DEEP LEARNING FOR FLOWER RECOGNITION

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AGENDA

- Introduction
- Data Preparation
- Model Selection and Training
- Results - ResNet9
- Results - ResNet50
- Model Comparison
- Deployment

INTRODUCTION

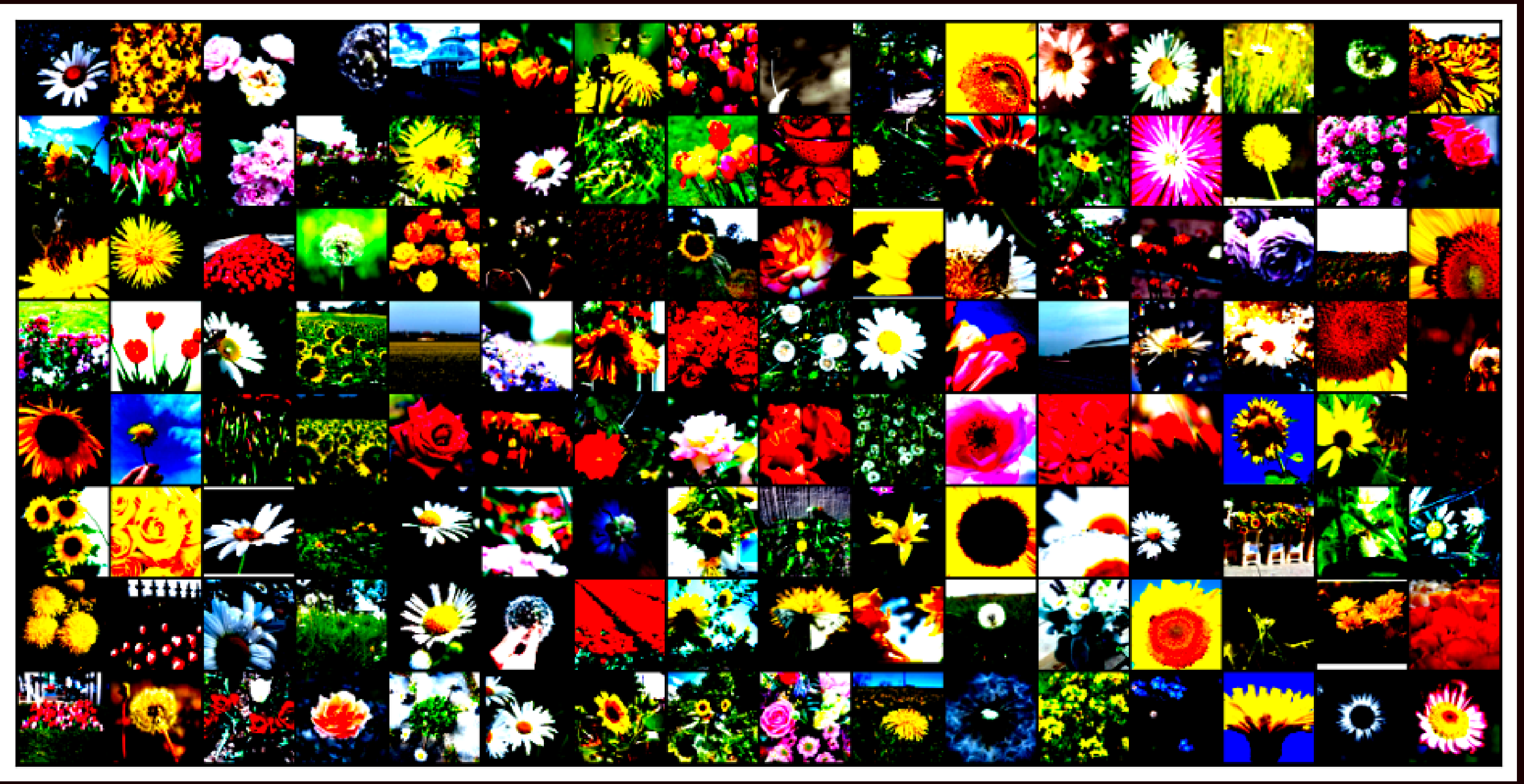
- **Motivation and Data Understanding:**
  - We were motivated by the importance of accurate flower recognition in botany, agriculture, and beyond.
  - We utilized a diverse Kaggle dataset with 4,242 images of various flowers, including chamomile, tulip, rose, sunflower, and dandelion.
  - The dataset's variety and complexity make it a realistic testbed for our deep-learning models.

- **Significance:**
  - Our project has practical implications, from automating plant identification in agriculture to enhancing customer engagement in the floriculture market.
  - It also contributes to conservation and ecological research, emphasizing the relevance of precise flower recognition in today's world.

