Grenze International Journal of Engineering and Technology, June Issue

# Hybrid Generative Approaches for Flower Classification

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***Abstract*— Various techniques have been employed in the development of image classification frameworks to enhance efficiency and accuracy. In this work, flower image classification is performed using multiple approaches, including edge detection and feature extraction combined with the K-Nearest Neighbor (KNN) algorithm. A Deep Convolutional Neural Network (CNN) is also integrated with traditional machine learning classifiers to improve the identification of flower species. To further enhance accuracy, we propose four distinct hybrid frameworks for flower classification. The dataset, sourced from Kaggle, includes five flower categories: rose, tulip, dandelion, sunflower, and daisy. Each model is evaluated using accuracy, precision, and F-score metrics. The experimental results show that the hybrid model combining ResNet with Support Vector Machine (SVM) achieves the highest accuracy among all proposed models. Overall, the study demonstrates the effectiveness of hybrid fusion-based classification techniques for flower image recognition.**

***Index Terms*— VGG, Googlenet, ResNet, SVM, AlexNet.**

## I. INTRODUCTION

The classification of flowers is currently a popular research topic in field of image analysis and classification. Organic substances are commonly used in medical fields in both developed and developing countries, which has increased the size of medicinal plants in the last two decades. The correct identification and classification of medicinal plants and flowers are most important factor contributing to avoid risks of herbal medications. So, this complex identification and classification problem significantly improved in current years by the efforts of many researchers. Manual identification and classification plants and flowers are time-consuming and challenging for even the skilled botanical professionals. As a result, automation plays a vital role for identification and classification plants and flowers by the help of machine learning, deep learning, artificial neural networks and Hybrid learning framework. Flowers exhibit high intra-class variability in terms of colour, shape, size, and texture, while also sharing inter-class similarities across species, making their accurate classification a challenging task. It motivates the study and implementation of hybrid approaches for flower classification. Here we proposed a hybrid classification framework for five flower species of rose, tulip, dandelion, sunflower and daisy to flower classification. We evaluate the proposed hybrid classification framework on Kaggle benchmark flower dataset which contains multiple species exhibiting high intra-class variation and inter-class similarity. The output of individual model's is evaluated with precision, F1-score and accuracy.

*Grenze ID: 01.GIJET.12.2.117_21*

## II. Related Work

Many frameworks including KNN, Random Forest, SVM and multi-layer perception were reached to classify floral images [1]. Hybrid deep learning framework using stacking ensemble learning to combine VGG-16 and MobileNet for classifying sunflower diseases [2]. Using a Google Photos dataset, their approach achieved 89.2% accuracy, outperforming other algorithms. [3] proposed a deep learning method for recognizing Esca Black Measles in grapevines, using a dataset of 1,807 images. By combining ResNet50 with transfer learning and precision optimization, the framework outperformed traditional machine learning methods in accuracy and efficiency. [4] reviewed methodologies for plant-related applications by using machine learning, deep learning, and artificial neural networks. Their study highlights soil quality assessment and plant's health challenges including identification, categorization, and forecasting, while identifying deficiencies and suggesting alternatives for improved plant development. It is significant to note that deep learning is not a limited learning method, but rather one that integrates a variation of processes is used to a wide range of intricate situations [5]and [6] Though, as deep learning is broadly used for classification complex images for knowledge them have certainly grown radically in proportion [7] and [8]. Apply ResNet50 with transfer learning to notice diseases from tomato, potato and corn and achieving better accuracy [9]. The ResNet50 is compared with VGG16 and CNN blends to train the model. ResNet50 achieved better accuracy.The technique are used to identify sixteen different types of plant's diseases that might be classified[10] three blends deep learning approach GoogLeNet, AlexNet and ResNet50—to classify images of five indigenous plant species, achieving 90% accuracy. Among the models, ResNet50 performed best with 88.93% accuracy. [11]; Bose et al., [12]The study highlights that integrating ML (machine learning), deep learning, and image processing methods enhances image detection and classification performance. Deep learning mainly used to enhances method performance and time utilization [13]. In the context of the machine learning application, current a system for plant's disease and it's treatment. Deep learning is the important period of machine learning and presently used to support in the mainly classification of plant images. In this work planned and analysed modern approaches for infection diagnosis by using deep learning method and CNN. The efficiency of this work depends on the capability to takings maximum profit from this huge data by using data analytics[14].Categorizing rice plant infections in the present era [15] is categorized by AI (artificial intelligence) and increased widespread used in many fields, the conclusion of this work was diagnose a real-time farming implements for future research work. The proposed [16]computer vision methods using machine and deep learning techniques . Here multilayered CNN used as the generator and regular CNN as the discriminator. Lijo et al [17] proposed three different learning techniques, InceptionV3, ResNet50 and DenseNet169 for image identification and calculates the individual's performance by using different quality measures with accuracy, recall, precision, and F1 score among others.
From the Following Gaps are identified based in the Survey .

