# Plant Seedlings Classification

Introduction to Computer Vision / PGP-AIML-BA-UTA-MAY23-A

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# Executive Summary

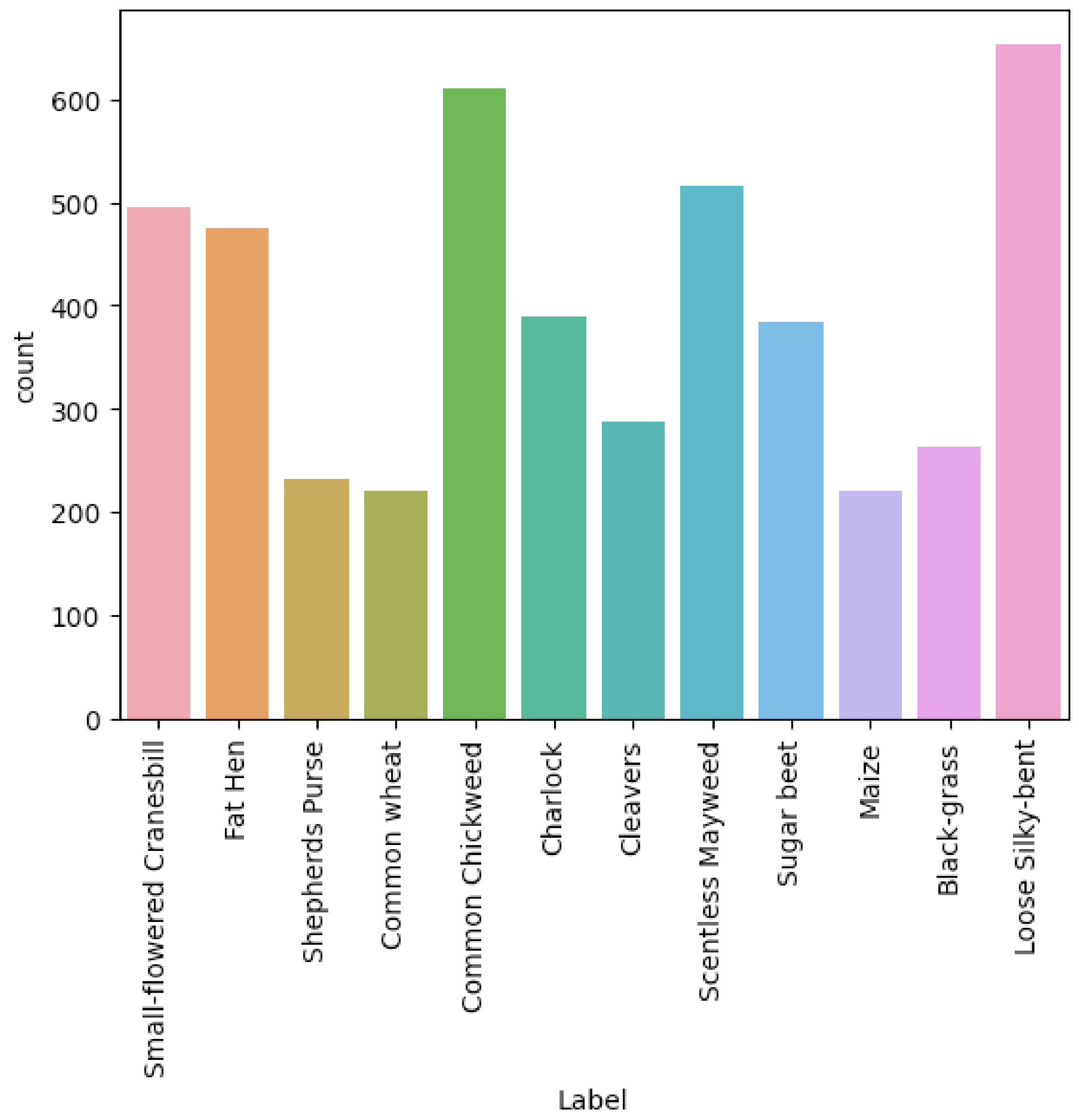
- In this analysis, 4,750 color images of 128x128 pixels were used. These images contain 12 species of seedlings. The dataset shows imbalances, and it is recommended to continue feeding the database, especially in classes where there is insufficient representation. Despite this, a model with an accuracy of 81% was achieved after some fine-tuning strategies and data augmentation.

# Business Problem Overview and Solution Approach

- Problem Definition: Modern agriculture demands technological innovation to reduce manual labor, particularly in plant identification tasks. Current methods are time-consuming and labor-intensive, impacting overall efficiency and sustainability.

