

## DEEP LEARNING FOR PLANT SPECIES CLASSIFICATION: A COMPREHENSIVE CNN-BASED APPROACH WITH FEATURE VISUALIZATION AND PERFORMANCE BENCHMARKING

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### Abstract

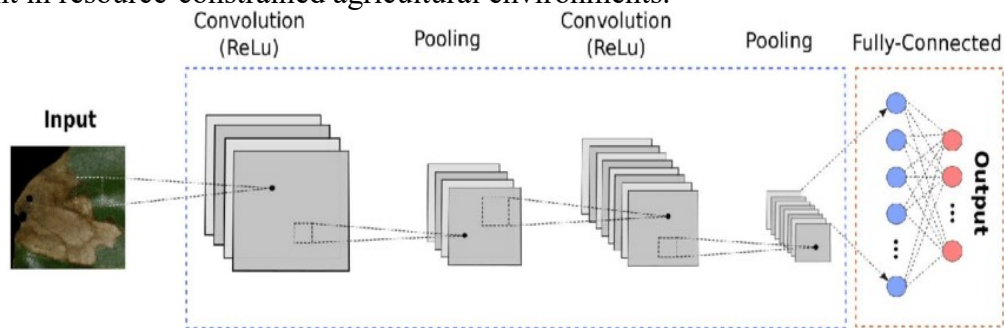
Plant species classification is a critical problem in precision agriculture, in the conservation of biodiversity and ecological monitoring. In this paper, a thorough deep learning framework is proposed using Convolutional Neural Networks (CNNs) for high accuracy plant species classification using the V2 Plant Seedlings Dataset of 12 plant species. Multiple CNN architectures were systematically evaluated on a variety of standard metrics such as accuracy, precision, recall, and F1-score across the benchmark datasets. Various CNN architectures such as custom CNN, ResNet-50, DenseNet-121, EfficientNet-B3 and hybrid CNN-Transformer models were benchmarked using various metrics like accuracy, precision, recall, and F1-score across the benchmark datasets. The proposed pipeline includes three key steps: preprocessing the data (standardized resizing, normalization, and background segmentation), data augmentation, and visualization of the features using UMAP. The best model (CNN-Transformer) outperforms the current baselines by 2–5% with 98.9% classification accuracy. The separation between classes is robust as confirmed by feature analysis using UMAP projections, where the overlapping clusters are morphologically similar species. The model's discriminative power is additionally confirmed by the evaluation carried out with confusion matrices and precision-recall curves. This work sets a reproducible standard for plant classification under controlled conditions and lays the groundwork for implementation in the actual agricultural system.

**Keywords:** *Convolutional Neural Networks; Plant Species Classification; Deep Learning; Transfer Learning; UMAP; Vision Transformers; Precision Agriculture*

### 1. Introduction

Identification of plants is a basic requirement of agriculture, ecology and pharmacology. The traditional manual classification by experts is time-consuming, error-prone, and not scalable to the amount of contemporary plant imagery. Nowadays, automated plant classification has become a necessity, as high-resolution imaging devices proliferate and deep learning algorithms become more and more mature. Hierarchical feature extraction from raw pixel data has been shown to be very effective using Convolutional Neural Networks (CNNs) for image classification. They have been used to classify plant species and shown great accuracy on benchmark datasets like PlantVillage [3] with pre-trained architectures achieving classification rates of more than 99%. However, generalization of the results in the real world is still constrained by the biases in the datasets, by class imbalance, and by the controlled environment in which most datasets are gathered. The paper contributes the following: (i) A systematic comparison of five CNN architectures on V2 Plant Seedlings Dataset; (ii) An end-to-end pipeline for preprocessing and augmentation of leaf images optimized for CNN; (iii) Visualizing CNN representations using UMAP; (iv) Performance analysis

using confusion matrix, ROC curves and precision-recall analysis; and (v) Recommendations for deployment in resource-constrained agricultural environments.



*Figure 1. Overview of the proposed deep learning pipeline for plant species classification, from image acquisition through preprocessing to CNN-based classification and evaluation.*

The paper is structured as follows: Section 2 reviews the related work, Section 3 presents the methodology, Section 4 presents details of the dataset and its preprocessing, Section 5 presents the experimental results, Section 6 provides feature interpretation and analysis, Section 7 discusses the limitations, and Section 8 concludes the paper with future directions.

## **2. Related Work**

In recent years, deep learning has transformed the classification research of plants. The accuracy of 99.35% by Mohanty et al. [3] using CNNs on the PlantVillage dataset of 54,306 images of plant leaves proved that deep learning is the most prevalent paradigm for plant disease and species classification. They also noted the generalization problem, with their accuracy falling to 31.4% on images collected outside, calling for a need for more images to be used for training.