- Although many studies use CNN-based models for flower classification, only a few works investigate hybrid combinations such as ResNet with SVM or CNN feature extractors with traditional classifiers.
- Existing literature typically evaluates only one or two hybrid models. A comprehensive comparison of multiple fusion strategies for flower classification remains limited.
- Many studies rely mainly on accuracy, while precision, recall, and F-score are often underreported, making it difficult to evaluate the robustness of proposed models.
- With the dominance of deep learning, the potential benefits of integrating edge-based and handcrafted features with deep features have not been extensively studied.
- Prior works often focus on fewer classes or non-standard datasets, resulting in limited generalization. More consistent experimentation on standardized datasets like the Kaggle Flowers dataset is needed.
- Certain flower species have high intra-class variability and inter-class similarity, which reduces classification performance. Hybrid models have not been fully explored to address this fine-grained challenge.

## III. Proposed Approaches

Hybrid classification is an approach which combines basic classification methods for data processing, model formulation, identification and classification of an images .To increase performance of classification, hybrid approachs are built with a blend of supervised and unsupervised techniques. The hybrid classification model is proposed for classification of flower with ML (machine learning) and deep learning. Different CNN are designed for feature extraction and selections. The table 1 shows that the CNN performance using Top-1 and Top-5 accuracy on ImageNet. Models like VGG, AlexNet, ResNet, ProxylessNAS, Res2Net, DenseNet, and

EfficientNet give better accuracy. On the other hand, GoogleNet, MobileNet, MobileNetV2, and IGCV2 reach only one accuracy level on ImageNet. A hybrid models combine different algorithms to improve performance for flower classification, Random Forest, KNN, SVM, and MLP are applied. GoogLeNet with Inception-v3 is also hybridized for classification, and VGG-16 with MobileNet used with SVM is used for identification and classification. Different algorithmic techniques are incorporated to develop 4 hybrid model for flower classification. The models are developed with the fusion of SVM. The models are tested and achieve improved accuracy.

TABLE I: CONVOLUTIONAL NEURAL NETWORK MODELS PERFORMANCE

| CNN model | ImageNet Accuracy | |
|---|---|---|
| | top1 | top5 |
| VGG | 76.3 | 93.2 |
| GoogleNet | - | 93.33 |
| AlexNet | 84.7 | 73.8 |
| ResNet | 92.43 | 96.43 |
| MobileNet | 70.6 | - |
| DenseNet | 79.2 | 94.71 |
| MobileNetV2 | 74.7 | - |
| IGCV2 | 70.07 | - |
| ProxylessNAS | 75.1 | 92.5 |
| Res2Net | 79.2 | 94.37 |
| EfficientNet | 84.3 | 97.0 |