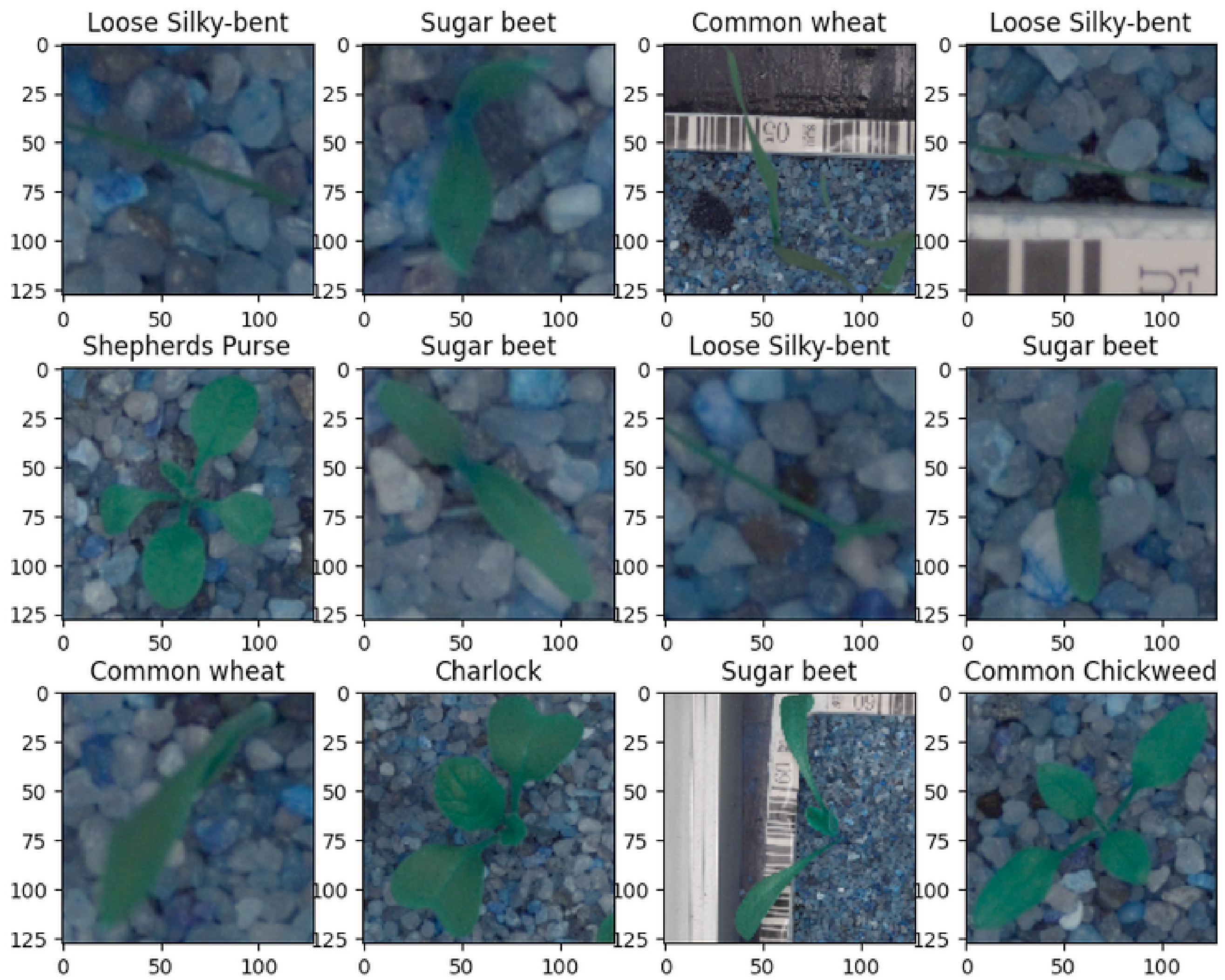
- Solution Approach: Developing a Convolutional Neural Network (CNN) to classify plant seedlings into their respective categories, enhancing efficiency and reducing the need for manual labor in agriculture.

