2023 International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE) | 979-8-3503-0570-8/23/$31.00 ©2023 IEEE | DOI: 10.1109/RMKMATE59243.2023.10369560

Flower Classification Using Deep Learning Approaches

S. Navya Kala
M. Tech student
Department of CSE
School of Engineering and Technology
SPMVV, Tirupati
navyakala2408@gmail.com

Dr. N. Padmaja
Department of CSE
School of Engineering and Technology
SPMVV, Tirupati
gowripadma99@gmail.com

Dr. P. Neelima
Department of CSE
School of Engineering and Technology
SPMVV, Tirupati
neelima.paneem@gmail.com

***Abstract*— Flowers are abundantly present in our surroundings and serve as nourishment for various insects, birds, animals, and humans. Additionally, they possess medicinal properties that are beneficial to both people and animals. To effectively identify new or distinctive flower species and determine their appropriate applications, a comprehensive comprehension of flowers is imperative. The term "deep learning" has gained significant popularity across multiple domains and sectors. Within this study, a classification model was developed, utilizing deep learning algorithms for the recognition and categorization of images. Over time, deep learning architectures have evolved with increased layers and improved models, enhancing their accuracy in addressing categorization challenges. Classification, a prevalent technique, is deployed to structure data and maintain its relevance across diverse fields. Here, the specific subset of machine learning known as deep learning was harnessed to classify flowers based on their inherent characteristics. The utilization of Tensorflow in classifying floral images yielded optimal outcomes. The findings highlight that Convolutional Neural Network (CNN) categorization surpasses traditional methods in accuracy. Given deep learning's capacity to swiftly and efficiently learn from extensive data inputs, it autonomously extracts features from incoming data. Both nature enthusiasts and botanists engaged in research can find immense value in this real-time flower categorization approach, as it has practical implications for their endeavors.**

Keywords*— *Convolutional Neural Network (CNN), Deep Learning, Artificial Neural Network (ANN), transfer learning.

I. INTRODUCTION

Everywhere we look, flowers are present. They are all edible to people, animals, birds, and insects. They are furthermore used as medicines by many animals and people. A thorough knowledge of flowers is important to identify newly discovered or endangered species. This will help the medical industry grow and will be advantageous. The approach recommended in the study can be used by hikers, botanists, and medical experts. It could potentially be extended to function as a visual search solution, allowing an image to be used as input in lieu of text. This approach would enable a deeper understanding of the subject being categorized, thereby tailoring the search process for optimal outcomes.. For several reasons, including the ability of harvesting robots to swiftly identify flowers, developing an automated system for flower identification is essential. With the benefits of saving time and effort, automated flower recognition enables persons with little knowledge of flower species to recognize a flower's species. Additionally, there has been a significant increase in demand for flowers, making floriculture a major economic enterprise in agriculture [11].

This system could be useful for commercial floriculture. Differentiating between different varieties of flowers is a highly difficult task for a number of reasons. Within each class of flowers, there are many different color variations, and within classes, there are many similarities. Some of them are so difficult to recognize that even knowledgeable gardeners and botanists struggle. Additionally, flowers are pliable things whose appearance is susceptible to a variety of environmental influences, including humidity, temperature, sunshine, nutrition, and food quality. For flower species identification and recognition, a capable automated system is required [11].

Classification is typically used to arrange data in a controlled manner and achieve relevance across all domains. Because flowers are utilized as food and medicine by people, animals, insects, and other organisms, putting them together is essential for a clear knowledge of the plant varieties, similarities, and interactions. This categorization was automated using a number of techniques as computer technology advanced. Here, the flowers have been categorized based on their characteristics using the machine learning subset of deep learning. The features are automatically retrieved from the input data since deep learning trains faster and more effectively when given hundreds of data streams.

II. LITERATURE STUDY

A literature review serves the purpose of examining various papers put forth by various authors and researchers. The analysis conducted during the literature review enhances the understanding and lucidity of the research subject. It is essential to present the assessment of the study in a manner that demonstrates a thoughtful analysis of how the recommendations from the research can be extended within the sector.