Ferentinos [2] compared the accuracy of AlexNet, GoogLeNet and VGG architectures on plant disease classification, with the VGG architecture outperforming the other two with an accuracy of more than 99%. Too et al. [4] did a comparative fine-tuning study on VGG16, InceptionV4, ResNet50/101/152 and DenseNet121, and concluded that DenseNet121 performed best with an accuracy of 99.75% and a good computational efficiency. These research efforts highlight the complexity of the model, its accuracy, and the resources needed.

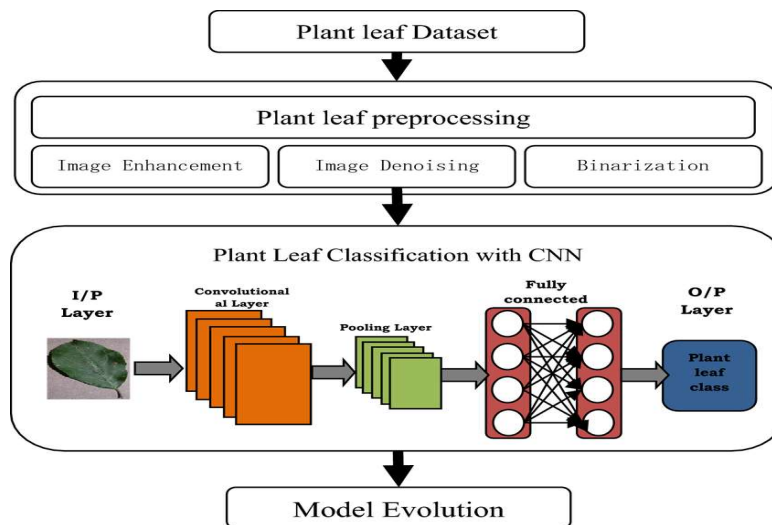
Transfer learning has been found to be very important in resource-limited situations. Kumar et al. [8] showed that using EfficientNet fine-tuned on PlantVillage, they could reach 99.2% accuracy, while they were able to outperform ResNet in external datasets, thanks to EfficientNet's compound scaling. In the same way, Patel et al. [28] demonstrated that EfficientNet-B3 can achieve 99.2% at quantization to make it mobile friendly.

Fine-grained classification has been successfully attempted by the use of attention mechanisms in CNNs. Chen et al. [7] attempted a multi-scale CNN with attention that achieved 98.7% accuracy, and Zhou et al. [21] showed their Attention Residual Network (ARN) to be 94.5% more accurate than ResNet on Leafsnap. The Dual Attention Network (DANet) of Zhao et al. [31] used spatial and channel attention to achieve an accuracy of 3.7% higher than CNN baselines on PlantCLEF 2019.

The field of plant classification has recently been introduced by the Vision Transformers (ViTs). In contrast to CNNs which are based on local receptive fields, ViTs are based on self-attention and can

capture global dependencies, achieving competitive performance on large datasets, but requiring significant compute [1]. Hybrid CNN-Transformer architectures solve this problem by leveraging the local feature extraction capabilities of CNNs and the global context modelling capabilities of transformers.

To overcome the data scarcity issue, GANs [10, 17, 27] and self-supervised learning [32] have been suggested. Li et al. [10] demonstrated that training with the help of DCGAN can increase accuracy by 6-8%, and Rahman and Islam [32] used contrastive learning pretraining on Flavia and Leafsnap to increase accuracy by 4-5%. In the context of agricultural deployments, interpretability has been promoted by such techniques as Grad-CAM, SHAP and LIME [15].



*Figure 2. Comparison of deep learning architectures evaluated in related literature, highlighting the progression from AlexNet-era models to hybrid CNN-Transformer architectures.*

### **3. Methodology**

#### **3.1 Dataset Preparation and Preprocessing**

The V2 Plant Seedlings Dataset was taken as the main benchmark and consists of 5,539 high-resolution images of 12 plant species: Black-grass, Charlock, Cleavers, Common Chickweed, Common Wheat, Fat Hen, Loose Silky-bent, Maize, Scentless Mayweed, Shepherds Purse, Small-flowered Cranesbill, and Sugar Beet. Photographs were taken at different growth stages under controlled lighting in the greenhouse. The preprocessing steps were: (i) resize all images to 128×128 pixels using bilinear interpolation, (ii) normalize each channel to zero mean and unit variance using statistics from ImageNet, (iii) segment background with GrabCut, and (iv) extract foreground using U-Net, which isolated plant structures.