DATA PREPARATION

Key Steps:

- Resized all images to 224x224 pixels for consistency.
- Augmented data with random resizing, cropping, and flips.
- Standardized pixel values using normalization.
- Organized data into folders by flower class.
- Managed data efficiently with DataLoader.
- Split data into training and validation sets.



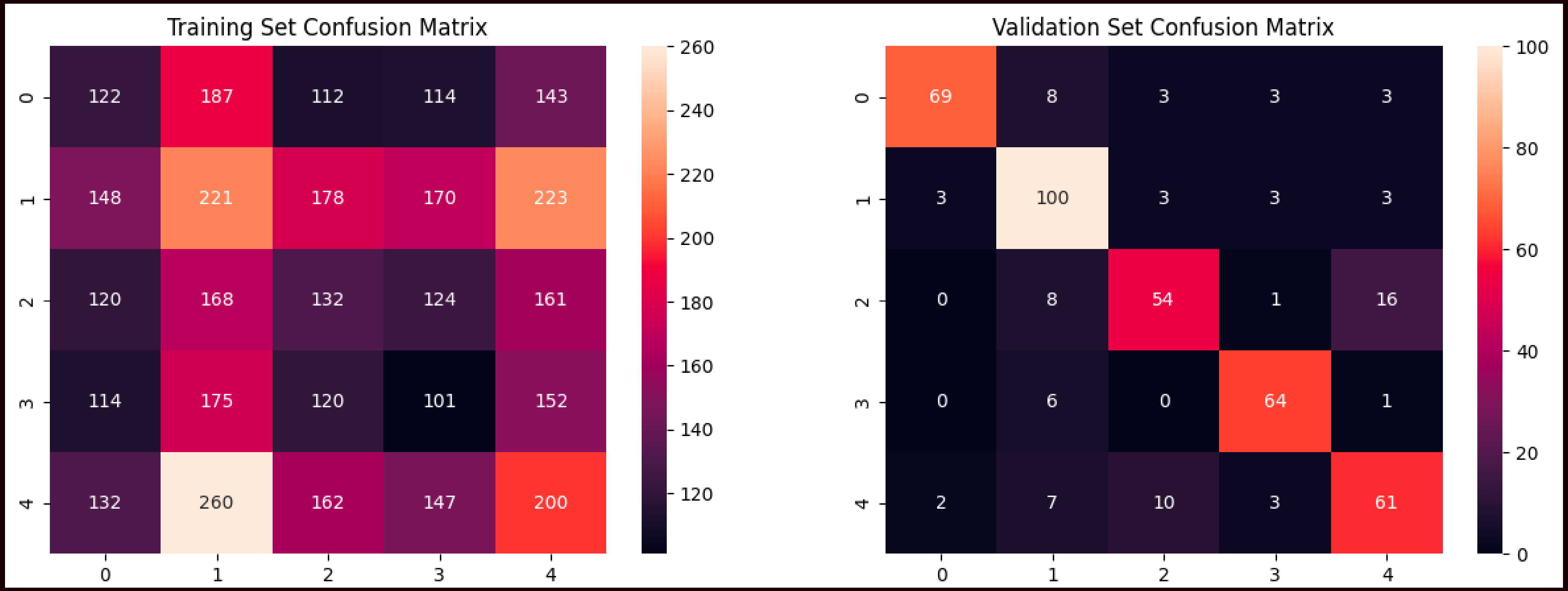
Display of a batch of images after creating Data Loaders

MODEL SELECTION AND TRAINING

- **Model Selection:**
  - We considered two deep learning models: ResNet9 and ResNet50.
  - **ResNet9:** A compact and efficient model suited for our dataset's size, reducing overfitting risk.
  - **ResNet50:** Deeper and more complex, requiring careful hyperparameter tuning.
- **Hyperparameters:**
  - For both ResNet9 and ResNet50, we focused on fine-tuning three key hyperparameters
    - Learning Rate: Set to a low value to ensure stable convergence during training.
    - Batch Size: Optimized to strike a balance between efficient computation and memory usage.
    - Early Stopping: Implemented as a safeguard against overfitting, crucial for smaller datasets.