FLOWER CLASSIFICATION USING SUPERVISED LEARNING

The Earth boasts an incredibly rich array of biodiversity, with around 360,000 distinct organisms contributing to the health of various ecosystems. Despite the external resemblance shared by some organisms in terms of form, size, and color, distinguishing between species poses a significant challenge. This analogy is mirrored in the categorization of iris flowers, which can be further divided into three subtypes: Serosa, Vesicular, and Virginia. Leveraging the easily accessible Iris flower dataset, we can explore these concepts. The dataset consists of three classes, each comprising 50 instances of Iris flowers. Employing machine learning techniques, the Iris-dataset facilitates the classification of these flower subtypes. The primary focus of this research is to examine the machine-learning algorithms can accurately and automatically determine the flower class with a high level of precision, moving beyond approximations. This process involves three key stages: segmentation, feature extraction, and classification. Various machine learning algorithms, including k-nearest-neighbors, support-vector-machines, logistic-regression, and neural-networks, are employed to achieve these objectives [1]. (A. Shukla et al., 2020).

IRIS FLOWER CLASSIFICATION USING MACHINE LEARNING

To classify IRIS flower species, we employ a semi-automated approach to extract knowledge from data using machine learning techniques. The classification process in this learning involves dealing with responses that are either categorical or belong to a limited, unordered set of values. To tackle the classification challenge, Scikit-learn tools were harnessed, streamlining the entire process. By evaluating attributes like petal and sepal sizes of IRIS flower images, the IRIS flower dataset is subjected to classification based on identified patterns. These patterns are then utilized to make predictions about the IRIS flower class. The study primarily involves training a machine learning model using available data. When confronted with new and previously unseen data, the trained predictive model draws upon the acquired knowledge from the training data to make informed forecasts about the species [2]. (Rao, T. S. Hema et al., 2021).

FLOWER CLASSIFICATION BASED ON DEEP LEARNING USING TENSORFLOW

Due to the large variety of flower species, which share characteristics such as form, look, or surroundings such as leaves and grass, classifying flowers is a difficult undertaking. To classify flowers from a variety of species, the authors of this work suggest a revolutionary two-step deep learning classifier. In order to localize the smallest bounding box around the floral region, the region is first automatically segmented. In a fully convolutional network architecture, the suggested flower image segmentation method is portrayed as a binary classifier. In order to discriminate between the many flower varieties, they create a strong convolutional neural network classifier. To ensure reliable, accurate, and real-time categorization, they suggest unique actions throughout the training phase [3]. (M. Rajalakshmi et al., 2021).

FLOWER RECOGNITION SYSTEM WITH OPTIMIZED FEATURES FOR DEEP FEATURES

The study employed a dataset consisting of 4317 photos representing 5 distinct flower species. In the first stage, deep-features were detected from the flower images using the Squeeze-Net Deep-Learning architecture, a transfer-learning technique. This initial stage was divided into three segments. Moving to the second stage, machine learning techniques, specifically neural networks and logistic regression, were employed to classify the 1000 extracted characteristics. Subsequently, in the third stage, a particle swarm approach was applied to enhance the deep features that had initially been extracted. The improved set of 488 features was then subjected once again to classification using machine-learning methods, including neural networks and logistic regression. Comparing the results from the two phases, it was observed that image classification with the optimized features significantly improved the success features. The success rate of image classification, when using deep feature image extraction, reached 85.1% for neural networks and 79.7% for logistic-regression. However, after feature optimization, these success rates were elevated to 90.1% for neural networks and 84.2% for logistic-regression. The study also delved into how the optimization of features impacted the overall classification performance [4]. (H Hiary et al., 2018).

FLOWER CLASSIFICATION USING DEEP CONVOLUTIONAL NEURAL NETWORKS

Due to the large variety of flower species, which share characteristics such as form, look, or surroundings such as leaves and grass, classifying flowers is a difficult undertaking. To classify flowers from a variety of species, the authors of this work suggest a revolutionary two-step deep learning classifier. In a fully convolutional network architecture, the suggested flower image segmentation method is portrayed as a binary classifier. In order to discriminate between the many flower varieties, they create a strong convolutional neural network classifier. To ensure reliable, accurate, and real-time categorization, they suggest unique actions throughout the training phase [5]. (R. Kursum et al., 2022).

