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# Automatic Flower Classification Using CNN Models

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***Abstract: This paper illustrates the flower categorization methods utilizing deep structured learning for the recognition of different flower types through images. Pre-trained MobileNetV2 is adopted to classify various flower types like daisy, dandelion, rose, sunflower, and tulip with precision and efficiency. Image analysis methods like photo resizing, normalization, and augmentation have been considered to increase the results of the system. The skilled Neural Networks model is coupled with an easy-to-use interface where users can feed flower images to get the predicted result along with its confidence score. The proposed system delivers robust performance at low cost, making it feasible for real world applications.***
***Keywords: Deep Learning, Flower Classification, MobileNetV2, Deep Convolutional Neural Network (DCNN), data Image Processing, ML, Computer-Vision, Image Classification.***

## I. INTRODUCTION

Advancements in ML and Neural Networks methods have led to a significant enhancement in computer image recognition capabilities. Some of the methods contain ConcNet, which regularly utilized in image classification because of their precision and efficiency.

Flower classification is one application in which Deep Neural Networks can be employed to differentiate between flower species based on visual attributes. In this project, a flower categorization framework has been executed utilizing the MobileNetV2 deep learning technique. The framework is trained to recognize various types of flowers such as daisy, dandelion, rose, sunflower, and tulip from uploaded images. Image preprocessing techniques including resizing and normalization are applied to improve prediction performance.

A simple and user-friendly web interface is also designed to allow users to upload flower images and obtain classification results instantly. The planned project produce precise results predictions with minimal computing resources. This project demonstrates that Deep Neural Networks can be effectively applied to solve image recognition problems and botanical studies.

## II. LITERATURE REVIEW

The issue of classifying images through neural networks methods has been explored by many scholars. In 2012, Alex Krizhevsky developed AlexNet, which demonstrated that ConvNets could be successful at recognizing objects within images. Though this model performed successfully, it needed great computational capabilities and took more time for training. Subsequently, Kareen Simoniyan and Andrw Ziserman came up with the architecture of VGG16, which helped extract more features through deeper layers. However, the model consumed large memory and had a very large size, making it less efficient for real-time applications. ResNet, designed by Kaiming He in 2015, used the technique of residual connections to address the issue of vanishing gradients and achieved improved classification in deep networks. However, although being an accurate method, the model was complex in structure and required high computing power.

The issue of reducing computational requirements gave birth to the development of lightweight models. MobileNetV2, created by Andrew G. Howard, used depthwise separable convolution to ensure quick computation using less memory. It is appropriate for use in mobile devices; however, its accuracy may be affected in complex cases.

For instance, Forrest N. Iandola presented the SqueezeNet, which is a lightweight efficient deep neural network architecture meant to decrease the parameter number while retaining high classification capability. While the network architecture is compact and faster, it might underperform for diverse image data sets. Considering previous study results, the lightweight deep learning architecture like MobileNetV2 has proven to be effective for flower classification systems since they offer an efficient tradeoff of accuracy and speed.

## III. DEEP LEARNING TECHNIQUES FOR FLOWER CLASSIFICATION

### A. *Deep Convolutional Neural Network (DCNN)*

ConvNet(Convolutional Neural Networks) are among the most highly demand neural networks procedures applied in image classification.

For flower classification, the use of convolutional neural networks enables automatic extraction of relevant characteristics from the flowers, such as their petal shapes, colors, textures, and patterns. The structural frameworks of the ConvNet(CNN) framework includes several levels like ConvNet(convolutional layers), pooling. layers, and dense layers. In comparison to TML(traditional-machine-learning) frameworks, ConvNet is more accurate and performs better.

### B. *Transfer Learning*

Transfer learning is an approach whereby the existing neural networks frameworks is reused to solve another problem through retraining. In this case, it is not mandatory to train the model right from the scratch but rather use the pre-existing features which has been taught by a large data set to increase efficiency.

TL (Transfer-learning) decreases training time and saves on computational resources. In flower classification systems, it ensures that maximum accuracy is attained despite having a small data set size.

### C. *MobileNetV2*

The usage of neural networks has been very useful and powerful in machine vision. MobileNetV2 is an architecture of deep learning which is lightweight and suitable for image classification. MobileNetV2 utilizes depthwise separable convolution for the purpose of reducing number of parameters and computational cost and improve its accuracy at the same time. In the case of this paper, MobileNetV2 is perfect for flower classification since it is capable of working under constraints in hardware devices.