### *A. VGG16+SVM MODEL*

The VGG16+SVM hybrid model is designed for flower classification and it improved accuracy and reduced computational time. The VGG-16 uses 16 layers,3x3 kernel-sized filters and 1×1 convolution filter is applied as a linear transformation of the input channels. Every convolution phase is fixed at 1 pixel with spatial padding applied to reserve the resolution, make sure that a 3×3 filter functions efficiently over the input.The model also used max-pooling with a 2×2 pixel and a step of 2 to reduce spatial dimensions. Afterward convolutional and pooling processes, the network contains 3FC (three fully connected) layers have 512 channels followed by the last step. Normally, the last layer in VGG16 is a Softmax and all hidden layers used ReLU activation functions to introduce non-linearity. In the hybrid method, instead of depend on Softmax, the extracted deep features from VGG16 are accepted to a SVM classifier. This hybrid model is applied to the standard kaggle dataset, which uses five flowers rose, tulip, dandelion, sunflower and daisy. Total 6027 total images for experimentation.

### *B. ResNet50+SVM Model*

The ResNet50 with SVM is hybrid model is designed for the classification of flowers and it improved accuracy and reduced computational time.It uses the 50-layer deep network of the CNN model. ResNet50 architecture is an ANN architecture which consists of multiple stacked residual blocks arranged sequentially to form a deep network. ResNet50 resolves the problem of deep networks by using skip connections. The skip connections in residual blocks are the main strength of ResNet50. This model achieve better results with the SVM .This hybrid classification model is applied to the standard kaggle dataset ,which uses five flowers rose, tulip, dandelion, sunflower and daisy. Total 6027 total images for experimentation.

### *C. GoogleNet + SVM Model*

The GoogleNet with SVM is hybrid model is designed for the classification of flowers and it improved accuracy and reduced computational time. The GoogleNet is a CNN model based on the inception architecture. The GoogleNet module is used to authorization the network to choice the numerous convolutional channel sizes into blocks. The stacks of Inception blocks carried the modules on top of each layer that contains the periodic max-pooling with stride two that divides the goal into the grid. It decreased the computational expense of preparing a broad network by reducing the dimensions. This hybrid classification model is applied to the standard kaggle dataset , which uses five flowers rose, tulip, dandelion, sunflower and daisy. Total 6027 total images for experimentation.

### *D. AlexNet + SVM Model*

The AlexNet with SVM hybrid model is designed for classification of flowers and it improved accuracy and reduced computational time.it refers to CNN architecture .The AlexNet includes 8 levels of parameters that may be learned. The model is composed of 5 layers, the first of which is a max pooling layer followed by three fully connected layers, and each of these levels, save the output layer, uses Relu activation. This hybrid classification model is applied to the standard kaggle dataset , which uses five flowers rose, tulip, dandelion, sunflower and daisy. Total 6027 total images for experimentation.

## IV. EXPERIMENTATION

The experimentation has been conducted by using primary factors to analyze model accuracy. Here we used confusion matrix to quantify the accuracy of visual categorization. The Figures 1 shows VGG16 with SVM confusion matrix with accuracy about five flowers. Rose is 87%, tulip is 93%, dandelion's is 82%, sunflower is 85% and daisy is 90%, results states that tulip flower achieves good accuracy followeds by rose and daisy. and sunflower and dandelion is less accuracy. The Figures 2 shows ResNet50 with SVM confusion matrix accuracy for the five flowers. Accuracy of rose is 93%, tulip is 92%,dandelion is 87%, and sunflower is 88% and daisy with 91%.The GoogleNet with SVM confusion matrix shows the model accuracy for the 5 flowers. Accuracy of Rose is 39%, tulip is 74%, dandelion is 43%, sunflower is 53% and daisy is65% is shown in figure:3. The AlexNet with SVM confusion matrix is shown in figure:4 for the 5 flowers .Accuracy of Rose is 11%, tulip's 68%, dandelion's is 55%, sunflower is 52% and daisy with 64%.Results states that tulip flower succeeds better accuracy than the other four flowers . Some hybrid models classify all five flower species very accurately and others models classify only a few flower species as shown in figure 1 to figure 4. The overall accuracy of proposed four hybrid models as shown in figure 5. Table 2 shows the overall accuracy of four proposed models and their precision and f1-score for better system classification.