HIBISCUS FLOWER HEALTH DETECTION TO PRODUCE OIL USING CONVOLUTION NEURAL NETWORK

The issue of post-harvest losses, which may range from 20 to 35%, is prompting farmers in the flower farming industry, often known as floriculture, to address their concerns. Classifying the product according to its state of health up till infection is the main goal. In order to reduce losses and boost efficiency, farmers may distribute it to the right consumer leads. The identification of healthy hibiscus flowers and the procedure for extracting their oil are the main topics of this research. When producing hibiscus oil of high export grade, the fresh bloom is extremely important. The obvious goal is to monitor the hibiscus flower's lifecycle, and machine learning techniques like deep learning and image classification are being used to assess the bloom's health and identify contagious blossoms (if any are found) [6]. (D. Srivastava et al., 2022).

III. Proposed Methodology

Convolutional Neural Network (CNN) and Mobile Net of Deep Learning, coupled with transfer learning techniques, are used in the purposed method to classify flowers as methods based on image analysis for detecting flowers. Therefore, accurate classification is crucial for understanding the characteristics of the flower, which our suggested method will make possible. Below is a procedure diagram of the suggested method.

Figure 1 illustrates the suggested approach for flower classification.

Data Source: The dataset employed in this study is sourced from Kaggle. It comprises images of seventeen distinct flower categories, including Bluebell, Buttercup, Coltsfoot, Cowslip, Crocus, Daffodil, Daisy, Dandelion, Fritillary, Iris, Lily valley, Pansy, Snowdrop, Sunflower, Tiger lily, Tulip, and Windflower.

Bluebell: 423 images, Buttercup: 523 images, Coltsfoot: 624 images, Cowslip: 450 images, Crocus: 620 images, Daffodil: 325 images, Daisy: 720 images, Dandelion: 630 images, Fritillary: 520 images, Iris: 840 images, Lily valley: 900 images, Pansy: 860 images, Snowdrop: 1025 images, Sunflower: 1145 images, Tiger lily: 530 images, Tulip: 829 images, Windflower: 420 images. The dataset comprises a multitude of images, each sized at approximately 320x240 pixels.

This dataset is partitioned into three subsets: the training dataset (70%), the validation dataset (15%), and the testing dataset (15%).

The proposed methodology encompasses five distinct phases: Data Preparation, Pre-processing, Transfer Learning, Model Construction, Model Compilation and Training, which includes Evaluation, Prediction, Fine-tuning, Model Validation, and ultimately, Testing the model using the designated test dataset [11].

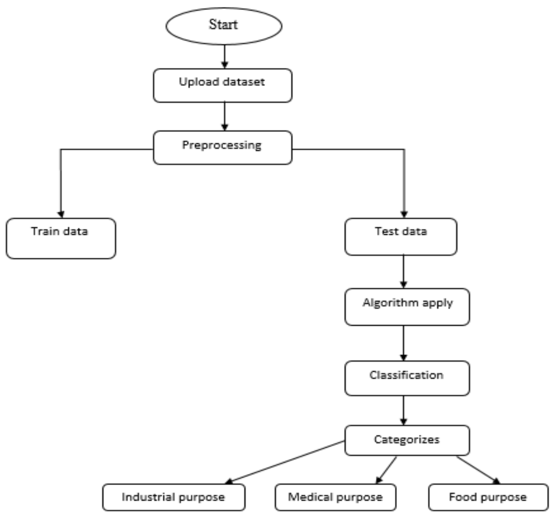

Figure 1: Proposed Methodology

A. *Dataset Preparation:* In this section, Collect or obtain a dataset of flower images. There are several publicly available datasets like the Oxford Flowers 17 dataset, TFlower17, and more. Organize the dataset into different classes, each representing a different type of flower.

B. *Pre-processing*: In this section, Resize images to a consistent size. Common choices are 224x224 or 299x299 pixels. Normalize the pixel values of the images (usually between 0’s and 1’s). divide the dataset into trained, validated, and test sets.

