

# Identification of Flower Types Using Deep Learning Neural Network

M. Ashraf<sup>1</sup>, N. Iqbal<sup>2</sup>, M. H. Hussain<sup>3</sup>, H. Ahmed<sup>4</sup>, H. Bello<sup>5</sup>, W. Sajjad<sup>6</sup>

<sup>1,2,3,6</sup>Department of Computer Science, University of Agriculture, Faisalabad, Pakistan

<sup>4</sup>College of Information Science and Electronic Engineering, Zhejiang University, Hangzhou, China

<sup>5</sup>Institute for Smart City of Chongqing University in Liyang, Changzhou, China

[nayyariqbal@uaf.edu.pk](mailto:nayyariqbal@uaf.edu.pk)

**Abstract-** Flowers play a significant role in various aspects of human life, renowned for their visual appeal and vibrant colors. The identification and classification of flowers are essential for ecological studies, agricultural practices, and conservation efforts. Previous work on flower identification has faced several challenges, including variations in lighting, viewpoint, scale, and performance. This study explores the feasibility of using deep learning algorithms, particularly Convolutional Neural Network (CNN), to automate the flower identification process. By reviewing existing literature, the study investigates the methodologies, datasets, and models employed in prior research to train deep neural networks for flower recognition. CNN are especially effective in learning intricate patterns and features from large datasets, making them well-suited for flower classification. This research improves the speed and accuracy of flower recognition by automatically categorizing them into types and varieties, eliminating the need for human-mediated identification systems. It also classifies flowers into their respective varieties, supporting conservation efforts and ecological research.

**Keywords-** CNN, Flower, Varieties, VGG, ResNet.

## I. INTRODUCTION

Ecological as well as agricultural, and the importance of flower identification and classification is not new. Traditionally, it was a manual process and the interpretation of the differences between species required the experience of a person, was subjective usually, and not scalable. The advent of deep learning has revolutionized this field and especially the implementation of Convolutional Neural Network (CNN) that have proved to represent superior features in image recognition. Such technologies can evaluate complicated floral patterns, to make such classification efficient and automatic.

The study is based on these developments as it uses CNN to classify flower types and their different varieties. The study solves the current problems of scalability and precision by using vast volumes of

image data, training high-quality models. Besides, the use of such speed assessment that is predictive makes it practical with special consideration to incorporate large-scale and real-time case scenarios. This way, the proposed work is consistent with the aim of the project of improving biodiversity inventories in the larger scheme of simplifying botanical work and aiding the conservation initiatives by automated means.

Additionally, the labor-intensive nature of manual identification poses challenges to scalability and efficiency in large-scale studies, limiting our ability to comprehensively document and understand floral diversity. The emergence of deep learning techniques has brought about a revolutionary shift in automated image recognition tasks, including the identification and classification of flowers. Deep learning algorithms can directly extract hierarchical representations of visual features from raw image data by utilizing convolutional architectures and deep neural networks. This allows for automatic flower identification with previously unheard-of levels of efficiency and accuracy [1].

In the literature, CNN have been applied to various agricultural and veterinary domains, such as in the detection and classification of cotton leaf diseases through a lightweight CNN architecture [2], the identification of grape leaf diseases via retrained CNN models [3], cattle disease identification in veterinary diagnostics through a CNN-SVM model [4], and the detection of diseases in potato leaves using a CNN [5].

CNN has revolutionized the process of flower recognition. By leveraging CNN, the identification of flowers from images has become increasingly automated, offering a more efficient and accessible approach. Applying deep learning to flower identification provides numerous advantages over traditional methods, including speed, scalability, and objectivity. Unlike manual identification, which may be influenced by subjective interpretations and taxonomic biases, deep learning models can objectively analyze and classify flowers based on their visual characteristics, independent of human judgment or expertise.

This research identifies flower types, and it also further classifies these flowers into their varieties. The following flowers are examined in this study.