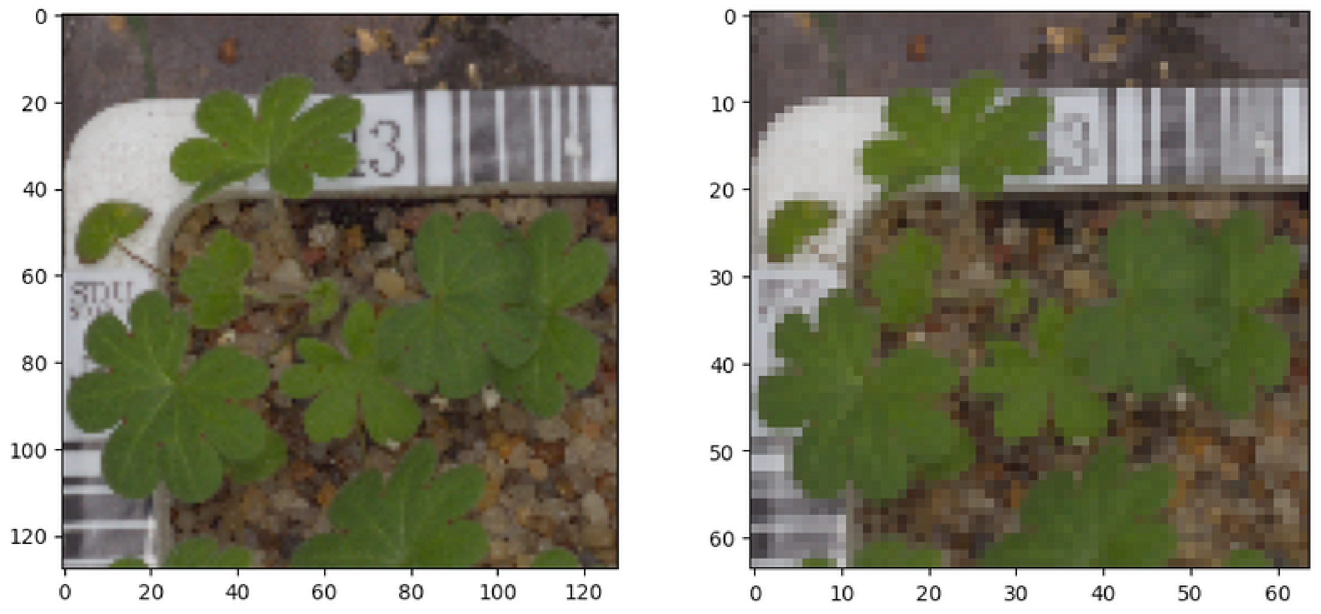
# EDA Results




Given the significant data imbalance, particularly in the Shepherd's Purse, Common Wheat, Maize, and Black Grass categories, special attention is required during model training. This imbalance can lead to biases in the model, potentially affecting its ability to accurately classify these underrepresented species.

# Data Preprocessing



- Convert BGR to RGB: Corrects color representation in images.
- Size Reduction: Images will be resized from 128 to 64 pixels, reducing computational load while maintaining essential features.
- LabelBinarizer Encoding: This encodes the plant species into a one-hot encoded format, resulting in a 12-column matrix without giving preference to any class, ensuring equal treatment in the model.
- Pixel Value Normalization: Pixel values will be normalized to a range of 0 to 1, instead of 0 to 255, aiding in model training by providing standardized input data.
- We will only use 10% of our data for testing, 10% of our data for validation and 80% of our data for training.

# Model Performance Summary: model1

*The model1 is a sequential neural network with the following structure:*

*Convolutional Layers: Each convolutional layer is paired with a corresponding max pooling layer.*

*The first convolutional layer has 128 filters and learns 3,584 parameters.*

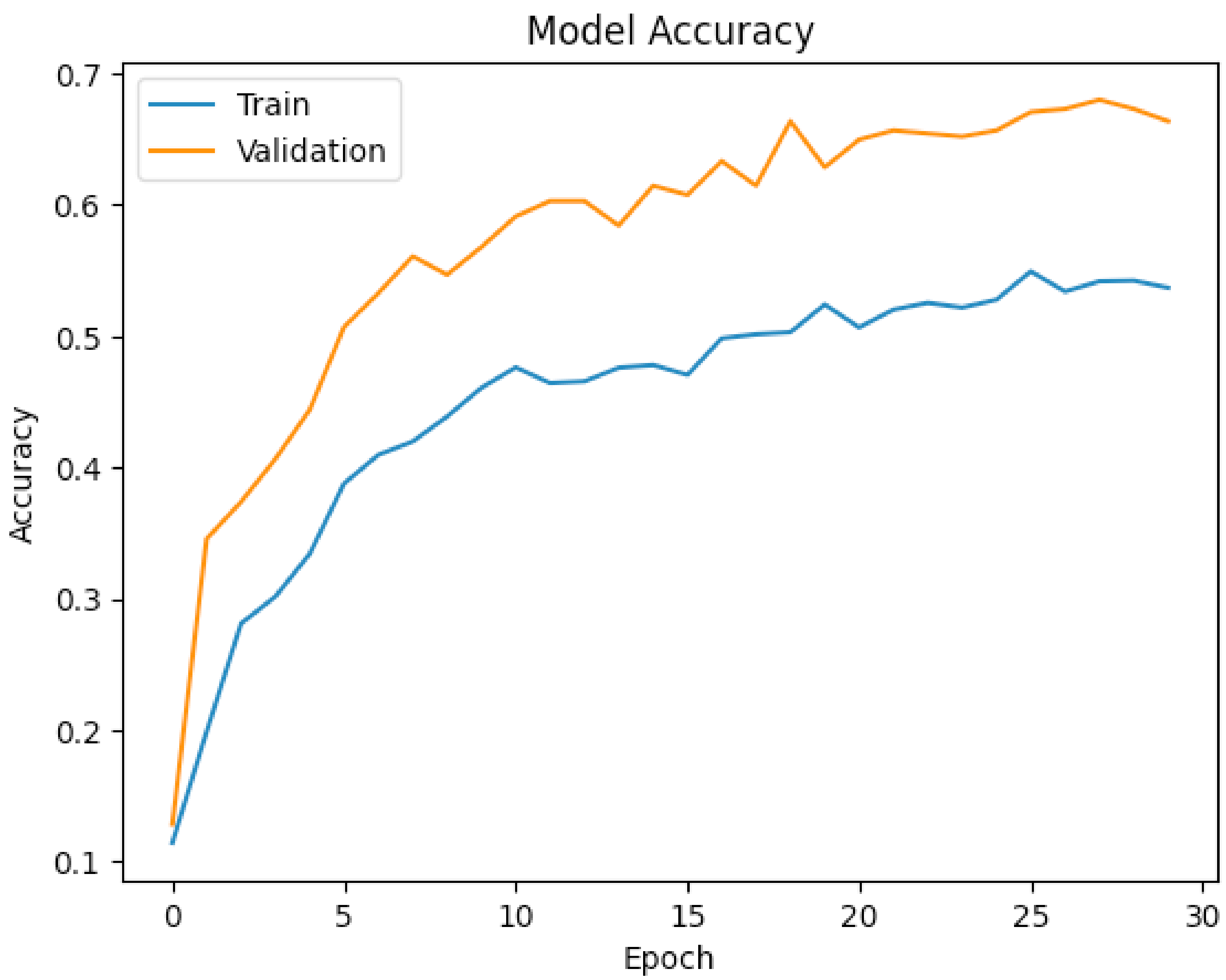
*The second layer has 64 filters with 73,792 parameters.*