C. *Transfer Learning:* In this section, Select a pre-existing CNN model as your foundation, with popular options including VGG, ResNet, Inception, or MobileNet.Eliminate the uppermost layers (fully connected) of the pre-trained model, as they were tailored for the initial purpose (like ImageNet classification). Lock the weights of the residual layers to prevent adjustments during the training process.

D. *Model Construction:* in this section, Integrate an additional suite of fully connected layers onto the existing pre-trained model. This newly devised structure will assume the role of classifying various types of flowers. The terminal layer must comprise an equal count of neurons as the quantity of distinct flower classes.

E. *Model Compilation and Training:* In this section, Configure the model by combining a suitable loss function (typically categorical cross-entropy) with an optimizer (like Adam or RMSprop).Conduct training on the model utilizing the predefined configurations with the training dataset. Carefully observe the validation accuracy to mitigate potential overfitting.

F. *Evaluation:* In this section, Assess the model's performance by subjecting it to evaluation using the test dataset. Compute mesurments such as accuracy, precision, recall, and f1-score for comprehensive analysis. If required, make refinements to the model's hyperparameters or architecture in order to enhance its overall performance.

G. *Prediction:* In this section, Use the trained model to classify new flower images. Make predictions on real-world flower images and visualize the results.

H. *Fine_tuning (Optional):* In this section, If your dataset is large enough and your task is significantly different from the original pre-trained task, you might consider fine-tuning the entire or part of the base model. Gradually unfreeze layers and train on your dataset with a lower learning rate.

IV. IMPLEMENTATION

The MobileNet architecture is meticulously crafted to ensure efficiency and lightweight characteristics, rendering it well-suited for applications constrained by limited computational resources, like mobile devices. This efficiency is accomplished by leveraging depth-wise separable convolutions and implementing various optimization strategies. Here is an overview of the MobileNet process within a convolutional_neural_network:

1. **Depth-wise Separable Convolutions:** In contrast to the conventional convolution process that combines spatial and channel-wise convolutions, MobileNet employs depth-wise separable convolutions. These entail two distinct steps: depthwise convolution and pointwise convolution.

- **Depthwise Convolution:** This phase applies distinct convolutional filters to each input channel, reducing computation by convolving each channel with its dedicated set of filters.

- **Pointwise Convolution:** Following the depth-wise convolution, a subsequent operation involves a 1x1 point-wise convolution. This particular step orchestrates the creation of a linear amalgamation of output channels produced by the preceding depth-wise convolution. This process effectively captures correlations that span across different channels.

2. **Width Multiplier and Resolution Reduction:** MobileNet offers a width multiplier to tailor the model's size. This multiplier reduces channel count in each layer, effectively decreasing the model's size and computational demand. Additionally, MobileNet often reduces the spatial resolution of input images (e.g., through strided convolutions or pooling), further curbing computation.

3. **Bottleneck Architecture:** MobileNet adopts a bottleneck architecture, combining 1x1 point-wise convolutions and 3x3 depth-wise separable convolutions. This design diminishes parameters and computational complexity while retaining the ability to learn significant features.

4. **Global Average Pooling:**By taking Instead of concluding with fully connected layers, MobileNet commonly concludes with global average pooling. This operation computes average values for each feature map, yielding a concise representation used for classification.

5. **Activation Functions and Non-linearity:** MobileNet frequently employs ReLU (Rectified Linear Unit) activation functions to introduce non-linearity. These functions facilitate the network in capturing intricate relationships within the data.

6. **Batch Normalization:** To enhance stability and expedite training, batch normalization is implemented. This normalization process stabilizes layer activations, enhancing optimization efficiency and reducing sensitivity to initialization.

7. **Skip Connections:** Certain MobileNet versions incorporate skip connections or residual connections to enhance gradient flow during training and support information propagation.

8. **Variants and Extensions:** Over time, diverse MobileNet variants have emerged, such as MobileNetV2 and MobileNetV3, each with advancements in accuracy and efficiency. These variants may introduce supplementary architectural components, activation functions, and other enhancements.