- **Rose:** Hybrid tea rose, climbing rose, floribunda rose, grandiflora rose, tree rose, shrub rose, miniature rose, groundcover rose, etc.
- **Tulip:** Single early tulips, Darwin hybrid tulips, double early tulips, fringed tulips, triumph tulips, lily-flowered tulips, parrot tulips, etc.
- **Sunflower:** Giant sunflower, edible sunflowers, dwarf sunflower, branching sunflower, colored sunflower, single-stem sunflower, etc.
- **Dandelion:** Red-seeded dandelion, pink dandelion, Korean dandelion, common dandelion, white dandelion, Japanese dandelion, Russian dandelion, alpine dandelion, etc.
- **Daisy:** Shasta daisy, oxeye daisy, gerbera daisy, African daisy, painted daisy, swan river daisy, gloriosa daisy, etc.

Furthermore, deep learning algorithms can process vast amounts of image data simultaneously, enabling the rapid identification of flowers across diverse habitats and geographical regions [6].

The rapid development of smartphones and digital cameras has created new opportunities for developing image-based methods for flower recognition and information retrieval. Users can conveniently take pictures of unknown flowers using digital devices and use these photographs as sample queries. This image-based approach to identifying and categorizing flower varieties can be widely utilized by suburban botanists, hikers, and educators who work in outdoor environments.

Furthermore, specialists can use this method for flower identification to collect data for environmental inventories, discover new horticultural or botanical species, and classify cultivars [7-10].

For professional flower biotechnologists, selecting and classifying flowers is a complex task. Deep learning techniques can automate this process, enhance the work of biologists, and serve as an

educational tool for non-experts in the field. Several studies have been conducted on automated flower classification [11-13].

Recognition of flowers is an area of research that has been explored for the past few decades. However, the use of computers and pattern recognition methods to automatically identify flowers from petal photographs has only recently gained attention. Most of the emerging technologies developed for this purpose are currently limited to certain species and still require human (botanical) involvement to determine criteria for material extraction and preprocessing. This highlights the need for a classification system that not only focuses on the classification algorithm but also gives equal importance to pre-processing and feature selection. Furthermore, the limited literature available indicates that this field is still in its early stages and requires further research to enhance both speed and accuracy.

CNN has been used in this research as shown in Figure 1 to classify flowers based on their appearance. The architecture starts with the several layers of convolutions, where every layer applies  $3 \times 3$  filters to achieve the key features, i.e. edges, shapes, and textures. These layers are then accompanied by ReLU activations to add non-linearities to the model. The max-pooling layers are interleaved so that the spatial dimensions are lowered and still a great portion of the features is retained. As network layer increases, it reduces to more complex learning of the abstract features that apply to flower types. So, they should avoid overfitting and generalize better, dropout layers are used in the dense layers with the rate of dropout 0.5. The convolutional block outputs are fed to the fully connected layers, which culminate into a SoftMax output layer, which yields probabilities of each class. Such architecture is tried and tested to be both accurate and efficient, which makes them suitable to represent the finding of practical flower recognition.