### D. *SqueezeNet*

SqueezeNet is another compact Deep-learning-model used for image recognition tasks. The main advantage of SqueezeNet is that it achieves accuracy comparable to larger CNN models while using significantly fewer parameters. This reduces storage requirements and improves processing speed. In flower classification, SqueezeNet helps in identifying flower species efficiently with lower computational complexity. However, the model may sometimes struggle with highly complex images when weighed to deeper architectures.

### E. *Data Augmentation*

Data augmentation is a process where training images are increased through certain techniques. The techniques include rotating, flipping, zooming, and cropping of the image among others. This allows for the neural network model to learn about different types of images and carry out smoothly when overlooked alongwith similar images in other situations. In flower recognition models, data augmentation helps to reduce overfitting and enhance accuracy.

### F. *Image Preprocessing*

Preprocessing of images is crucial to increase the standard of input images prior to giving them into the deep learning system. Some common forms of image preprocessing involve resizing, normalization, and removal of noise. Resizing makes sure that all the images have uniform sizes, whereas normalization allows pixels to be scaled appropriately to facilitate faster training.

### G. *Advantages & Constraints of CNN Methods*

Advantages of using deep learning algorithms include high accuracy rate, automatic extraction of features, and quicker image identification than traditional approaches. DLA(Deep learning algorithms) are capable to classify more complicated flower datasets accurately.

However, there are few drawbacks linked along with DL(deep learning) methods as well. For instance, they require bigger data sets, more time to train, and robust hardware components. Poor illumination, background distractions, and low image quality can lower their performance. Nonetheless, deep learning algorithms remain one of the best ways to develop flower classification systems..

## IV. SYSTEM ARCHITECTURE

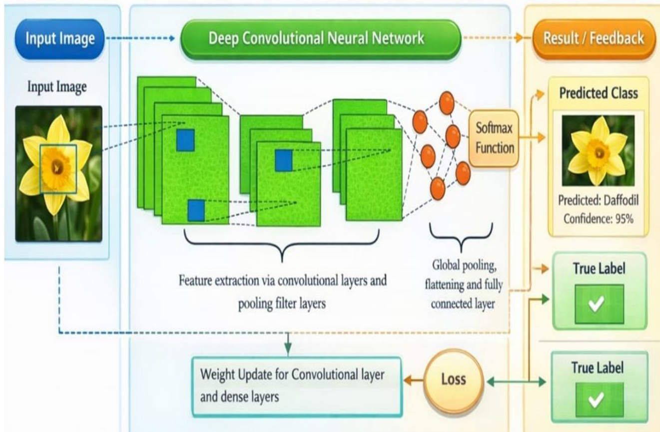



Figure1:System Architecture for flower classification

The structure of the flower recognition system provides information about the whole procedure of functioning of this application, from uploading a photo of a flower to making predictions. This structure make certain that there will be an effective approach to classify flowers by implementing deep learning technologies. First of all, the user uploads a picture on which there is a flower. Afterward, the image is transmitted to the pre-processing step. The aforementioned pre-processing steps perform vital part in elevating the standard of the input image and making it compatible with the DL algorithm. Once pre-processing is done, the image is sent to the feature extraction and classification phase. In the current study, the use of the MobileNetV2 model is made to conduct the deep learning task. The model examines different visual features including color pattern, petal shape, texture, and flower structure to group the flower. MobileNetV2 is considered a lightweight and proficient CNN(convolutional-neural-network) model that makes fast predictions with satisfactory results. As a result of training the framework, the predicted chance values are aquired for each flower class. Then the flower class having the highest probability value is selected and displayed on the screen. The architecture is designed to support real-time image classification while maintaining low computational complexity. This makes the system suitable for educational applications, agricultural assistance, botanical research, and intelligent image recognition systems.

## V. RESULTS

The categorization of flowers was performed effectively by applying DLA(deep learning algorithms). The suggested model was trained on various sorts of images belonging to various flowers such as Daisy, Dandelion, Rose, Sunflower, and Tulip. As a result, the system became capable of classifying the images and making predictions by providing a web-based interface.