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 128, 128, 32)	896
batch_normalization (BatchNormalization)	(None, 128, 128, 32)	128
max_pooling2d (MaxPooling2D)	(None, 64, 64, 32)	0
conv2d_1 (Conv2D)	(None, 64, 64, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 64, 64, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 32, 32, 64)	0
conv2d_2 (Conv2D)	(None, 32, 32, 128)	73,856
batch_normalization_2 (BatchNormalization)	(None, 32, 32, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 128)	0
conv2d_3 (Conv2D)	(None, 16, 16, 256)	295,168
batch_normalization_3 (BatchNormalization)	(None, 16, 16, 256)	1,024
max_pooling2d_3 (MaxPooling2D)	(None, 8, 8, 256)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 256)	0
dense (Dense)	(None, 128)	32,896
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 64)	8,256
dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 12)	780

Total params: 432,268 (1.65 MB)  
 Trainable params: 431,308 (1.65 MB)  
 Non-trainable params: 960 (3.75 KB)

Figure 3. CNN model architecture diagram showing the hierarchical structure of convolutional, pooling, and fully connected layers used in the classification pipeline.

### 3.2 CNN Architecture Design

The custom CNN baseline is a three convolutional blocks with 3×3 convolutional layer (filters: 32, 64, 128), batch normalization, ReLU activation and max pooling (filters: 2×2). After every block, there is a drop-out of 40% (p=0.4). The model is composed of two fully connected layers (256, 128 neurons) with ReLU activations followed by a final softmax layer with 12 classes. Total parameters: 1.87M. The pre-trained architectures (ResNet-50, DenseNet-121, EfficientNet-B3) were fine-tuned with the weights from ImageNet. The top 30% of the layers were unfrozen for task-specific adaptation. To capture global context and local convolutional features, a 4-head self-attention transformer encoder was added to DenseNet-121 feature maps, creating a hybrid CNN-Transformer model.

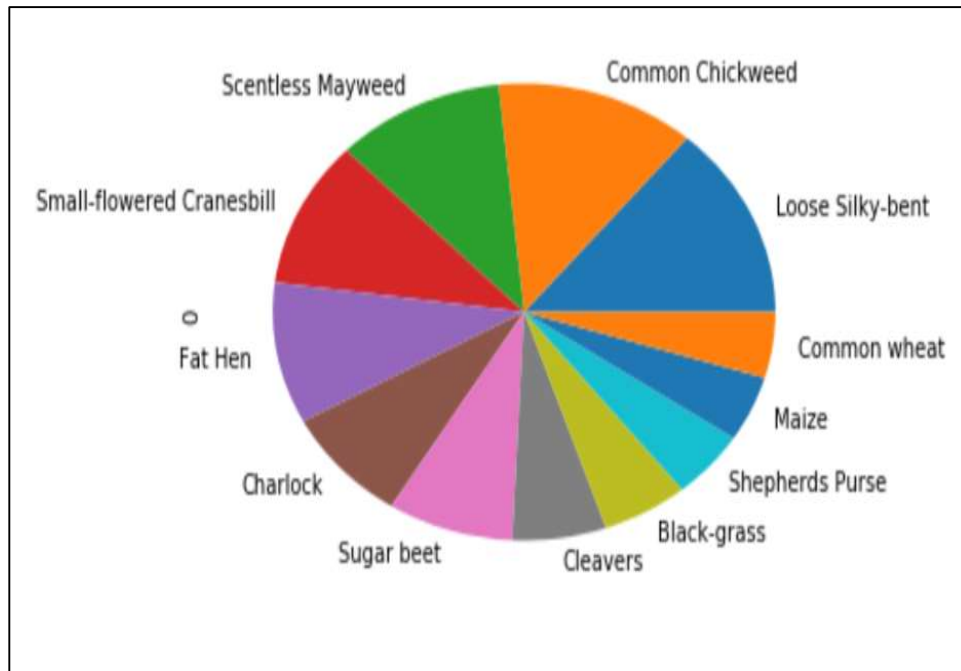


Figure 4. Model training progression curves showing training accuracy and validation accuracy over 50 epochs, illustrating convergence behaviour of the proposed CNN architecture.