*The third layer has 32 filters and learns 18,464 parameters.*

*Fully Connected Layer: After the convolutional layers, there's a fully connected (dense) layer with 16 neurons, learning 32,784 parameters.*

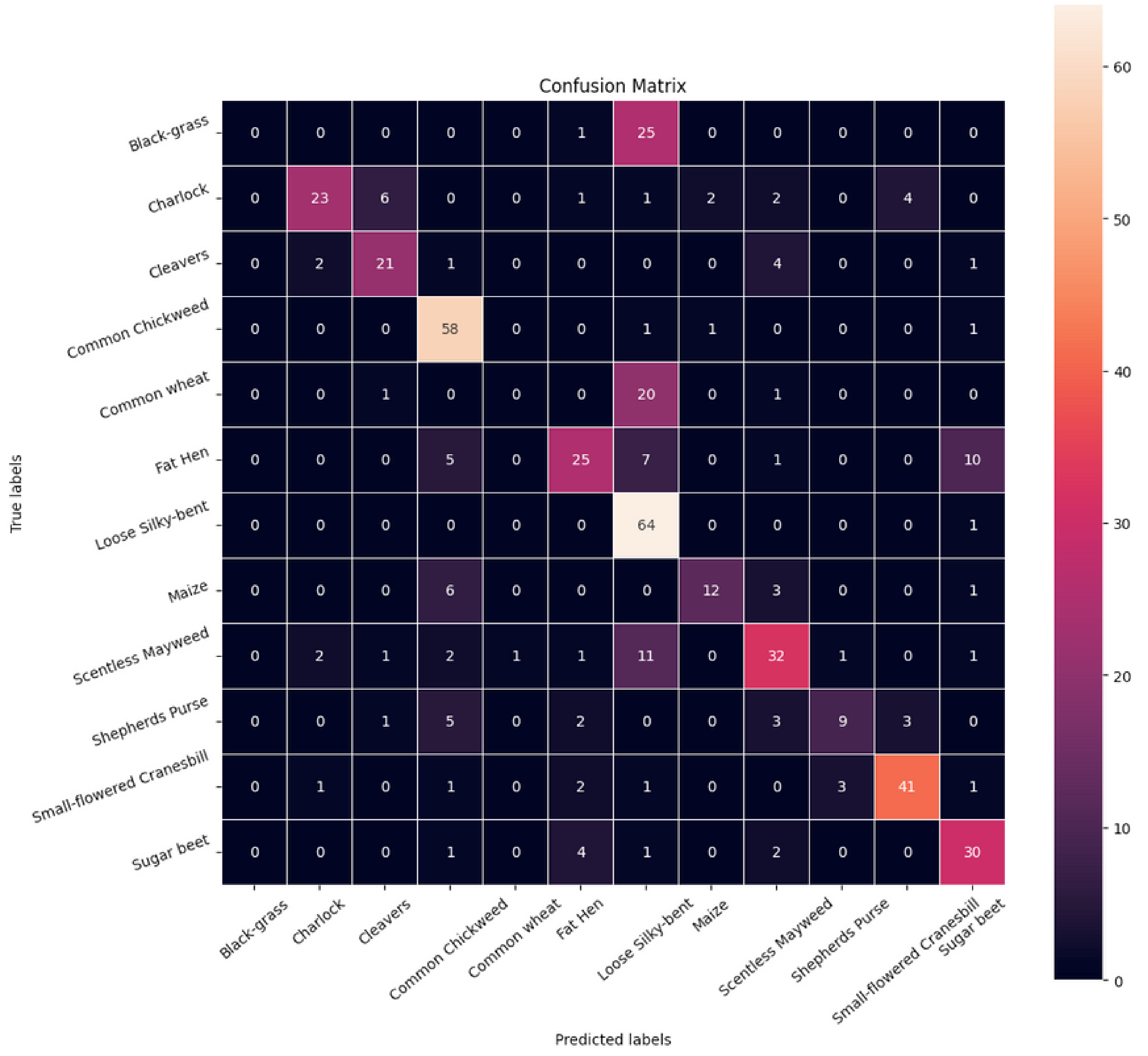
*In total, the model learns 128,828 parameters. This architecture allows for feature extraction at various levels of abstraction, followed by a dense layer for classification.*