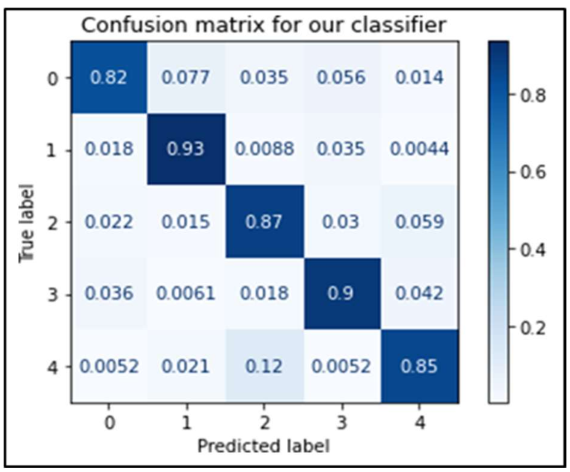


Figure 1: Confusion Matrix of VGG16 + SVM Model

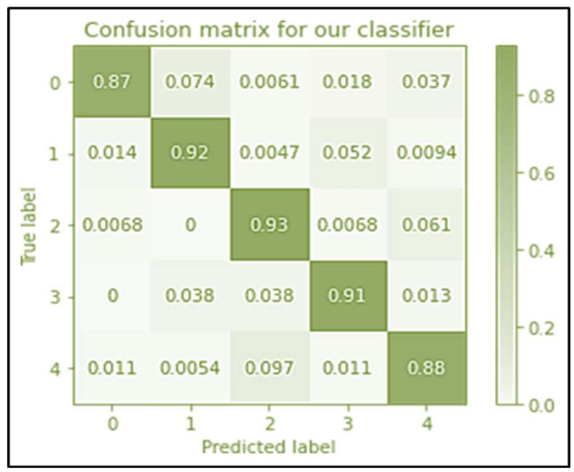


Figure 2: Confusion Matrix of ResNet50 + SVM Model

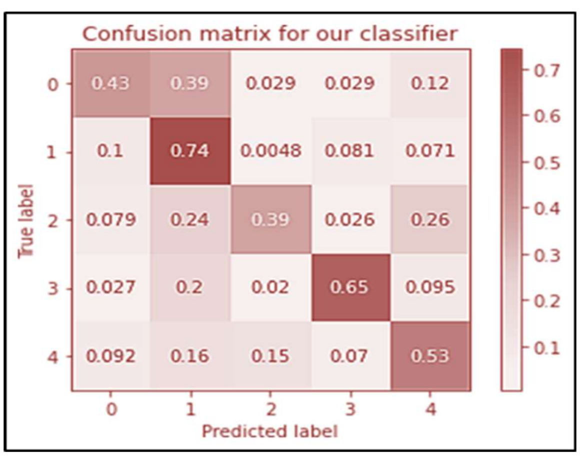


Figure 3: Confusion Matrix of GoogleNet + SVM Model

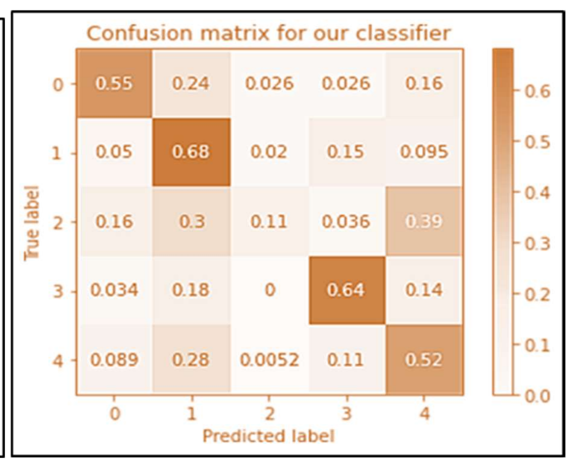


Figure 4: Confusion Matrix of AlexNet + SVM Model

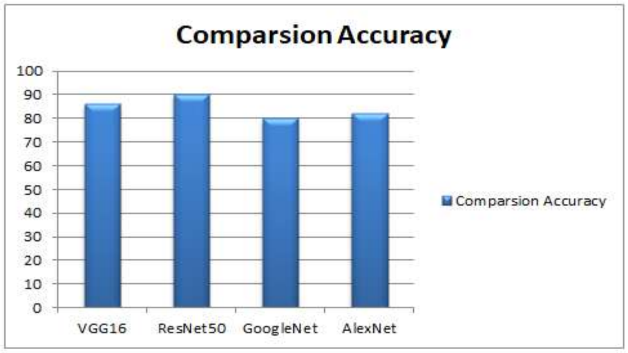


Figure 5: Comparative Analysis of the Proposed Models

TABLE II: COMPARATIVE ANALYSIS OF HYBRID MODELS

| Model | Flower Species | Features | Precision | F1-Score | Accuracy (%) | Overall accuracy (%) |
|---|---|---|---|---|---|---|
| VGG-16 + SVM | Rose | | 0.79 | 0.78 | 89.82 | |
| | Tulip | | 0.76 | 0.75 | 86.43 | |
| | Dandelion | | 0.77 | 0.71 | 85.68 | |
| | Sunflower | | 0.74 | 0.75 | 86.73 | |
| | Daisy | 1000 | 0.74 | 0.77 | 86.31 | 86.82% |
| ResNet-50 + SVM | Rose | | 0.86 | 0.85 | 92.24 | |
| | Tulip | | 0.84 | 0.83 | 90.12 | |
| | Dandelion | | 0.83 | 0.85 | 89.27 | |
| | Sunflower | | 0.8 | 0.85 | 90.02 | |
| | Daisy | 1000 | 0.81 | 0.85 | 90.01 | 90.01% |
| AlexNet + SVM | Rose | | 0.75 | 0.7 | 81.33 | |
| | Tulip | | 0.74 | 0.73 | 80.11 | |
| | Dandelion | | 0.78 | 0.7 | 80.91 | |
| | Sunflower | | 0.69 | 0.66 | 79.12 | |