In summary, the MobileNet process entails the strategic design of a neural network architecture that finds a balance between model size, computational efficiency, and classification performance. This balance is achieved by integrating depth-wise separable convolutions, width multipliers, global average pooling, and other techniques to create an efficient and effective convolutional neural network.

Figure: 2 a

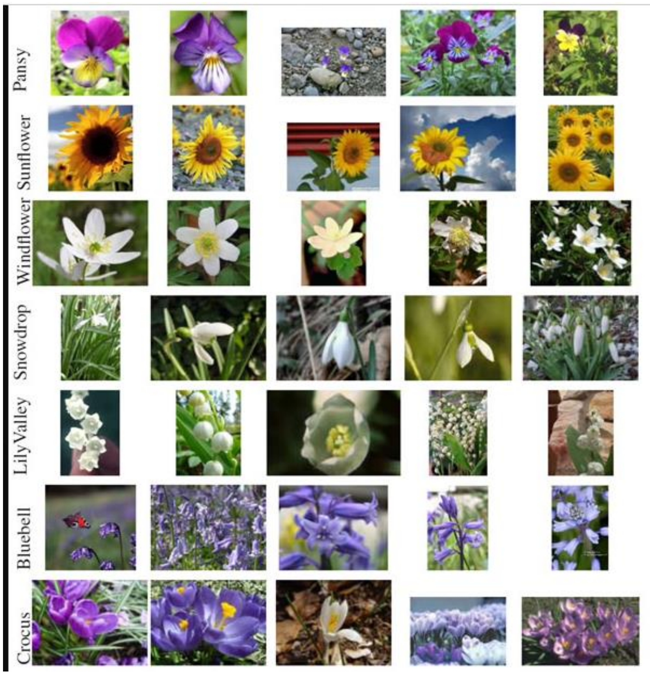

Figure: 2 b

Figure: 2 c

Figures A, B, and C depict a collection of seventeen flower image categories, including Bluebell, Buttercup, Coltsfoot, Cowslip, Crocus, Daffodil, Daisy, Dandelion, Fritillary, Iris, Lily valley, Pansy, Snowdrop, Sunflower, Tiger lily, Tulip, and Windflower.

V. CONVOLUTION NEURAL NETWORK

1. Convolutional Neural Network:

Step 1a: convolutional operation:

The starting point in our strategic approach involves the convolution operation. Within this phase, we will closely examine the notion of feature detectors, which act as filters within the neural network. This exploration will cover feature maps, the process of learning parameters for these maps, the mechanics behind pattern recognition, the layered hierarchy of detections, and the subsequent mapping of the identified patterns.

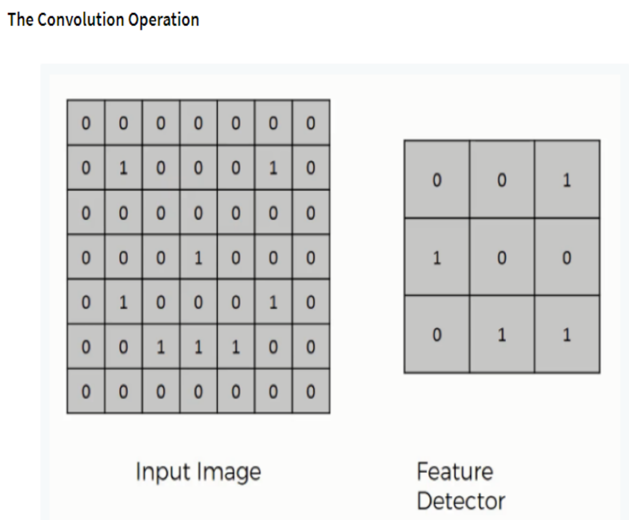

Figure 3: Convolutional Operation

Step 1b: ReLU Layer: The subsequent segment of this phase will encompass the Rectified-Linear-Unit, commonly referred to as ReLU. We will delve into ReLU layers and delve into the interplay of linearity within the Convolutional Neural Networks framework. While not imperative for comprehending CNNs, a brief supplementary lesson can only contribute positively to your skill enhancement.