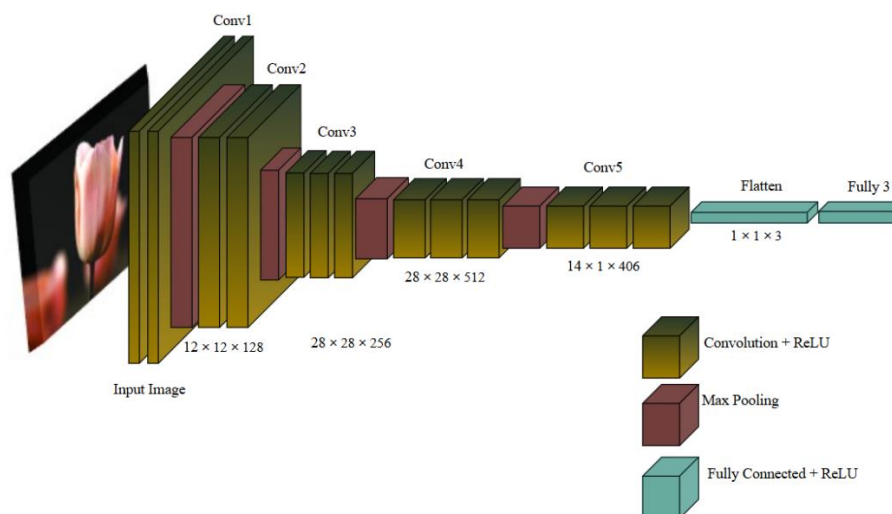


Figure 1: CNN Architecture

Regardless of the abundance of diversity and ecology of flowers, identifying and the classification of flowers have always been a challenge because of the changes in the appearance of the flowers in terms of lighting, angle, and scale. The use of manual identification techniques is usually slow, subjective, and un-scalable which becomes an impediment in scaling to ecological and agricultural practices. Moreover, an accurate, fast and automated system balancing a high accuracy classification and realistic speed of processing to use in the real world is required.

The objectives of the study were as follows: To explore and examine the current methods and strategies of deep learning especially CNN based approaches being applied in automatic identification of flowers. To build a CNN based framework that could classify the types of flowers and their varieties with the image datasets with high accuracy. The determination of assessing the accuracy of the proposed model was to consider the accuracy of the classification results and predicting speed. To learn how the automated flower classification can help ecological studies, conservation and invasive species diagnosis.

## II. LITERATURE REVIEW

In [14], a fractal analysis approach for flower recognition and classification was proposed, based on a pixel recovery method. The study calculated the fractal components of 102 flowers collected from the Xuzhou city factory. The findings indicated that contour fractal dimensions, despite certain variations in drawings, could differentiate between different flower types based on their contour and rib fractal sizes. The study highlighted that rib fractal analysis provided a more effective means of distinguishing flowers compared to contour analysis alone. The accuracy of classification was significantly improved, emphasizing the necessity and feasibility of fractal-based classification in industrial applications. However, challenges were identified in quantifying and calculating fractal modules for flowers with more complex structures. The study employed a pixel overlap method to measure the fractal dimension of flower images. Additionally, both the outline and veins of flowers were analyzed through the fractal axis of the contour to refine classification and identification techniques. Fractal theory was utilized to describe detailed vein structures and various shape characteristics, enabling more precise flower recognition and identification based on specific morphological details.

In [15], researchers conducted a literature review of various studies that describe techniques for flower arrangement using their take-offs.

Many flower species have a single type of petal that varies in characteristics such as shape, texture, shading, and tip. The researchers study focused on two of these characteristics: shape and texture. The shape-based approach aimed to isolate the unique signature of each flower type and applied the Jeffrey-disparity test to quantify the variations between them. To analyze the full-scale texture of the vine, edge angle analysis was introduced. Using the cumulative grouping estimate, the results of these methods were consolidated.

According to [16], research on flower phenology primarily focuses on flavonoids and phenolic acids due to their significance in plant and human health. These compounds, abundant in edible flowers and herbs, exhibit antioxidant and potential anti-carcinogenic properties. They act as free radical scavengers, singlet oxygen quenchers, and oxidative stress reducers. Moreover, their role in disease prevention, including cancer mitigation, highlights their importance in both botanical and medical research.

In [17] discussed the system for automatic specimens and flower classification. Many herbaria undertake large-scale digitization programs and produce massive collections of pictures in this way, to improve connection and preserve delicate specimens. Flower traits were significant for classifying and differentiating species, and they could be quantified from specimens in the herbarium. Here, scientists have demonstrated that floral features may be automatically retrieved from herbarium photos using the right tools. Researchers have discovered the low-cost digitization technique they utilized to create a collection of 1895 photos of *Tilia L.* samples, and innovative applications for botanical image processing. The software's production was a compilation of flower characters. The length and width of a vast number of flowers, automatically derived from photos or photographs as a demonstration of this strategy. They found that the widths and lengths they derived were very closely correlated, but also consistently lower, with the values in the published description of the cultivated flowers.