# Model Performance Summary: model1




From the image, we can see that the training accuracy is increasing steadily, which is a good sign that the model is learning. However, the validation accuracy is also increasing but with some fluctuations and is consistently lower than the training accuracy, which could be an indication of overfitting

# Model Performance Summary: model1




Many off-diagonal elements are showing for Classes 0 & 4 (indicating misclassifications) and a dense column for Class 6 (indicating other classes being mislabeled as this one). High values on the diagonal for Classes 3 and 10 would be expected, showing correct predictions. The imbalance and misclassifications highlighted need to be addressed, potentially by collecting more data for underperforming classes or implementing class weighting.

# Model Performance Summary: model1

| | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| 0 | 0.00 | 0.00 | 0.00 | 26 |
| 1 | 0.82 | 0.59 | 0.69 | 39 |
| 2 | 0.70 | 0.72 | 0.71 | 29 |
| 3 | 0.73 | 0.95 | 0.83 | 61 |
| 4 | 0.00 | 0.00 | 0.00 | 22 |
| 5 | 0.69 | 0.52 | 0.60 | 48 |
| 6 | 0.49 | 0.98 | 0.65 | 65 |
| 7 | 0.80 | 0.55 | 0.65 | 22 |
| 8 | 0.67 | 0.62 | 0.64 | 52 |
| 9 | 0.69 | 0.39 | 0.50 | 23 |
| 10 | 0.85 | 0.82 | 0.84 | 50 |
| 11 | 0.65 | 0.79 | 0.71 | 38 |
| Accuracy | | | 0.66 | 475 |
| Macro Avg | 0.59 | 0.58 | 0.57 | 475 |
| Weighted Avg | 0.63 | 0.66 | 0.63 | 475 |

- Classes 0 & 4: The model failed to correctly predict any samples from these classes (0% precision and recall).
- Class 6: High recall (98%) but lower precision (49%), indicating that while the model is good at identifying this class, it's also incorrectly labeling many other classes as Class 6.
- Class 3: Best performing in terms of recall (95%), with decent precision (73%), indicating effective identification with some misclassifications.
- Class 10: Exhibits strong precision (85%) and recall (82%), showing that the model reliably identifies and predicts this class.
- Overall: The accuracy across all classes is 66%, with a macro average precision and recall of 59% and 58%, respectively. This suggests there's a significant imbalance in how the model performs across different classes.

# Model Performance Summary: model2

*Data Augmentation: Applying a rotation range of 20 degrees to enhance the model's robustness to variations in input data.*

*Model Architecture:*

- *The model is sequential.*
- *The first convolutional layer has 64 filters, paired with max pooling, learning 1,792 parameters.*
- *The second convolutional layer adds 32 neurons and learns 18,464 parameters.*
- *This is followed by Batch Normalization, which helps in stabilizing the learning process.*
- *A Fully Connected layer with 16 neurons is added, learning 131,088 parameters.*