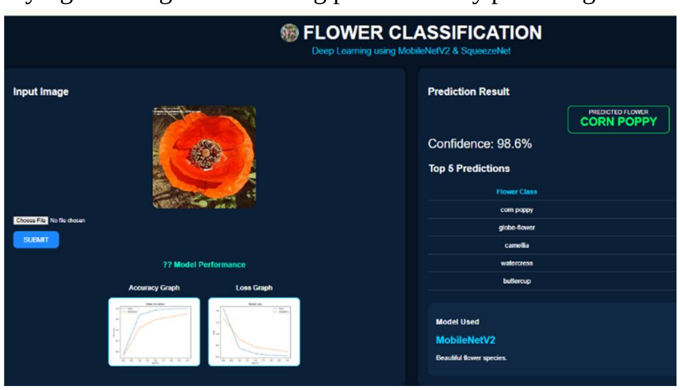



Figure1: Flower classification screenshot

The above Figure1 shows the output for flower classification. From the outcome of flower classification, it is evident that the MobileNetV2 was able to perform efficiently with respect to its accuracy rate and speed. The image preprocessing techniques such as resizing, normalizing, and augmenting championed in enhancing the learning capacity of the framework.

The flower images used for the testing process were many in number, and in most instances, the predicted output correlated with the flower categories. In addition to the prediction itself, there was also a level of confidence that showed up on the model screen and gave further insight into the preciseness of the prediction..

The Execution of the system was evaluated based on the accuracy and loss.

*1) Accuracy Formula*

Accuracy is being used to compute the percentage of correctly classified images.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \times 100$$

Where:

- Correct Predictions = No. of images classified correctly
- Total Predictions = Total no. of test images

*2) Loss Function*

Loss function is the difference between actual output and predicted output of model. The lower the loss the better the model performance.

$$Loss = Actual\ Output - Predicted\ Output$$

During training, the loss value slowly declined, which demonstrates that the model improved its prediction capability over time.

*3) Precision Formula*

Precision calculates how many projected flower classes are actually correct.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

*4) Recall Formula*

Recall measures how effectively the model identifies all correct flower classes.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

*5) F1-Score Formula*

F1 score is the symphonic mean of precision and recall.

$$F1Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Output resulted from samples shows that the designed flower classifier system is able to classify flowers accurately, with high efficiency. Implementation of both the deep learning approach and transfer learning approaches in the classification process helped increase accuracy, while decreasing training complexity. It can further be applied in agricultural monitoring, education sector, and plant species classification systems..

Following Figure shows a graphical representation of accuracy and loss

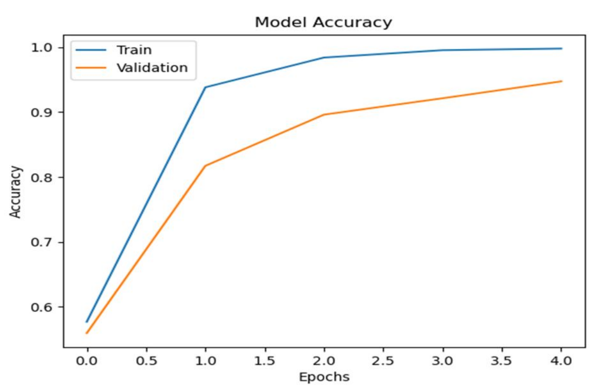



Figure2: Model Accuracy

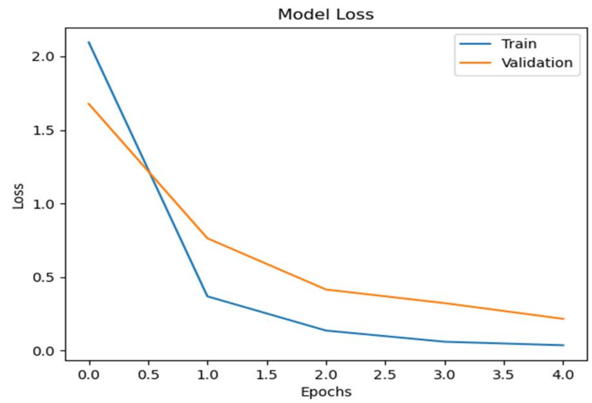



Figure3: Model loss

| Metric | Value (on Test Set) |
|---|---|
| Accuracy | 92% |
| Loss | 0.25 |
| Precision | 91% |
| Recall | 90% |
| F1-Score | 90.5% |