Although several classical methods in literature e.g., shape-texture analysis, botanical trait extraction, and fractal analysis have been examined to classify flowers, the methods tend to depend largely on hand-designed features and preprocessing in the fields. Upon comparison, instead of the above-mentioned classical methods, this paper will use deep learning based CNN model with spatially learned features for better generalization. Clearly abandoning the manual approach, this work fits into the category of deep learning to provide a solution with the scalable and high-performance characteristics of the conventional methods.

### III. MATERIALS AND METHODS

These procedures include acquiring the images, pre-processing, training labeling, and the proposed method. Figure 2 represents the framework for flower identification using deep learning.

The design of this research is experimental, which consists of CNN [18-19] deep learning techniques. The main objective of this research is to identify different flower types and categorize them into their respective varieties.

A Kaggle-sourced dataset consisting of over 800 images per class for five flower types, daisy, tulip, rose, sunflower, and dandelion was used. Figure 3 represents the bird's eye view of a selected dataset of flowers. Each image had a resolution of  $320 \times 240$  pixels.

After processing and cleaning of the dataset, the raw data was removed. All images were resized to a uniform resolution of  $256 \times 256$  pixels, and their

pixel values were normalized to the range 0-1 using min-max scaling.

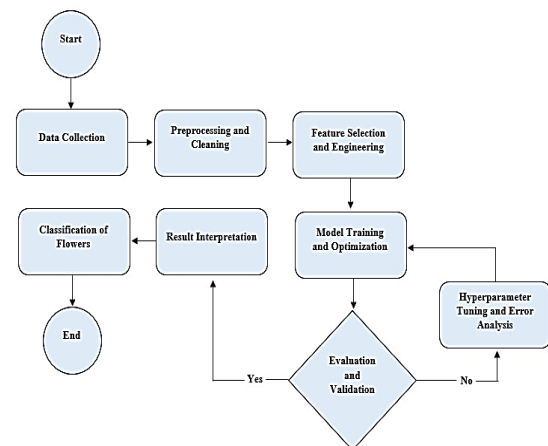


Figure 2: Framework for Flower Identification



Figure 3: Bird's Eye View of Selected Dataset of Flowers

Rotation, flipping, and zooming techniques were used to improve the generalization ability of the model. The dataset is split into 80-20 ratio:

- Training set: 80% images
- Testing set: 20% images

CNN architecture includes convolutional layers, pooling layers, and dynamic layers. Activation function is ReLU. SoftMax function is used in the final layer, which is suitable for multi-class classification. Python libraries like Keras, NumPy, Seaborn, Pandas and TensorFlow played an important role in the development of this model. The model was developed using Jupyter notebook. This research utilized supervised learning, a paradigm of machine learning. A labeled dataset is used in which each input sample is accompanied by a corresponding output label. This approach is adopted for classification tasks, in which the model is trained using features and their corresponding labels. The training dataset was input to the model in the form of feature-label pairs, and the goal was

for the model to predict correct labels for unseen data.

The model was trained for 30 epochs, and the loss and accuracy were measured after each epoch. The performance matrix of this model includes the following: F1 score, accuracy, precision, recall, confusion matrix, and accuracy vs loss score. The total testing phase and time per sample are measured to evaluate the performance of the model. These metrics measure the performance and scalability of the model.

In case of unsatisfactory results obtained at evaluation and validation levels, the process is repeated by going through model training and optimization to redefine it. The model was trained using a learning rate of 0.001, the Adam optimizer, and categorical cross-entropy as the loss function. Nevertheless, when the desired performance is accomplished, the flow of work shifts to interpretation of the results in order to provide final analysis.

Testing times show that the model makes relatively fast predictions, which is suitable for real-time applications such as mobile-based flower recognition tools. The total testing time can be proportional if the dataset size is large. Optimization techniques such as model pruning or quantization may be considered for future improvements. The model was tested on real-world images, achieving 98.56% training accuracy but 99.39% accuracy in validating the data. Model predictions analyzed using confusion matrix. To evaluate the model's performance, we selected commonly used metrics for classification. The selection matrix is used to evaluate the performance and accuracy of the model from every angle.