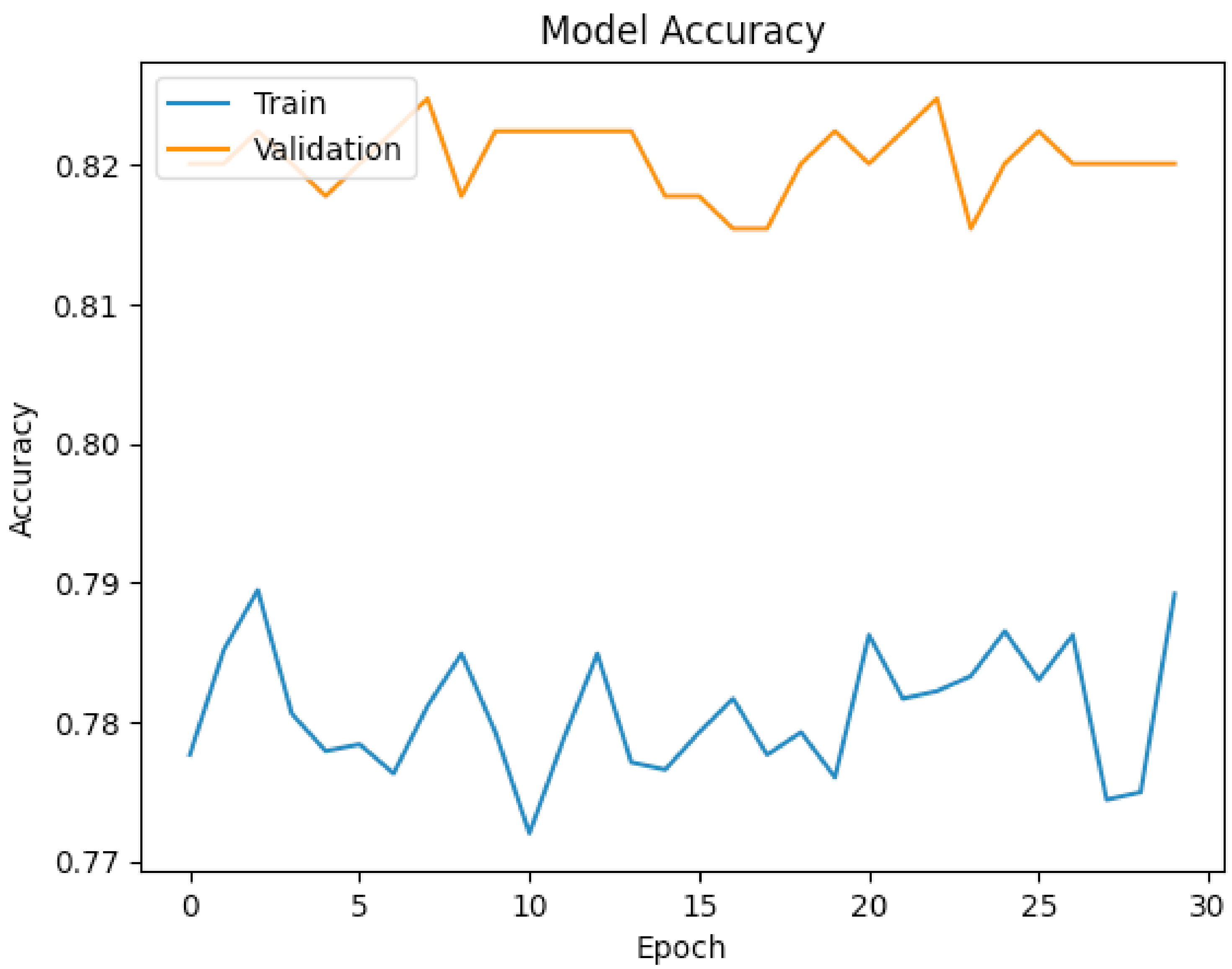
*Total Parameters: The model learns a total of 151,676 parameters.*

*Class Balancing: Some of the imbalanced classes are addressed, through class weighting.*

*Training Configuration:*

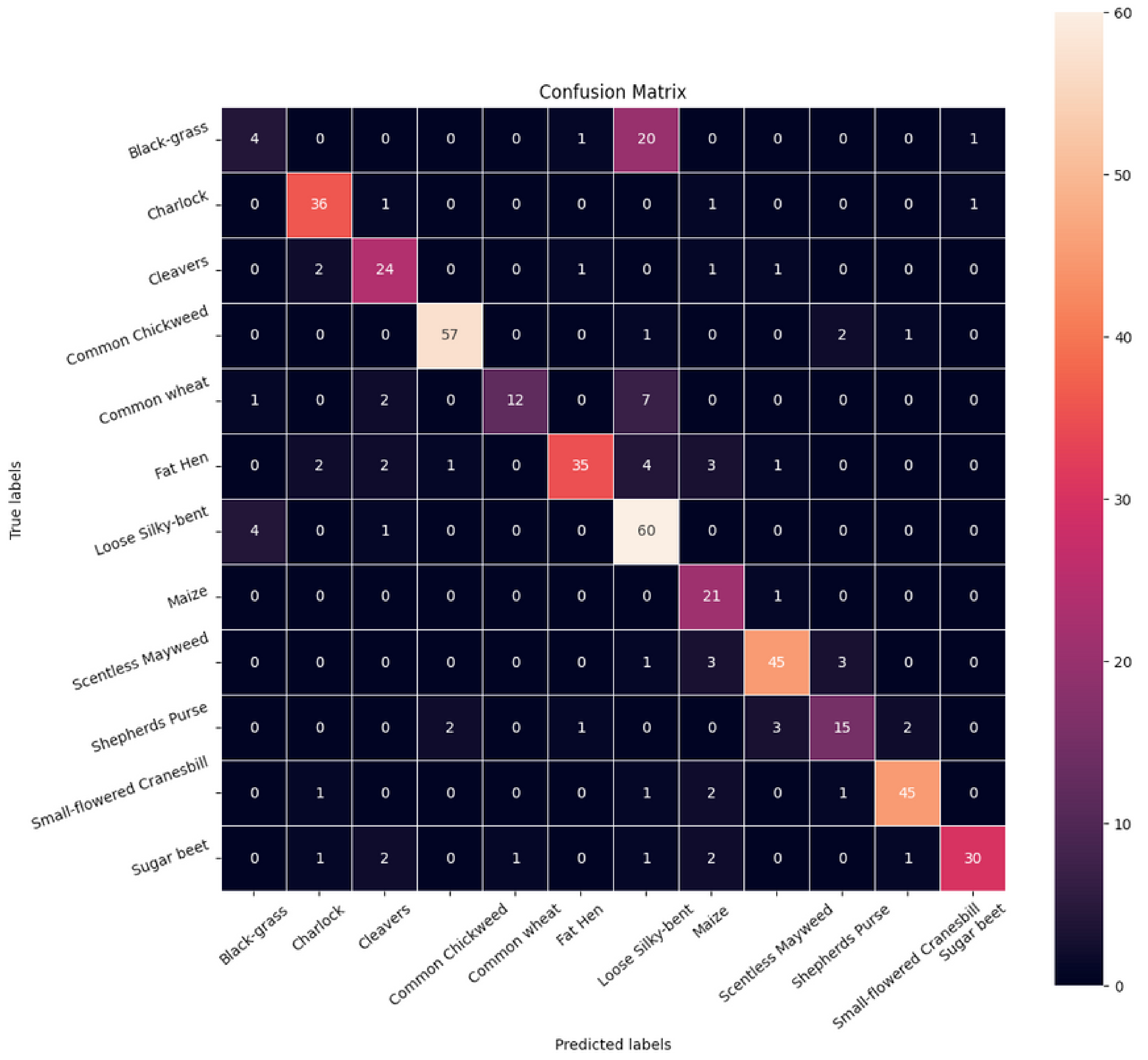
- *The model is trained for 30 epochs.*
- *Batch size is set to 128. (for stability purposes)*
- *A Learning Rate Reduction is included in the Callbacks, likely to adjust the learning rate dynamically for better convergence.*
- *This model, with its augmented data and refined architecture, is designed to be more versatile and effective in handling the imbalanced dataset.*

