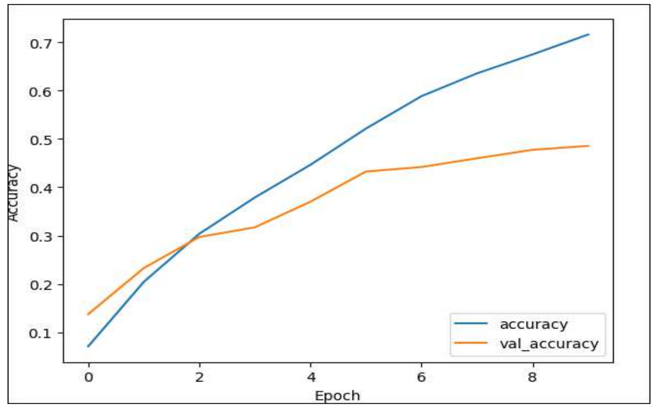

Figure 18. Inference for Training and Validation Accuracy Graphs of a 3-Conv CNN Model

- Training Accuracy: The training accuracy increases steadily over the training epochs. Reaching a maximum of approx. 72%.
- Validation Accuracy: The validation accuracy also increases but plateaus around epoch 5.

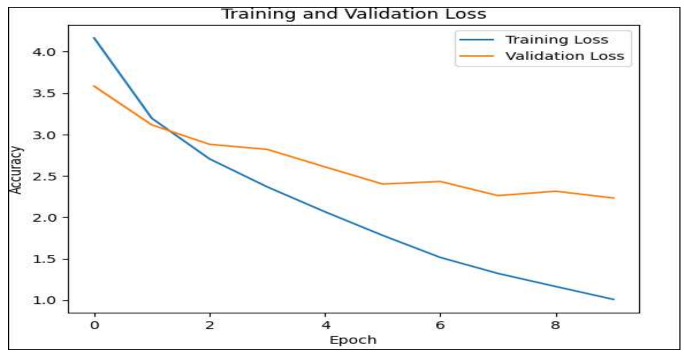

Figure 19. Inference for Training and Validation Loss Graphs of a 3-Conv CNN Model

- Training Loss: the training loss decreases rapidly over the training epochs.
- Validation Loss: The validation loss initially decreases but starts to diverge from the training loss around epoch 3.

4.2.3: 4-Conv CNN: CNN with four Convolution Layer**(as per Figure 27 and Figure 28).**

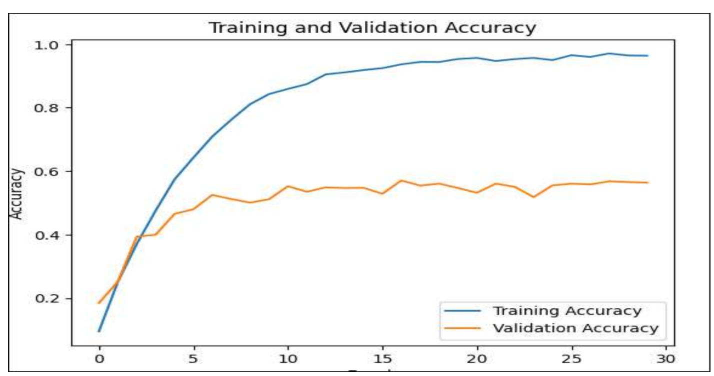

Figure 20. Inference for Training and Validation Accuracy Graphs of a 4-Conv CNN Model

- Training Accuracy: The training accuracy increases rapidly till 10 epoch and then become constant over the training epochs. Reaching a maximum of approx. 97%.
- Validation Accuracy: The validation accuracy increases initially then it also become constant with little variations around epoch 5.
-

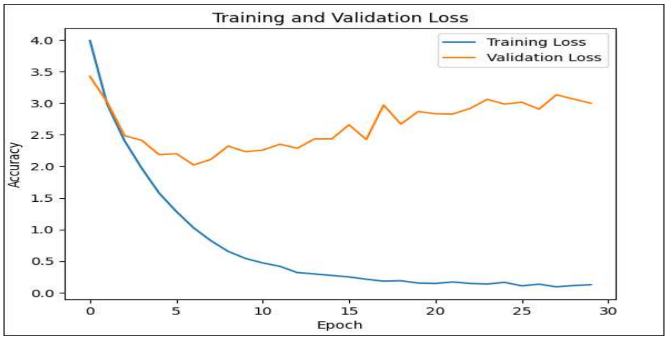

Figure 21. Inference for Training and Validation Loss Graphs of a 4-Conv CNN Model

- Training Loss: The training loss decreases rapidly over the training epochs until 15 epoch and then become constant.
- Validation Loss: The validation loss initially decreases but starts to increasing from the training loss around epoch 5.