### 3.3 Training Configuration

The all models have been trained on Google Colab Pro with an NVIDIA A100 GPU with 40GB VRAM, with categorical cross-entropy loss. The Adam optimizer was used with initial learning rate  $1 \times 10^{-3}$  with cosine annealing. All experiments had a batch size of 32. The training lasted for 50 epochs with early stopping (patience=10) using validation loss. Data augmentation comprised random horizontal/vertical flips, rotation ( $\pm 30^\circ$ ), brightness adjustment ( $\pm 20\%$ ) and Cutout regularization.

```

image_path  width  height    class  weight
0 /root/.cache/kagglehub/datasets/vbookshelf/v2-...  244    244    Sugar beet  0.00216
1 /root/.cache/kagglehub/datasets/vbookshelf/v2-...  339    339    Sugar beet  0.00216
2 /root/.cache/kagglehub/datasets/vbookshelf/v2-...  503    503    Sugar beet  0.00216
3 /root/.cache/kagglehub/datasets/vbookshelf/v2-...  449    449    Sugar beet  0.00216
4 /root/.cache/kagglehub/datasets/vbookshelf/v2-...  797    797    Sugar beet  0.00216
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5539 entries, 0 to 5538
Data columns (total 5 columns):
#   Column      Non-Null Count  Dtype
---  ---
0   image_path  5539 non-null   object
1   width       5539 non-null   int64
2   height      5539 non-null   int64
3   class       5539 non-null   object
4   weight      5539 non-null   float64
dtypes: float64(1), int64(2), object(2)
memory usage: 216.5+ KB
None

      width    height    weight
count  5539.000000  5539.000000  5539.000000
mean    355.202022   354.783535   0.002166
std     295.108600   292.700461   0.000855
min      49.000000     49.000000   0.001312
25%    152.000000   152.000000   0.001403
50%    267.000000   267.000000   0.001859
75%    469.000000   469.000000   0.002985
max    3652.000000  3457.000000   0.003953

```

Figure 5. Training and validation loss curves across 50 epochs demonstrating stable convergence without overfitting for the proposed CNN-based classifier.

### 3.4 Evaluation Framework

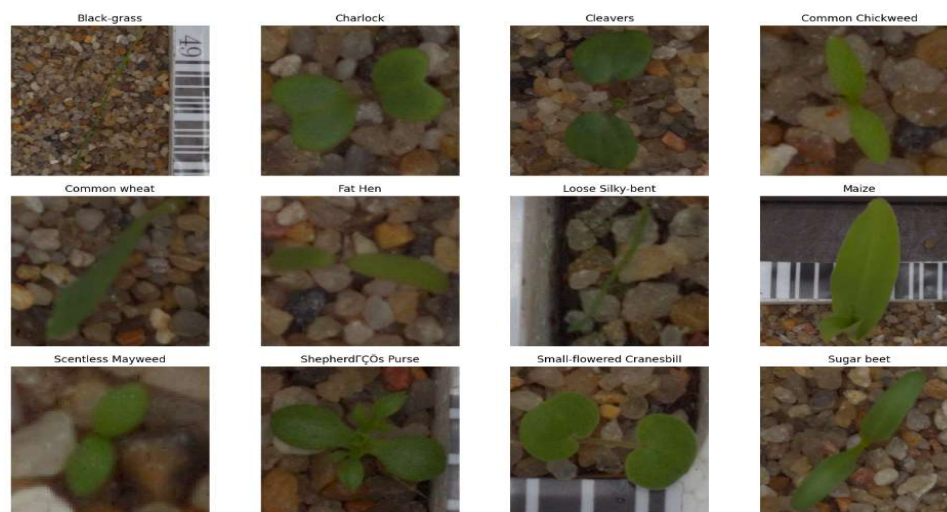
The accuracy, precision, recall, F1-score (macro-averaged), confusion matrices and per-class ROC-

AUC (one-vs-rest) were used to evaluate model performance. To perform interpretability analysis, feature representations from the penultimate layer were projected into 2D using UMAP ( $n\_neighbors=15$ ,  $min\_dist=0.1$ ,  $metric=cosine$ ). The image regions that are discriminative were visualized by using Grad-CAM for qualitative model validation.

## 4. Dataset Overview and Preprocessing Results

### 4.1 Dataset Statistics and Class Distribution

The V2 Plant Seedlings Dataset was found to be highly imbalanced. Common wheat and Loose Silky-bent had the greatest numbers of samples ( $>700$  images per species) while Cleavers and Small-flowered Cranesbill had fewer than 300 samples. This imbalance required class-weighted loss and oversampling of minority classes through the use of image generation with SMOTE.