RESNET 9 MODEL

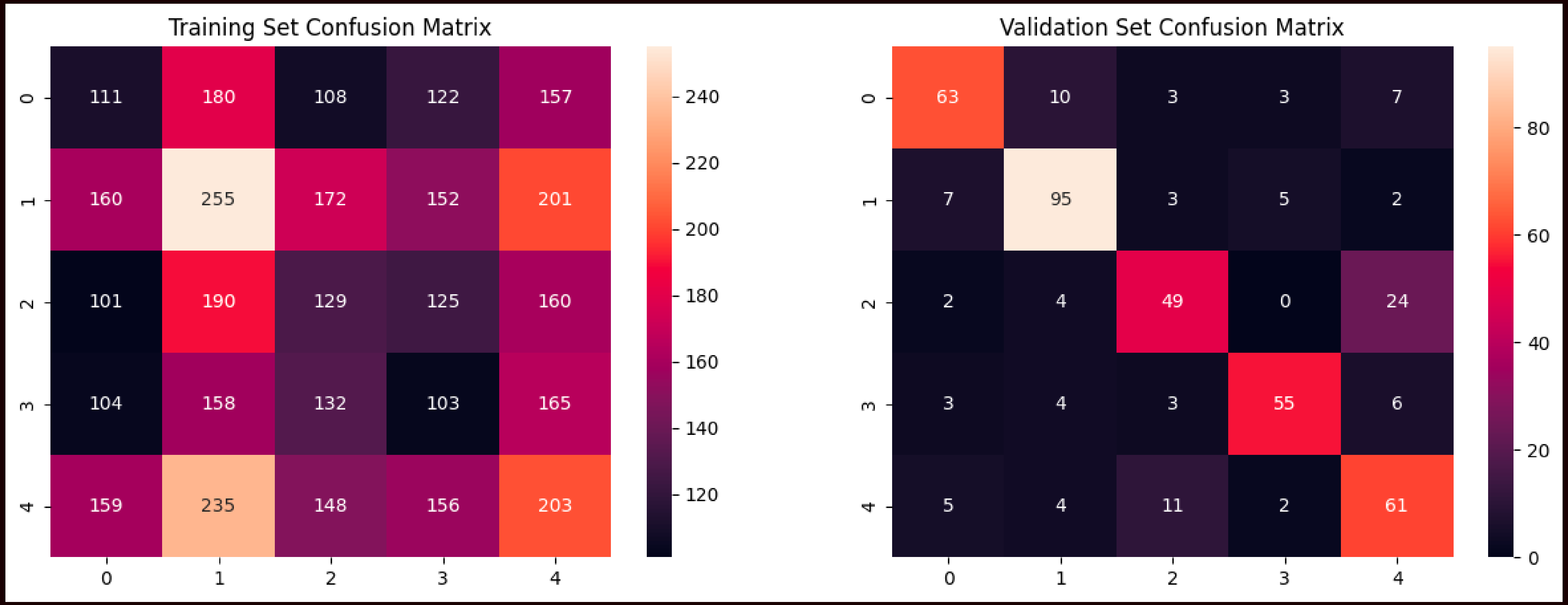
The ResNet9 model achieved notable results in flower classification. It demonstrated a high overall accuracy of 81%, outperforming the ResNet50 model in most metrics. The model showed particular strength in classifying 'daisy' and 'sunflower' species, evidenced by its precision and recall rates.



	precision	recall	f1-score	support
daisy	0.93	0.80	0.86	86
dandelion	0.78	0.89	0.83	112
rose	0.77	0.68	0.72	79
sunflower	0.86	0.90	0.88	71
tulip	0.73	0.73	0.73	83
accuracy			0.81	431
macro avg	0.81	0.80	0.81	431
weighted avg	0.81	0.81	0.81	431

RESNET 50 MODEL

The ResNet50 model in our project showed a robust learning capability with an overall validation accuracy of about 75%. It excelled in recognizing the 'dandelion' class but faced challenges with 'rose' and 'tulip' categories, indicating areas for improvement. This performance, while respectable, highlighted the necessity of aligning model complexity with dataset characteristics, ultimately leading to the selection of the more efficient ResNet9 for our specific flower recognition task.



	precision	recall	f1-score	support
daisy	0.79	0.73	0.76	86
dandelion	0.81	0.85	0.83	112
rose	0.71	0.62	0.66	79
sunflower	0.85	0.77	0.81	71
tulip	0.61	0.73	0.67	83
accuracy			0.75	431
macro avg	0.75	0.74	0.75	431
weighted avg	0.76	0.75	0.75	431

MODEL COMPARISION

Overall Accuracy:

- ResNet9: 81%
- ResNet50: 75%

Precision:

- ResNet9: Higher precision for 'daisy' and 'sunflower'
- ResNet50: Higher precision for 'dandelion'

Recall:

- ResNet9: Outperforms in 'daisy', 'sunflower', and 'tulip'
- ResNet50: Slightly higher recall for 'dandelion', lower for 'rose'

F1-Score:

- ResNet9: Higher f1-scores for all classes except 'dandelion'