4.2.4: ResNet50:(as per Figure 29 and Figure 30).

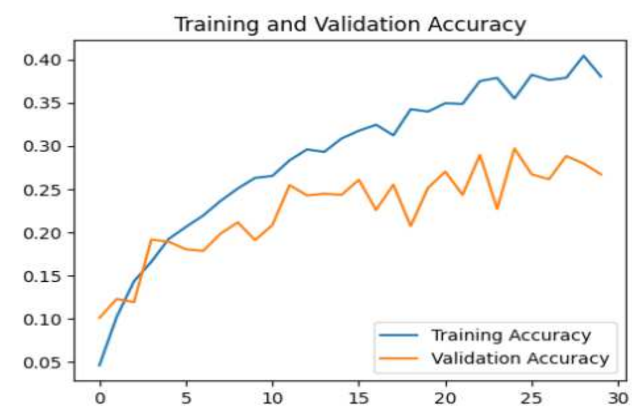

Figure 22. Inference for Training and Validation AccuracyGraphs of a ResNet50 Model

- Training Accuracy: The training accuracy increases steadily over the training epochs.
- Validation Accuracy: The validation accuracy also increases but plateaus around epoch 10.

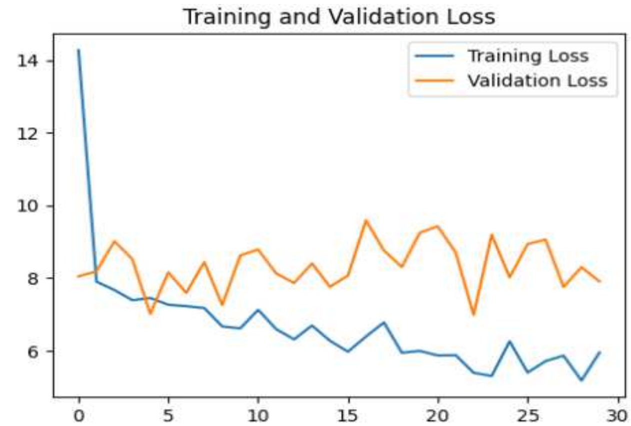

Figure-23. Inference for Training and Validation Loss Graphs of a ResNet50 Model

- Training Loss: The training loss initially decreases rapidly and then form plateaus over the training epochs.
- Validation Loss: The validation is neither increasing nor decreasing majorly and forms plateaus over the training epochs.

C. Prediction

Some prediction made by 4-Conv CNN**:** CNN with four Convolution Layer on randomly chosen images**(as per Figure 30).**

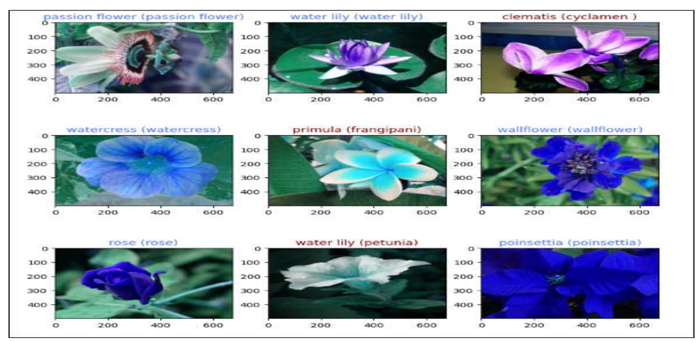

Figure 24. Prediction Results for Testing Graphs

D. Discussions and Inferences

Table 2.Models Comparison

Model	**Size**	**Accuracy**	**Total Parameters**	**Trainable Parameters**	**Non-Trainable Parameters**
4-Conv CNN	25.14MB	0.9710	6591014	6591014	0
4-Conv CNN	24.84MB	0.7160	6511462	6511462	0
4-Conv CNN	196.05 MB	0.5851	51394406	51394406	0
ResNet 50	129.03 MB	0.4044	33823718	10236006	23587712

The supplied data presents a performance comparison of four distinct convolutional neural network (CNN) models designed for image classification tasks. The table details each model's name, size, accuracy, total parameters, trainable parameters, and non-trainable parameters.**(as per Table 2)**.