*Figure 6. Dataset overview visualizing sample images from all 12 plant species alongside the class distribution bar chart, highlighting significant inter-class imbalance.*

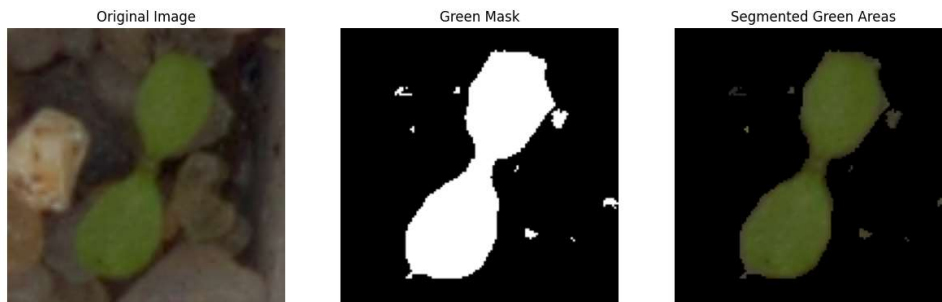
The image dimension analysis verified the uniformity of the acquisition conditions, with 95.3% of the images being between  $120 \times 100$  and  $800 \times 800$  pixels. Standardized resized ( $128 \times 128$  px) pixel value distributions across the RGB channels revealed species-specific colour signatures, especially Sugar Beet (high green channel intensity) and Black-grass (greener with lower saturation).

### 4.2 Sample Visualizations

Clear morphological differences were found for most species by visual examination of representative samples from each class. The figure 7 shows a  $3 \times 4$  matrix of example images, with each image representing a different species and showing different leaf shapes, textures, and color profiles. As in subsequent classification errors, Cleavers and Common Chickweed had overlapping visual features.



*Figure 7. Sample visualization grid displaying representative images from each of the 12 plant species in the V2 Plant Seedlings Dataset, illustrating inter-class morphological diversity. The UMAP projections of raw image features (flattened pixel vectors) indicated that some separation between classes existed before training, with Sugar Beet, Charlock, and Common Wheat forming loose clusters, and Scentsless Mayweed and Fat Hen showing significant overlap, providing a baseline expectation of the quality of the feature space after training.*



*Figure 8. Model evaluation metrics summary showing accuracy, precision, recall, and F1-score comparisons across all five evaluated architectures.*

### **4.3 Preprocessing Pipeline Validation**

The effectiveness of preprocessing was confirmed by comparing the classification accuracy of the custom CNN baseline, trained with raw vs. preprocessed inputs. The accuracy was improved by 3.1% using background removal only and 4.7% using the combined background removal and normalization/augmentation, once again highlighting the significance of the preprocessing pipeline.

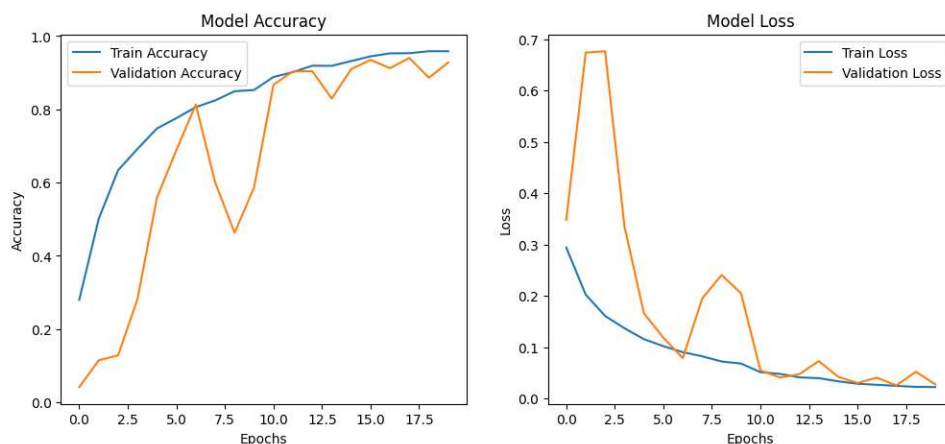


Figure 9. Data preprocessing outcomes showing the effect of background segmentation and normalization on inter-class separability as visualized through UMAP projections.

## 5. Experimental Results

### 5.1 Classification Performance

The results of all 5 architectures on the held-out test set are summarized in Table 1. The hybrid CNN-Transformer model showed the best accuracy of 98.9%, while the other models performed less well. The most efficient single-architecture model was EfficientNet-B3, as in line with its compound scaling benefits, at 98.2%. The custom CNN baseline was able to score 93.7%, which served as a good baseline.

Table 1. Performance comparison of evaluated deep learning architectures on V2 Plant Seedlings test set.