# Model Performance Summary: model2




it's clear that while the training accuracy is relatively stable and high, the validation accuracy has more variance and is generally lower than the training accuracy, though it does show a general upward trend.

# Model Performance Summary: model1




- The main diagonal represents correct classifications, where we can expect to see high numbers for classes with high precision and recall.
- Class 6 likely has a high value on its row, showing many predictions as Class 6, which explains the lower precision.
- Off-diagonal cells with high values indicate confusion between classes. For example, if any cells in the row for Class 0 have high values, that would mean Black-grass is often misclassified as other classes.

# Model Performance Summary: model1

| | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| 0 | 0.44 | 0.15 | 0.23 | 26 |
| 1 | 0.86 | 0.92 | 0.89 | 39 |
| 2 | 0.75 | 0.83 | 0.79 | 29 |
| 3 | 0.95 | 0.93 | 0.94 | 61 |
| 4 | 0.92 | 0.55 | 0.69 | 22 |
| 5 | 0.92 | 0.73 | 0.81 | 48 |
| 6 | 0.63 | 0.92 | 0.75 | 65 |
| 7 | 0.64 | 0.95 | 0.76 | 22 |
| 8 | 0.88 | 0.87 | 0.87 | 52 |
| 9 | 0.71 | 0.65 | 0.68 | 23 |
| 10 | 0.92 | 0.90 | 0.91 | 50 |
| 11 | 0.94 | 0.79 | 0.86 | 38 |
| Accuracy | | | 0.81 | 475 |
| Macro Avg | 0.80 | 0.77 | 0.77 | 475 |
| Weighted Avg | 0.82 | 0.81 | 0.80 | 475 |

- Class 1 and Class 3 stand out with precision and recall above 90%, indicating very effective classification.
- Class 6, despite having a lower precision of 63%, has a high recall of 92%, meaning the model predicts most of the positive cases correctly but also includes false positives.
- Class 7 shows high recall (95%), which is good, but precision at 64% suggests some confusion with other classes.
- Class 0 has the lowest performance with a precision of 44% and recall of only 15%, indicating difficulty in correctly identifying this class.
- The overall accuracy of the model is 81%, with the weighted average of precision, recall, and F1-score around 80%, reflecting a well-performing model across classes, but with room for improvement in certain classes.

# Model Performance Summary: model1

### model1

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| 10 | 0.85 | 0.82 | 0.84 | 50 |
| 11 | 0.65 | 0.79 | 0.71 | 38 |
| Accuracy | | | 0.66 | 475 |
| Macro Avg | 0.59 | 0.58 | 0.57 | 475 |
| Weighted Avg | 0.63 | 0.66 | 0.63 | 475 |