Based on the provided data, the following inferences can be drawn:

Model Accuracy: The 4-Conv CNN model achieves the highest accuracy (0.9710), followed by the 3-Conv CNN model (0.7161), the 1-Conv CNN model (0.5851), and the ResNet50 model (0.4044).

Model Size: The 1-Conv CNN model has the largest size (196.05MB), followed by the 3-Conv CNN model (24.84 MB), the 4-Conv CNN model (25.14MB), and the ResNet50 model (129.03 MB).

Model Trainable Parameters: The number of trainable parameters varies across the models. The 1-Conv CNN model has the most trainable parameters (51394406), followed by the 4-Conv CNN model (6591014), the 3-Conv CNN model (6511462), and the ResNet50 model (10236006).

Model Non-Trainable Parameters: Only the ResNet50 model has non-trainable parameters (23587712). This suggests that the ResNet50 model uses pre-trained layers that are not updated during training.

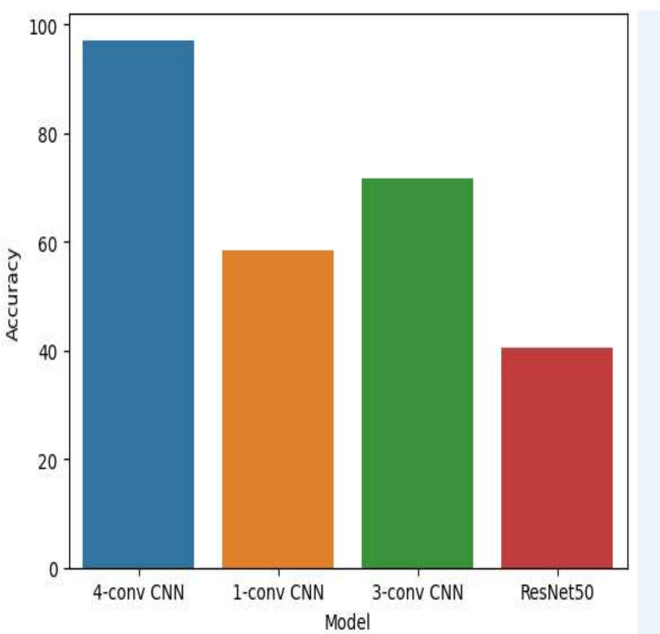

Figure 25. Accuracy comparison of four models applied in this project.

This plot illustrates a comparison of the accuracy of four distinct convolutional neural network (CNN) models specifically designed for flower image classification (refer to Figure 31). The four models considered are:

1. CNN with 1 Convolutional Layer
2. CNN with 3 Convolutional Layers
3. CNN with 4 Convolutional Layers
4. ResNet50

The accuracy values for these CNN models range from 0.4044 to 0.9710.

VI. CONCLUSIONS

In this study, we have introduced an efficient and versatile convolutional neural network (CNN)-based model designed for flower detection, localization, and classification. The proposed Flower Species model offers capabilities in both localization and recognition, providing flower names, taxonomy, and implementing multi-labeling techniques. The research indicates that certain flower classes may share similarities in size and color, while others might be better distinguished by external shapes rather than internal ones. Identifying flowers is considered an effective means of recognizing a plant, as flowers are often the most visually appealing and distinctive features. This approach enables the acquisition of comprehensive information about the plant. The proposed system takes an image of a flower as input and, in addition to the common name, outputs the family name of the flower. Leveraging a convolutional neural network, a highly influential image classification method, enhances the reliability of the proposed system.

A. TECHNICAL CONCLUSION

In this investigation, the performance of four distinct convolutional neural network (CNN) models for image classification tasks was scrutinized. The evaluation was conducted using a dataset comprising 102 flower categories. The findings revealed that the 4-Conv CNN model exhibited the highest accuracy, outperforming the 3-Conv CNN model, the 1-Conv CNN model, and the ResNet50 model. Despite having the largest size, the 4-Conv CNN model demonstrated superior accuracy and efficiency.

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