Table1: Performance Metrics

## VI. CONCLUSION WITH UPCOMING PROJECTS

The flower classification system developed in this project demonstrates the effective usage of neural network techniques for automated image recognition. By using the MobileNetV2 architecture, the system successfully classifies different flower categories with good accuracy and reduced computational complexity. The integration of image preprocessing, feature extraction, and classification techniques helped improve the overall performance of the model. The web-based interface further enhances user interaction by allowing users to upload images & instantly receive predicting outputs by means of confidence level and performance graphs. The model main features how ML(machine learning) and computer vision can simplify botanical identification tasks that normally require manual observation and expertise. The obtained output shows that neural networks system can efficiently recognize flower patterns, colors, and textures even under different image conditions. In addition, the lightweight nature of MobileNetV2 makes the model suits for real-time applications and devices with limited processing power. In future developments, the project can be expanded by increasing the number of flower categories and using larger datasets to improve classification accuracy. ADLM(Advanced deep learning models) such as EfficientNet, ResNet, or Vision Transformers can also be executed for excellence characteristic filter and performance. The system may further be integrated with mobile applications so users can identify flowers directly using smartphone cameras. Additional features such as disease detection in plants, multilingual support, voice assistance, and cloud-based prediction systems can also be included. These future improvements can make the system more useful in agriculture, education, environmental monitoring, and biodiversity conservation.

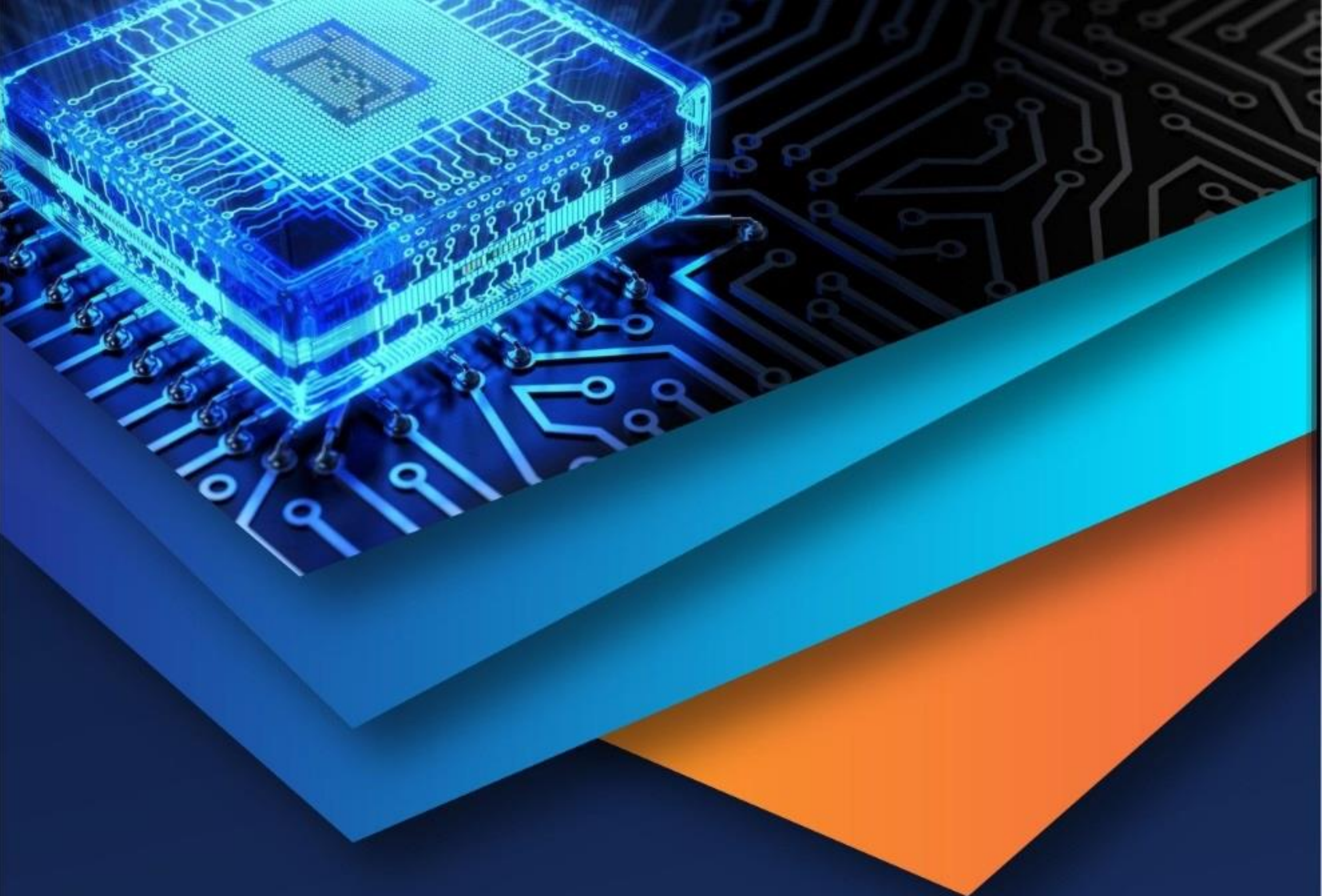
## VII. DATA AVAILABILITY

This paper examines, the dataset was composed of images of different types of flowers taken from publicly accessible websites and online open-access databases that are regularly used in deep learning projects. The dataset includes many classes of flowers including daisy, rose, sunflower, tulip, and dandelion. The images in the dataset were used to train the classifier model.