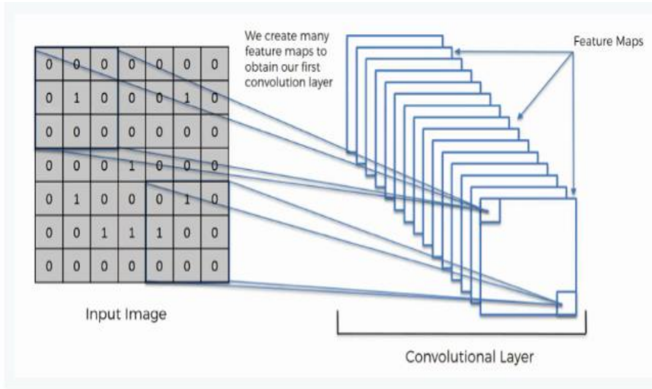

Figure 4: Convolutional Layer

Step 2: Pooling Layer: In this section, we will delve into the topic of pooling and develop a thorough understanding of its general functioning. Specifically, our focus will be directed towards a particular pooling technique: max pooling. Nonetheless, we will also touch upon alternative methods, such as mean (or sum) pooling.

Step 3: Flattening: Here, we'll provide a concise overview of the flattening procedure and the transition from pooled layers to flattened layers in the context of Convolutional-Neural-Networks.

Step 4: Full_Connection: In this segment, all the concepts we've explored throughout this section will converge. By grasping this integration, you'll gain a comprehensive perspective on the functioning of Convolutional_Neural_Networks and how the resulting "neurons" contribute to learning image classification.

Summary: Towards the conclusion, we will consolidate all the information and provide a concise review of the concepts discussed in this section. If you believe it would be advantageous (and it certainly will be), consider exploring the supplementary tutorial that delves into Softmax and Cross-Entropy. While not obligatory for the course, gaining familiarity with these concepts will prove highly beneficial as you engage with Convolutional Neural Networks.

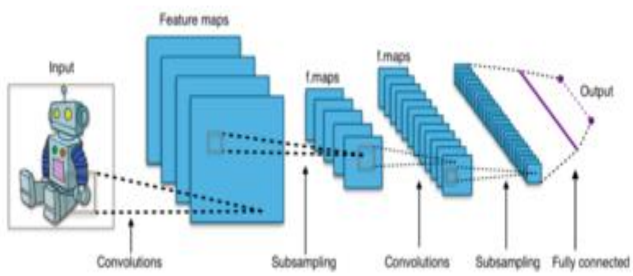

Figure 5: Convolutional Neural Network

2. Artificial Neural Network (ANN): Artificial-Neural-Networks (ANN) architecture is designed in emulation of the structural and functional aspects of biological neural networks. Much akin to the neurons within the human brain, ANNs are composed of neurons arranged into distinct layers. Notably, the feedforward neural network is a prominent example of this arrangement. This network encompasses an input layer for assimilating external data for pattern recognition, an output layer that presents solutions to the problem, and a hidden layer acting as an intermediary – setting it apart from other layers.

The neurons extending from the input-layer to the output-layer are interconnected through non-cyclic pathways. In the training phase, ANN utilizes an algorithm that adjusts neuron capacity based on the disparity between the target and Actual outputs. Backpropagation algorithm is typically employed for training to learn from datasets. The figure's illustration offers a comprehensive overview of the fundamental structure of ANN.

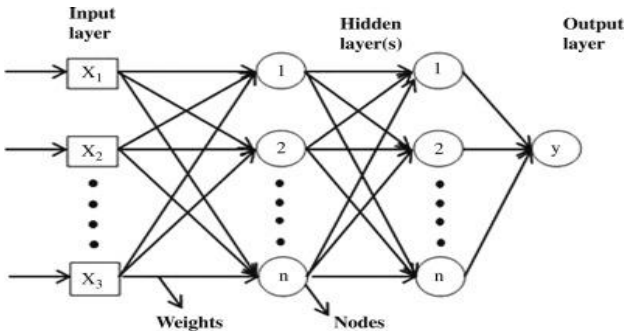

Figure 6: Artificial Neural Network

3. MobileNet: True to its name, the MobileNet model is tailored for mobile applications, marking TensorFlow's initial foray into mobile computer vision models. MobileNet employs depthwise separable convolutions, which notably curtail parameter count compared to networks featuring conventional convolutions of the same depth. This optimization yields leaner deep neural networks.