#### IV. RESULTS AND DISCUSSION

To evaluate comprehensively the model needs additional evaluation measures that include the precision-recall curve and recall statistics together with F1-score and accuracy metrics. The results from cross-validation gives a more durable explanation of model performance between different data sections. The current model demonstrates reliable structures yet further development together with additional stringent evaluations increases its classification performance for flowers.

In the evaluation process, 5-fold cross-validation took place to guarantee the strength of the model in the varying data splits. It demonstrated a high degree of accuracy with low standard deviation across folds which means that the model has stable performance and good generalization property. These findings strengthen the validity of the model across multiple trains-test split.

##### *Classification of Flowers Varieties*

The data collection for this study is organized into folders, one folder for each flower. During this section, noisy data was eliminated, and the info package cleaning was also completed. Some unnecessary elements have been removed from the file and cleared from the pertinent data; data has been prepared and arranged in files so that tests and training cannot provide any challenges. Five types of flowers are identified in the pictures: daisy, tulip, rose, sunflower, and dandelion. There are over 800 pictures for every class. Pictures have a low resolution of  $320 \times 240$  pixels. Photographs are not limited to one size; instead, they have several dimensions. Figures 4, 5, 6, 7, 8 represent types of flowers such as roses, tulips, sunflowers, dandelions, and daisies respectively identified by CNN.



Figure 4: Flower Type - Rose



Figure 5: Flower Type – Tulip



Figure 6: Flower Type – Sunflower



Figure 7: Flower Type - Dandelion



Figure 8: Flower Type – Daisy

**Training Process**

**Epochs:** This ensures that the model performs well on new, untested data. To check the validation of this model, 30 epochs were applied which showed the results. It proved that the model is showing its best performance.

Table 1: Epochs Accuracy

Matrix	Daisy	Dandelion	Rose	Sunflower	Tulip
TPR	0.16065	0.219454	0.22132	0.16925	0.2145
TNR	0.83157	0.7589251	0.79073	0.8288602	0.7849
FPR	0.16842	0.2410748	0.20926	0.1711397	0.2150
FNR	0.83934	0.7805456	0.77867	0.8307426	0.7854

As Table 1 indicates, the model shows good results regarding True Negative Rate (TNR), which shows that the model is sound in correctly labeling untargeted classes and reducing false positivity. Although the True Positive Rate (TPR) is low, it indicates the spaces where the model can still be improved, identifying correct flower type, probably

because of similarities within classes. False Positive Rate (FPR) is also low, and this is a good indication since it shows a high precision. Despite the relatively high False Negative Rate (FNR), in quite a few instances the model provides good performance. In general, there are some apprehensive but correct classification trends.

**Testing Time**

It is the crucial stage of machine learning where performance metrics like precision, F1-score, recall, specificity, and accuracy are measured by systematically evaluating trained models using various test datasets [20-21]. It also involves performance testing to assess how they behave under different operating conditions. Model predictions analyzed using confusion matrix. The performance of this model improved with the help of hyperparameters tuning. The flask framework was used to deploy the final optimized model. It took 68.6891 seconds to calculate performance on the complete test dataset.

Table 2: Final Evaluation Results for Individual Flower Categories

Flower Class	Model Performance Metrics			
	Precision = $\frac{TP}{TP+FP}$	Recall = $\frac{TP}{TP+FNR}$	F1 Score = $\frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$	Specificity = $\frac{TN}{TN+FP}$
Daisy	0.983	0.979	0.981	0.988
Dandelion	0.991	0.995	0.993	0.994
Rose	0.974	0.967	0.970	0.982
Sunflower	0.996	0.993	0.994	0.997
Tulip	0.987	0.990	0.988	0.990
<b>Training Accuracy</b>	98.56 %			
<b>Validation Accuracy</b>	99.39 %			

At several stages, the performance of the model under investigation was analyzed in order to achieve the steady and valid outcomes of its classification. Table 1 represents raw diagnostic yielded that is an insight on the class level detection behavior in training. Whereas Table 2 presents the final evaluation results for individual flower categories, it portrays high-quality performance across all categories, demonstrating strong precision, recall, F1 score, and specificity, which indicate a well-balanced model.