### model2

| | Precision | Recall | F1-Score | Supp |
|---|---|---|---|---|
| 0 | 0.44 | 0.15 | 0.23 | 26 |
| 1 | 0.86 | 0.92 | 0.89 | 39 |
| 2 | 0.75 | 0.83 | 0.79 | 29 |
| 3 | 0.95 | 0.93 | 0.94 | 61 |
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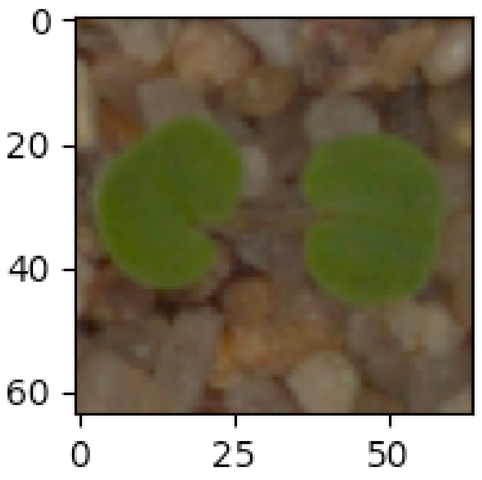
| Weighted Avg | 0.82 | 0.81 | 0.80 | 475 |

# Model Performance Summary: model1

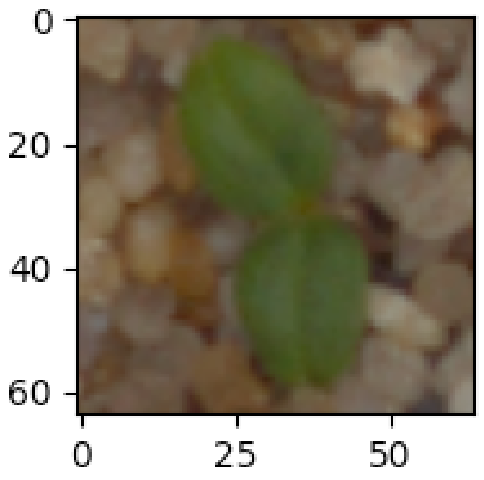
- Overall Performance: Model2 outperforms model1 with a total accuracy of 81% compared to 66%. The macro and weighted averages for precision, recall, and F1-score are also higher in model2.
- Class 0 and Class 4: Both models struggle with these classes, but model2 shows a marked improvement in Class 0 with some ability to correctly identify this class, whereas model1 fails entirely.
- Class 3: Model2 has excellent performance, with high precision and recall, significantly outperforming model1.
- Class 7 (Scentless Mayweed): Model2 shows a remarkable improvement, particularly in recall, indicating a better ability to identify this class correctly.
- High-Performing Classes: Both models perform well on Class 1, Class 2, Class 8, Class 10, and Class 11, with model2 generally improving upon the results of model1.
- Classes with No Recognition in model1: Model1 completely fails to identify Classes 0 and 4, with zero precision and recall, suggesting it didn't learn distinguishing features for these classes. In contrast, model2, while not perfect, shows capability in identifying these challenging classes.

# Conclusion

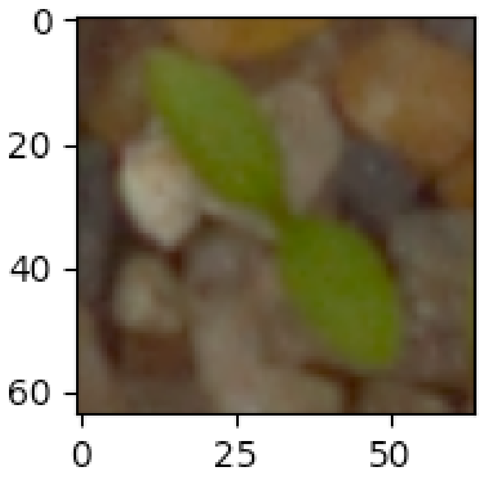
Model 2 demonstrated effective generalization capabilities, yielding satisfactory results in relevant tests as shown below. To achieve better predictions, it's advisable to expand the dataset for all poorly represented classes.



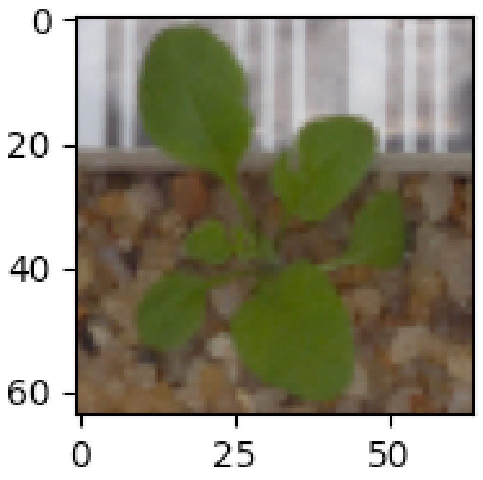

Predicted Label ['Small-flowered Cranesbill']
True Label Small-flowered Cranesbill




Predicted Label ['Cleavers']
True Label Cleavers




Predicted Label ['Common Chickweed']
True Label Common Chickweed




Predicted Label ['Shepherds Purse']
True Label Shepherds Purse

# APPENDIX

# Data Background and Contents

The Aarhus University Signal Processing group, in collaboration with the University of Southern Denmark, has provided the data containing images of unique plants belonging to 12 different species.

Happy Learning !