A depthwise separable convolution is constructed from two constituent operations:

- Depthwise convolution.
- Pointwise convolution.

Google has introduced MobileNet as a category of CNN through open-source sharing. Consequently, this furnishes an excellent foundational framework for training incredibly compact and rapid classifiers.

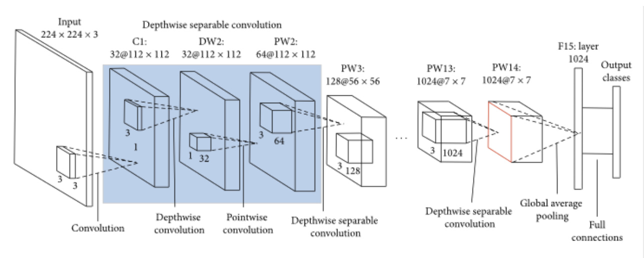

Figure 7: MobileNet

The velocity and energy usage of the network correlate with the quantity of MACs (Multiply-Accumulates), a metric gauging the amalgamation of Multiplication and Addition operations.

Depth-wise Convolution: The inception of this convolutional approach stems from the concept that a filter's depth and spatial measurements can be disentangled, giving rise to the term "separable." For instance, let's consider the Sobel filter, which is commonly employed in image processing to identify edges.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Figure 8: Depth wise Convolution

The dimensions of these filters can be disentangled, considering the height and width separately. For instance, the Gx filter can be envisioned as the matrix product of [1 2 1] transposed with [-1 0 1]. Remarkably, the filter has managed to obscure itself in a way. Although it appears to possess nine parameters, it truly comprises only six. This achievement is attributed to the segmentation of its height and width dimensions.

Pointwise convolution: A convolution employing a 1x1 kernel, designed to amalgamate the features generated via the depthwise convolution. The computational expense associated with this operation is...

$M * N * Df^2$.

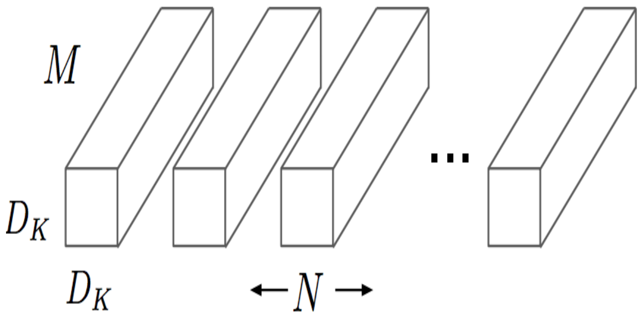

Figure 9: Point wise Convolution

The primary differentiation between the MobileNet architecture and a standard CNN resides in the application of a single 3x3 convolutional layer, followed by batch normalization and ReLU activation. In contrast, MobileNets divide the convolution process into a 3x3 depth-wise convolution accessed by a 1x1 pointwise convolution, as depicted in the diagram.

VI. RESULTS AND DISCUSSION

This study utilized the MobileNet approach, implementing a convolutional neural network through TensorFlow. The images were provided in the JPEG format, conforming to the RGB color space. The Kaggle dataset was employed for training, validating, and testing the MobileNet approach.

The dataset consisted of seventeen discrete flower image categories, with varying quantities of images for each category: 423 images of Bluebells, 523 images of Buttercups, 624 images of Coltsfoot, 450 images of Cowslips, 620 images of Crocuses, 325 images of Daffodils, 720 images of Daisies, 630 images of Dandelions, 520 images of Fritillaries, 840 images of Irises, 900 images of Lily valleys, 860 images of Pansies, 1025 images of Snowdrops, 1145 images of Sunflowers, 530 images of Tiger lilies, 829 images of Tulips, and 420 images of Windflowers. These images were approximately sized at 320x240 pixels [11].