**Confusion Matrix**

It provides a comprehensive examination of the algorithm's performance by comparing the predicted values of the model with the actual target values. The matrix makes it easy to understand the many types of errors the classifier is making. Figure 9 represents the confusion matrix of the different flowers.

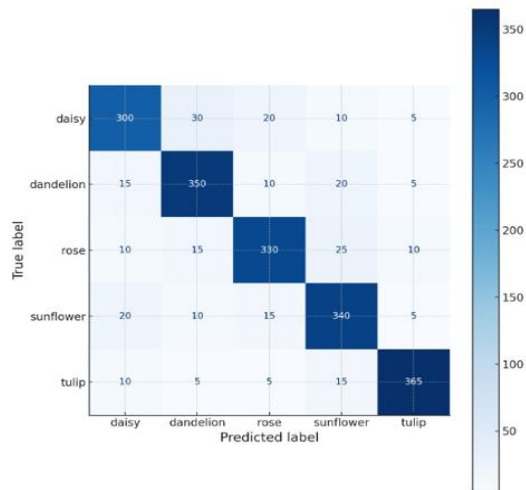


Figure 9: Confusion Matrix

The confusion matrix indicates that the overall classification performance is high with each of the flower classes recording high true positive rates. Minor misclassifications were seen between visually similar classes e.g. daisy-dandelion and rose-tulip indicating feature representations overlaps in all classes.

*Accuracy vs Loss:* The graph clearly illustrates that our model does not appear to be over-fitted in the training and validation accuracy.

In addition, a strong learning rate is shown by the training and validation loss in the graph.

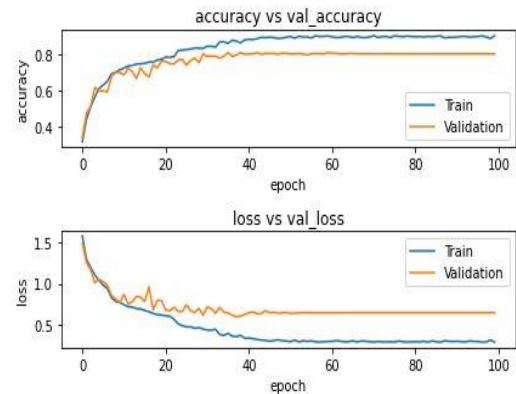


Figure 10: Accuracy and Loss

The results of the performance indicate that the validation accuracy is a little bit better compared to the training accuracy. This might be the case because of regularization methods like dropout which are in effect during training but not during validation causing a more stable measurement. Also, it is possible that applying such techniques as early stopping or batch normalization helps improve generalization on the validation set. It also indicates that the model is not overfitting and has memorized features that work well with unseen data.