| | Daisy | 1000 | 0.75 | 0.71 | 82.13 | 80.27 |
| GoogleNet + SVM | Rose | | 0.75 | 0.74 | 84.65 | |
| | Tulip | | 0.76 | 0.72 | 82.81 | |
| | Dandelion | | 0.79 | 0.74 | 84.25 | |
| | Sunflower | | 0.69 | 0.68 | 79.65 | |
| | Daisy | 1000 | 0.72 | 0.71 | 81.92 | 82.54 |

## V. CONCLUSION

Four hybrid classification models were designed and developed for effective flower categorization. The performance of these proposed models was evaluated using precision, F-score, and accuracy metrics on a Kaggle dataset consisting of five flower species: rose, tulip, dandelion, sunflower, and daisy. Experimental results show that the hybrid model combining ResNet-50 with Support Vector Machine (SVM) achieved the highest accuracy among all models. Specifically, VGG-16 with SVM achieved an accuracy of 86.82%, ResNet-50 with SVM achieved 90.01%, AlexNet with SVM achieved 80.27%, and GoogleNet with SVM reached 82.54%. These findings demonstrate that ResNet-50 is an effective feature extractor for flower classification when paired with SVM. Future work can extend this study by applying more advanced machine learning and deep learning techniques to larger and more diverse datasets to further improve classification performance and generalization.

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