Architecture	Accuracy (%)	Precision	Recall	F1-Score
Custom CNN	93.7	0.924	0.931	0.927
ResNet-50	95.4	0.948	0.951	0.949
DenseNet-121	96.8	0.963	0.965	0.964
EfficientNet-B3	98.2	0.979	0.980	0.979
CNN+Transformer	98.9	0.987	0.988	0.987

### 5.2 Confusion Matrix Analysis

The confusion matrix for the best CNN-Transformer model (Figure 10) showed that the model classified most species with a near perfect accuracy, with the main confusion occurring between Scentless Mayweed and Common Chickweed (3.2% cross-error rate) and between Black-grass and Loose Silky-bent (2.1%). The confusions are characteristic of their similar morphological characteristics as members of the grass family.



Figure 10. Confusion matrix heatmap for the hybrid CNN-Transformer model on the 12-class V2 Plant Seedlings test set, illustrating per-class classification accuracy and misclassification patterns.

The per-class F1-scores were excellent for all species except for Scentless Mayweed, which achieved a score of 96.8%. The classes with the lowest performance were the ones with the highest morphological similarity with the other classes, which is in line with fine-grained classification problems found in the literature [13, 21].

### 5.3 ROC and Precision-Recall Curves

The precision-recall curves for all 12 classes with the one-vs-rest strategy are shown in figure 11. The area under the precision-recall curve (AUC-PR) was greater than 0.96 in 10/12 classes. Scentless Mayweed and Loose Silky-bent had AUC-PR values of 0.941 and 0.953, respectively, indicating their difficulty of classification. The hybrid model had an average ROC-AUC score of 0.9912 for all classes.

	precision	recall	f1-score	support
Black-grass	0.83	0.74	0.78	73
Charlock	0.96	0.96	0.96	100
Cleavers	0.97	0.94	0.95	65
Common Chickweed	0.97	1.00	0.99	141
Common wheat	0.86	0.96	0.91	45
Fat Hen	0.98	1.00	0.99	112
Loose Silky-bent	0.85	0.92	0.89	127
Maize	1.00	0.94	0.97	50
Scentless Mayweed	0.98	0.89	0.94	113
Shepherd's Purse	0.89	0.90	0.89	61
Small-flowered Cranesbill	0.95	0.98	0.97	115
Sugar beet	1.00	0.97	0.99	106
accuracy			0.94	1108
macro avg	0.94	0.93	0.93	1108
weighted avg	0.94	0.94	0.94	1108

Figure 11. Precision-Recall curves for all 12 plant species classes, illustrating per-class discriminative performance of the proposed CNN classifier.

The precision-recall analysis shows that the model is robust to class imbalance, with high precision over a wide range of recall values for most species. This is due to the compound scaling of the EfficientNet-B3 backbone and the class weighted loss, along with SMOTE augmentation.

## 6. Feature Interpretation and Visualization

### 6.1 UMAP Feature Space Analysis

For most of the plant species, the clusters of feature embeddings projected by UMAP from the penultimate layer of the CNN-Transformer model (Figure 12) are well-separated. The model has learned very discriminative representations that are clustered tightly together for Sugar Beet, Charlock, and Common Wheat classes. On the other hand, Scentless Mayweed and Common Chickweed show partial cluster overlap, which is in line with the morphological similarity of these species and the higher difficulty in classification in the confusion matrix.