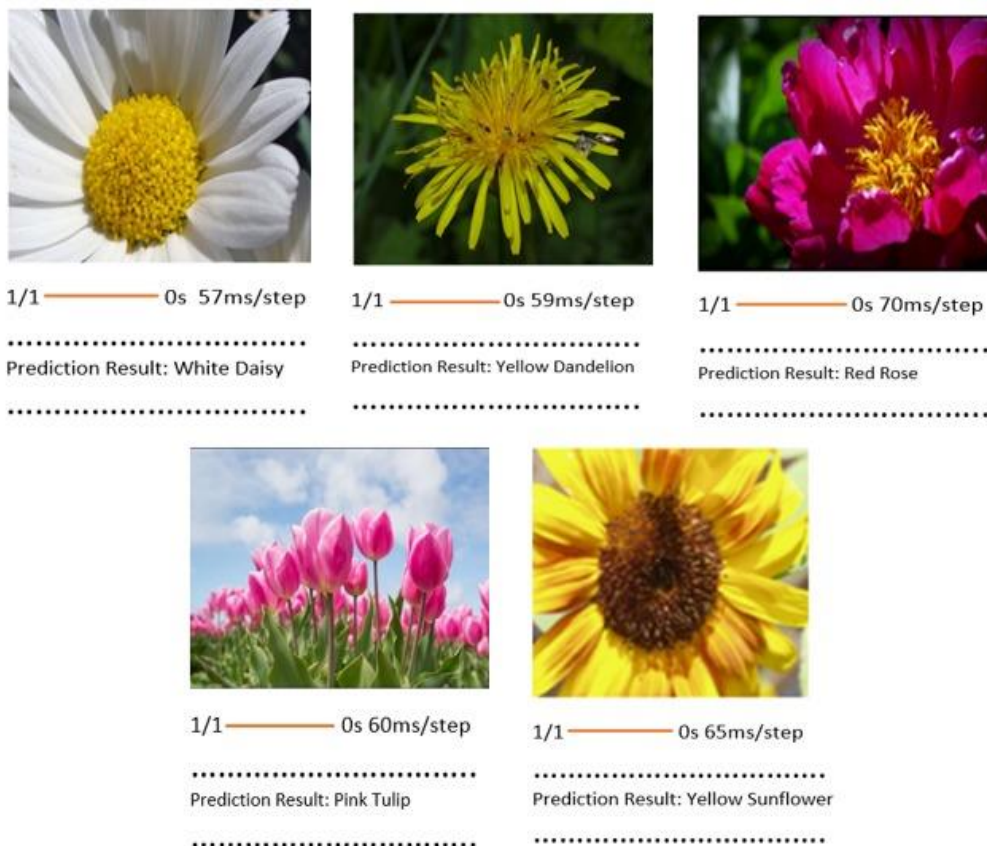


Figure 11: Results of Flower Varieties

The CNN network's ability to understand image spatial relationships stands as one of its main benefits along with its ability to optimize hierarchical spatial understandings.

The model achieved 98.56% training accuracy but 99.39% accuracy in validating the data. At present the accuracy reaches commendable levels, however perfection remains out of reach alongside the need to resolve class confusion issues.

These flaws can be tackled through multiple remedies. The performance outcome can benefit from adopting CNN architectural types that include VGG and ResNet as well as inception. The outcomes of this work could be enhanced by implementing feature engineering with transfer learning procedures and hyperparameter optimization techniques as well as class balancing methods. The creation of predictive models becomes more accurate when different models are combined by ensemble methods and their individual forecasts are synthesized together. Figure 11 shows the identification of flower varieties using a CNN.

This study demonstrates that CNN is effective in the issue of automatic flower (various types) classification. Using more than 30 epochs of model training and optimization of the most important hyperparameters, the system demonstrated balanced accuracy and recall, as well as with the F1-scores of all classes, and the most successful results were high precision and the ability to distinguish a true negative. Combining dropout and optimized architecture allows avoiding overfitting, and the deployment via Flask also makes the model practically usable. Generally, the work adds a stable, high-throughput, and modifiable way of flower identification that can be used to conduct ecological research, teaching, as well as practice botanical uses.

## V. CONCLUSION

In this study, we tested a deep learning approach to learn the discriminatory characteristics of flower images with classifiers for flower identification. Before building the model with Keras, the data is split into training and testing sets to allow for a reliable evaluation. CNN architecture is designed to handle the complexity of classifying floral photos. It consists of layers for pooling, convolution, and fully connected networks to extract and learn features. A confusion matrix is used to evaluate the model's performance in order to guarantee high accuracy and pinpoint areas that require improvement. In future, the research can be expanded by incorporating greater variety of flower data to overcome the limitation of fewer classes and inaccurate classification. Transfer learning as well as exploring advanced CNN architectures such as ResNet or Inception might improve the extraction of features and general accuracy.

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