In terms of dataset organization, 80% of the dataset was dedicated to training, with an allocation of 10% each for validation and testing. The evaluation of the proposed MobileNet model and its TensorFlow implementation was performed using accuracy as the chosen performance metric. The results of these model evaluations are outlined in Table 1.

Serial No	Model	Validation Accuracy (%)	Testing accuracy (%)
1.	Convolutional Neural Network	87.56%	85.45%
2.	MobileNet	99.67%	97.86%
3.	Artificial Neural Network	85.67%	82.37%

Table 1: Accuracy of various approaches

The research focused on categorizing flowers through the utilization of diverse deep-learning models: Convolutional-Neural-Network, Mobilenet, and Artificial-Neural-Networks. The dataset containing flower information was collected from Kaggle. The Convolutional Neural Network (CNN) architecture consisted of 4 convolution-layers, 4 max-pooling-layers, and 3 dense-layers that integrated Relu and Softmax activation functions. The images were processed using efficient 3x3 filters. Notably, Mobilenet showcased remarkable performance, reaching a remarkable accuracy of 99% when trained on the flower dataset [11].

VII. CONCLUSION AND FUTURE WORK

In this project, we have successfully classified images for flower identification along with their attributes, paving the way for their application in various sectors. The project delved into the application of Deep Learning and Transfer Learning techniques, including CNN and MobileNet, for diverse purposes. Notably, the MobileNet approach trained from scratch using the flower dataset exhibited the highest accuracy. Employing multiple deep learning models facilitated the accurate categorization of flowers. Among these models, the one trained from the ground up using the flower image dataset achieved the highest accuracy. Further improvements can be realized by employing larger datasets, as they effectively reduce testing errors and enable the model to generalize more efficiently by learning from a broader range of data.

REFERENCES

1. Shukla, A., Agarwal, A., Pant, H., & Mishra, P. (2020). Flower classification using supervised learning. Int. J. Eng. Res, 9(05), 757-762.
2. Rao, T. S., Hema, M., Priya, K. S., Krishna, K. V., & Ali, M. S. (2021). Iris Flower Classification Using Machine Learning. Network, 9(6).
3. Rajalakshmi, M., Kavitha, R., & Karpagavalli, S. (2021). Flower Classification Based On Deep Learning Using Tensorflow. NVEO-NATURAL VOLATILES & ESSENTIAL OILS Journal| NVEO, 5125-5131.
4. Hiary, H., Saadeh, H., Saadeh, M., & Yaqub, M. (2018). Flower classification using deep convolutional neural networks. IET Computer Vision, 12(6), 855-862.
5. Kursun, R., Cinar, I., Taspinar, Y. S., & Koklu, M. (2022, June). Flower recognition system with optimized features for deep features. In 2022 11th Mediterranean Conference on Embedded Computing (MECO) (pp. 1-4). IEEE.
6. Srivastava, D. K., & Jha, D. N. (2022, November). Hibiscus Flower Health Detection to Produce Oil Using Convolution Neural Network. In 2022 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC) (pp. 1-5). IEEE.
7. Aman, B. K., & Kumar, V. (2022, August). Flower Leaf Image Classification using Machine Learning Techniques. In 2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT) (pp. 553-558). IEEE.
8. Shankar, R. S., Srinivas, L. V., Raju, V. S., & Murthy, K. V. S. S. (2021, February). A Comprehensive Analysis of Deep Learning Techniques for Recognition of Flower Species. In 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV) (pp. 1172-1179). IEEE.
9. Prasad, M. V. D., Lakshmamma, B. J., Chandana, A. H., Komali, K., Manoja, M. V. N., Kumar, P. R., ... & Kiran, P. S. (2018). An efficient classification of flower images with convolutional neural networks. International Journal of Engineering and Technology (UAE), 7(1.1), 384-391.
10. Cıbuk, M., Budak, U., Guo, Y., Ince, M. C., & Sengur, A. (2019). Efficient deep features selections and classification for flower species recognition. Measurement, 137, 7-13.
11. Giraddi S, Seeri S, Hiremath PS, Jayalaxmi GN. Flower classification using deep learning models. In2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE) 2020 Oct 9 (pp. 130-133). IEEE.