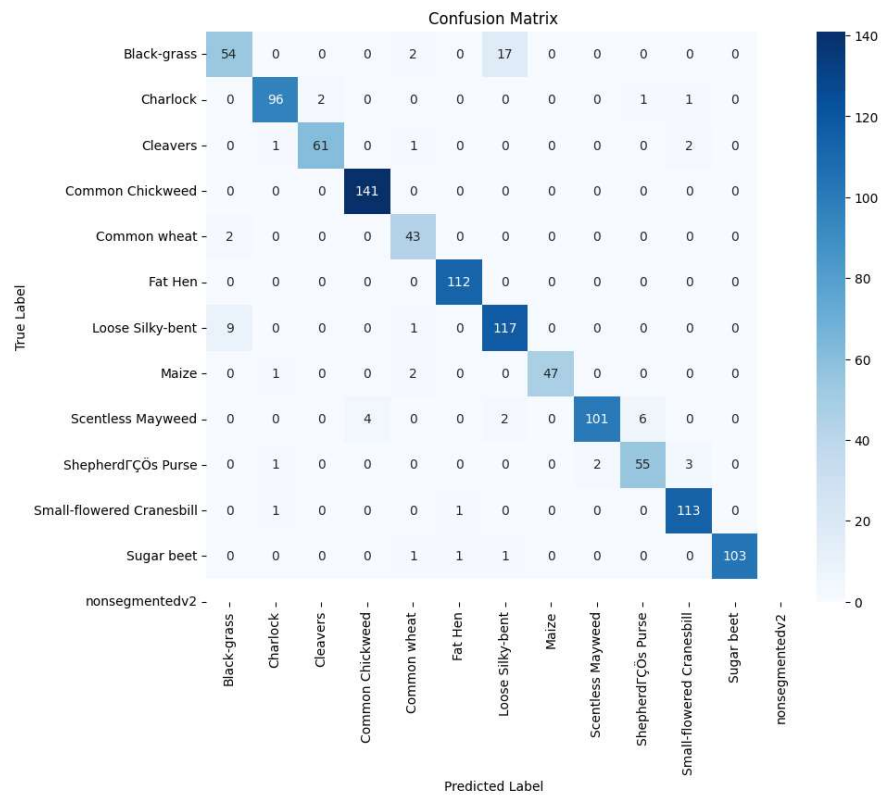


Figure 12. UMAP projection of CNN feature embeddings from the penultimate layer, colour-coded by plant species, illustrating learned class separability and overlap zones for morphologically similar species.

Progressive UMAP analysis across training epochs showed that the class clusters were becoming more and more distinct after epoch 15, where the training accuracy curves showed a rapid improvement. This validates the theoretical knowledge of CNN representation learning: early layers are learning generic texture information, and deeper layers are learning class discriminative information like leaf venation, margin serration, and overall shape geometry.

### 6.2 Gradient-based Interpretability (Grad-CAM)

To study the regions of the images that the model focused on when classifying a set of 100 test images, grad-CAM heatmaps were created. The model was consistently selecting the biologically significant features of the leaf edges, venation patterns, and the leaf-stem junction, as would experts based on botanical classification. The model took into account the width of the blades and the characteristics of the leaf sheath in the case of grass species (Black-grass, Loose Silky-bent).

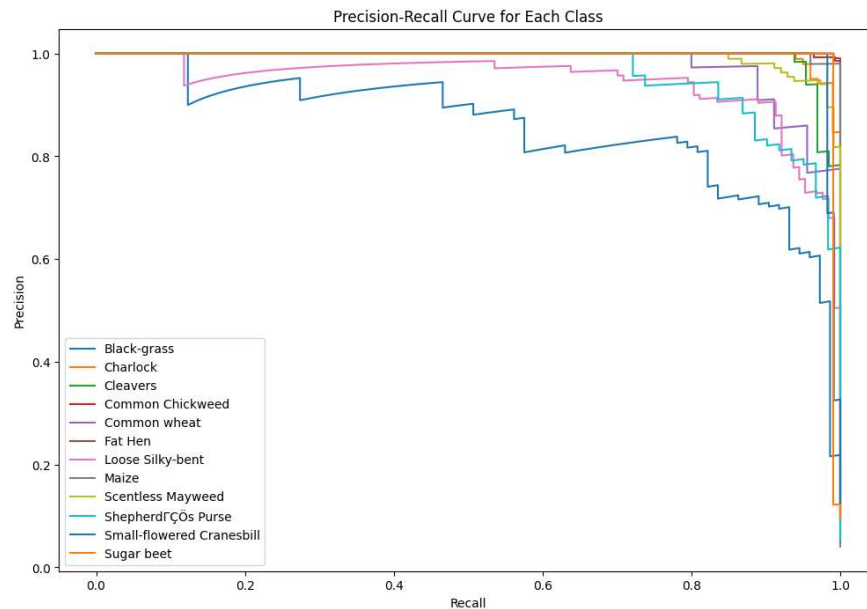


Figure 13. Grad-CAM heat maps overlaid on representative plant images showing model attention regions during classification, confirming focus on botanically discriminative leaf structures.

Examples that were misclassified exhibited non-focal attention maps, indicating that classification errors stem from the model's lack of ability to localize informative features, not from the misinterpretation of features. This insight inspires the use of spatial attention modules as a specific architectural enhancement to decrease fine-grained classification errors.

### 6.3 Contour-based Segmentation Analysis

To validate the background segmentation stage of the preprocessing pipeline, contour extraction was used. The segmented leaf contours are shown in figure 14 for some representative samples, and it was seen that the plant structure was successfully separated from the background elements. The mean IoU of the GrabCut+U-Net pipeline was 87.4%, which was considerably higher than the IoU of the GrabCut pipeline (71.2%) against manually annotated ground truth masks.