To get the model able to learn better, the images were pre-processed prior to training using image conditioning, image transformation, and data wrangling techniques. The dataset can be further expanded by adding other flower classes and real-time images for enhanced performance. Overall, the trained model, its training process, and pre-processing techniques used are completely reproducible and can be adaptable to similar studies.

## REFERENCES

[1] Y. LeCune, Y. Bengeio, and G. Hineton, “Deep Learning Model,” Nature, vol.. 521, no. 7573, p.p. 436–444, 2015.
[2] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. Chen, “MobileNetV2: Inverted Residuals and Linear Bottlenecks,” in case of the IEEE Confernce on System Vision and Pattern Identification (CVPR), 2018.
[3] A. Krizhevsky, I. Sutkever, and G. Hineton, “ImageNet Clasification with Deep Convolutional Neural Networks(DNN)” in progress in Neueral Information, Processing Model, 2013.
[4] K. Simaonyan and A. Ziserman, “Very Deep Convolutional(VDC) Networks for Greater-Scale image Identification,” Internatonal Conferences on Learning Representations (ICLR), 2015.
[5] K. Hes, X. Zhaneg, S. Reen, and J. Sune, “Neural Residual Learning for Image Recognition,” in Procedings of the IEEE Confernce on System Vision & Pattern Identification (CVPR), 2016.
[6] F. N. Iandola, S. Haan, M. Moskewiczz, K. Ashreaf, W. Daly, and K. Keuytzer, “SquezeNet: AlexNet-Step Accuracy with 40x Lesser Parameters & <0.5 MB Model-Size,” arrXiv preprint arXiv:1602.07360, 2017.
[7] I. Goodfellow, Y. Bengieo, and A. Courvile, Deep Learning, MITG Press, 2016.
[8] R. Szeliski, Computer Vision: Algorithms and Applications, Springer, 2011.
[9] A. Gurnani, V. Mavani, V. Gajjar, and Y. Khandhediya, “Flower Identification using Deep CNN,” arXiv preprint arXiv:1708.03763, 2017.
[10] A. Howard et al., “Searching for MobileNetV3,” Procedings of the IEEE International Conference on Computer Vision (ICCV), 2019.
[11] S. Kosankar and V. Khan, “Flower Classification using MobileNet: An Optimized Deep Learning Model,” Inter-national Publication of Advanced Research in Computer and Communication Engineering (IJARCCE), vol. 81, no. 4, 2019.
[12] V. Ayumi, “Flower Object Recognition Depending on Deep neural Learning Using ResNet50 and MobileNetV2,” Journal Scientific and Applied Informatics, vol. 6, no. 3, 2022.
[13] S. Navyuakala, N. Paddmaja, and P. Nelima, “A Studied on Flower-Classification-Using-Deep Learning-Techniques,” International Journal of Computer Engineering in Research Trends, vol. 10, no. 4, 2023.
[14] V. Praskatama, G. F. Shidik, and A. P. Ningrum, “Comparative Study: Flower Classification using Deep Learning, SMOTE and Fine-Tuning,” Journal of Applied Informatics and Computing, vol. 8, no. 2, 2024.
[15] E. Yulisara, N. Husna, D. Martin, and C. Ariesta, “Comparative Study of Convolutional Neural networks Strucures and Optimizers for Flower Image Classification,” Public Research Journal of Engineering, Data Technology and Computer Science, 2025.
[16] A. I. Ramadhona, W. S. Astuti, D. Hartama, A. P. Windarto, and A. Wanto, “Enhanced Flower Image Identification by Using MobileNetV2 with Optimized Performance,” JITK Journal of Computer Science and Technology(CST), vol. 11, no. 1, 2025.
[17] TensorFlow Documentation, “TensorFlow: Open Source Machine Learning Framework,” Available: https://www.tensorflow.org
[18] Keras Documentation, “Keras Deep Learning API,” Available: https://keras.io
[19] Flask Documentation, “Flask Web Framework for Python,” Available: https://flask.palletsprojects.com
[20] NumPy Documentation, “NumPy Numerical Computing Library,” Available: https://numpy.org

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