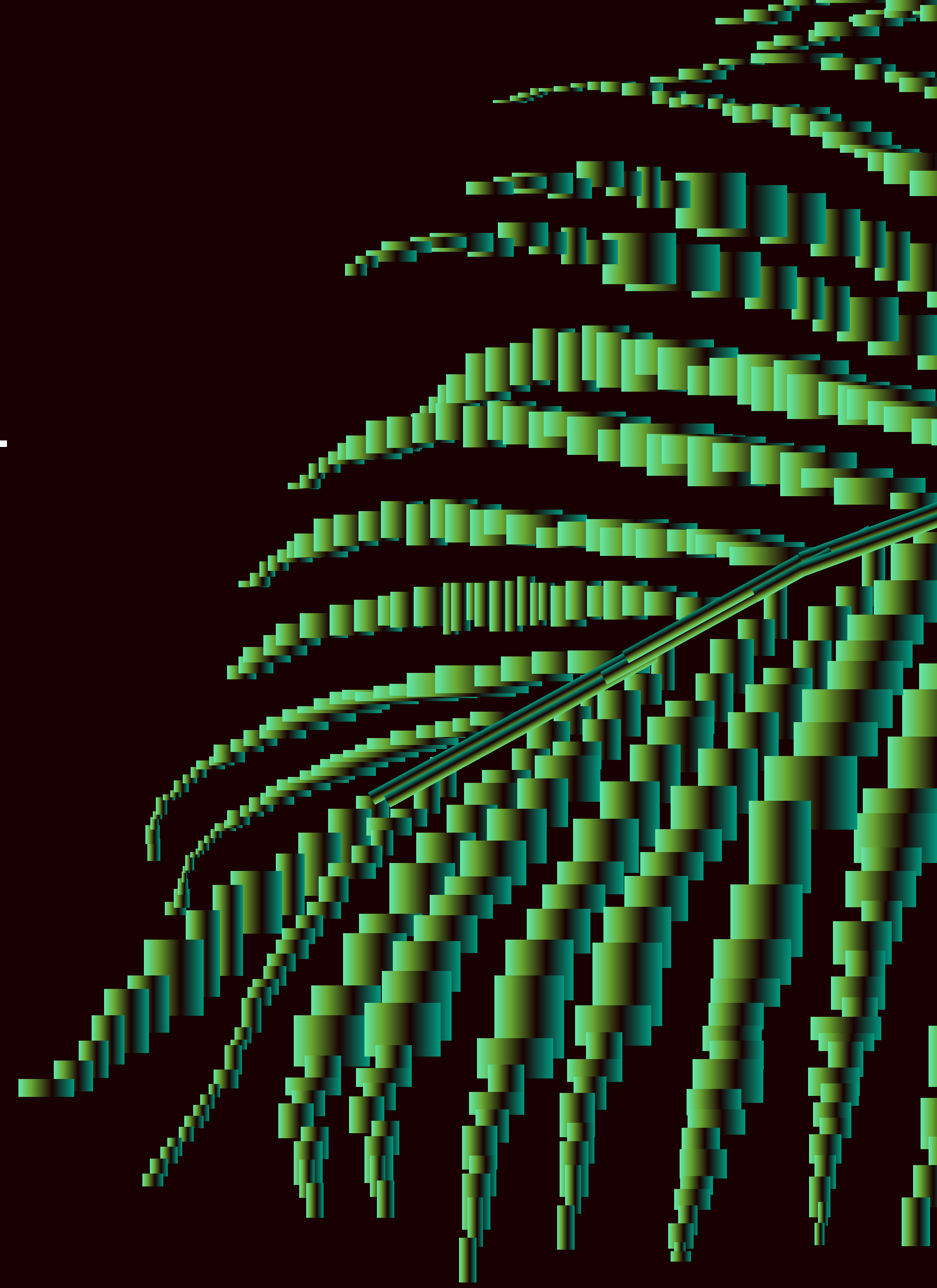
Support:

- Equal for both models, allowing direct metric comparison

Key Takeaway:

- ResNet9 demonstrated superior performance across most metrics, indicating better consistency in classification across flower types

DEPLOYMENT STRATEGY



1. **Strategy:** Integration into a cloud-based botanical research platform enables real-time image classification.
2. **Technical Needs:** Robust server infrastructure GPU resources for model inference.
3. **Data Security:** Strict data protection and encryption for user privacy.
4. **Ethical Use:** Ensure transparency and prevent biased classifications.
5. **Risk Management:**
   - **Data Drift:** Regular model updates with diverse data
   - **Privacy:** Adherence to data protection laws
6. **Future Plans:** Continuous improvement and expansion to more species

THANK YOU!