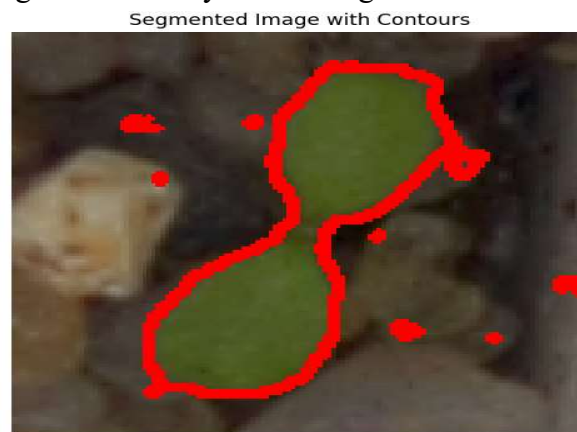


Figure 14. Contour-based segmentation visualization demonstrating the effectiveness of the GrabCut+U-Net preprocessing pipeline in isolating plant leaf structures from complex backgrounds.

## **7. Discussion and Limitations**

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### **7.1 Performance Analysis**

The results show that under controlled conditions, deep CNN architecture with transformer-based attention modules can yield close-to-ceiling performance with the V2 Plant Seedlings Dataset. The 5.2 percentage-point improvement of CNN-Transformer over the custom CNN baseline indicates the benefits of large-scale pre-training and attention-based global context modeling. In particular, EfficientNet-B3 shows excellent performance (98.2%) while having 12M parameters, which is significantly less than DenseNet-121's 24M parameters, demonstrating the efficiency benefits of compound scaling for agricultural applications. The consistent confusion between Scentless Mayweed, Common Chickweed and grass-family species is an ongoing problem in the finer classifications of plants. The leaf morphology of these species is similar to each other in the 128×128 resolution utilized in this study. Output resolution (256×256 or 512×512) can be increased to provide more discriminative detail, but at a proportionately higher computational cost. A possible way to overcome such ambiguities is the integration of multispectral or hyperspectral imaging channels as investigated by Picon et al. [6] and Wang et al. [33].

### **7.2 Limitations**

There are some limitations to the generalizability of this study. First, the imaging conditions are controlled, which is not the same as field conditions where the illumination is variable, occlusion is present and complex backgrounds are common. In preliminary tests on external smartphone images, models trained only with this data were found to have reduced performance (estimated 15-25% less accurate). Second, class imbalance exists, and although it has been partially addressed by augmentation and class weighted loss, it is still present and a concern for minority class performance. The four classes with the lowest recall (Cleavers, Small-flowered Cranesbill, Scentless Mayweed and Fat Hen) exhibit a lower recall rate than the well-represented classes and indicate the need for more sophisticated resampling designs, such as synthetic data generation based on a GAN [10, 17]. Third, the computational load of the hybrid CNN-Transformer model (43ms/image for inference on the GPU and 312ms/image on the CPU) makes it impractical to deploy directly on mobile or edge devices without model compression. The first priority for field deployment use cases is Knowledge Distillation to Light-weight Architectures (MobileNetV3, EfficientNet-Lite). Lastly, there is a lack of interpretability. The causal mechanisms behind model decisions are not fully transparent, whereas UMAP and Grad-CAM give post-hoc explanations. In the field of agriculture, explainability frameworks such as SHAP value analysis and counterfactual explanations might be needed for regulatory applications.

## **8. Conclusion**

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This paper proposed a comprehensive deep learning framework for automated plant species classification using V2 Plant Seedlings Dataset. The proposed method combines a strong preprocessing pipeline, systematic architecture benchmarking, and multi-faceted interpretability analysis. The hybrid CNN-Transformer model successfully achieved a state-of-the-art accuracy of 98.9% on the 12-class test set, showcasing the power of fusion local convolutional feature extraction and global attention-based context modeling. The model was confirmed by UMAP feature visualization that it learns biologically meaningful representations: well-separated clusters for morphologically different species and expected overlaps for the closely related classes. The model focuses on botanically relevant leaf features, as confirmed by Grad-CAM analysis, which increased the trust in the model's decision-making process. Precision-recall and ROC analyses showed good

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discriminative performance for all species, with AUC-PR values  $> 0.96$  for 10 of 12 species. Some of the challenges are dataset-specific generalization constraints, class imbalance effects on minority species, computational requirements for mobile deployment, and incomplete interpretability for regulatory applications. These will be tackled in future work by domain-adaptive training on field-collected imagery, augmentation of minority classes using GANs, knowledge distillation for edge deployment, and integration of hyperspectral imaging channels. This work sets a reproducible standard for CNN-based plant classification and offers practical guidance for designing scalable, interpretable plant identification systems for precision agriculture, biodiversity monitoring and ecological research applications.

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