# Plant Seedlings Classification Analysis

## Introduction to Computer Vision

Date 7/11/2024

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# Executive Summary

## Project Overview

Developed a Convolutional Neural Network (CNN) to classify 12 distinct plant seedlings, enhancing agricultural management by reducing manual labor and increasing accuracy.

## Key Achievements

**Accuracy**- Achieved an overall accuracy of 78%, on Model2 after data augmentation.

**Data Augmentation Impact-** Improved model performance with data augmentation, increasing the accuracy by 13%.

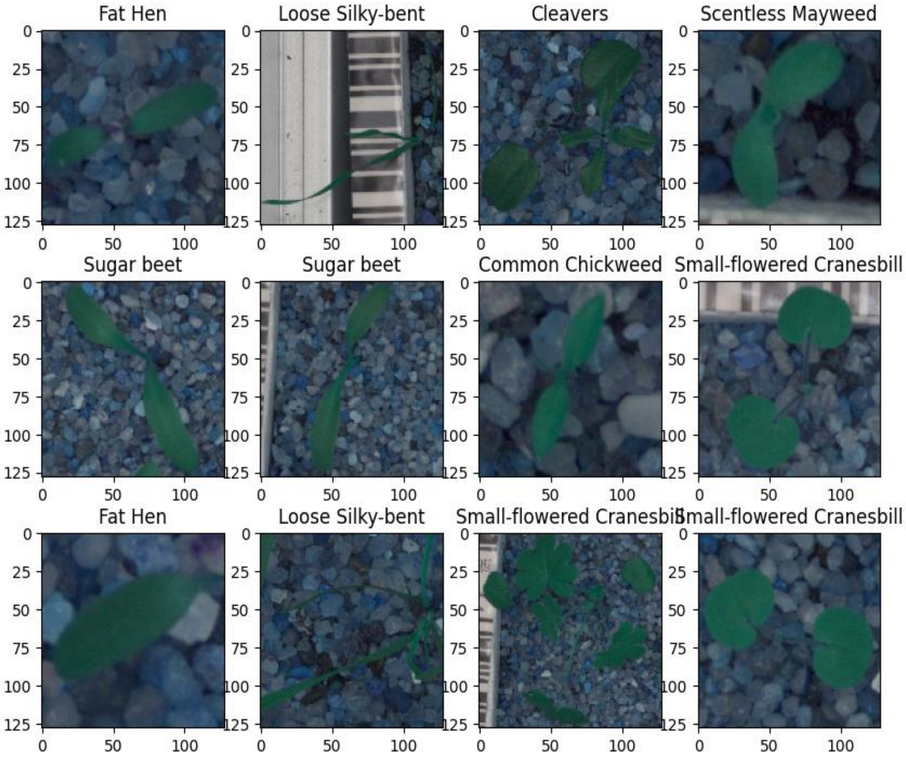
# Business Problem Overview and Solution Approach

## Problem Statement

**Manual Identification Issues-** Previously, the manual process of identifying plant seedlings had an extremely high probability of error. This system of inaccuracy significantly hampered agricultural efficiency, with misidentified plants leading to improper cultivation strategies.

## Challenge

**Labor Intensity and Error Prone-** The manual identification of plant seedlings is notably labor-intensive and time-consuming, with a high propensity for errors due to human limitations. This challenge restricts efficient crop management and increases operational costs.



# Business Problem Overview and Solution Approach (cont)

## Objective

**Goal-** Deploy a Convolutional Neural Network (CNN) for accurate plant seedling classification across 12 categories.

**Efficiency Improvement-** Leverages AI to boost identification accuracy and reduce manual error.

**Technological Advancement-** Utilizes AI to improve the accuracy and efficiency of seedling identification.

# Business Problem Overview and Solution Approach (cont)

## Solution Approach

**AI-Driven Automation**: Leveraged the capabilities of artificial intelligence and deep learning to automate the classification of plant seedlings. This approach is designed to significantly boost productivity, reduce errors, and aid in more informed decision-making within agricultural practices. The implementation of the CNN model will effectively decrease the error probability considerably, thereby demonstrating the model's efficacy in real-world agricultural scenarios.

# Business Problem Overview and Solution Approach (cont)

## Impact

**Cost Reduction-** Targets a reduction in labor costs through automation.

**Enhanced Crop Management-** Ensures accurate seedling identification of 78% to improve yields and advance farming practices.

**Reduction in Manual Labor-** Automates seedling classification to free up labor for strategic tasks.

**Increased Crop Yields and Efficiency-** Boosts crop yields and sustainability through precise agricultural practices tailored to each plant species.

# EDA Results

## Dataset Description

***Source-*** *Aarhus University and University of Southern Denmark.*

***Volume-*** *4750 images across 12 species.*

***Format-*** *.npy and .csv file format for efficient data handling.*

***Data Characteristics-*** *High variability in image backgrounds and lighting conditions.*

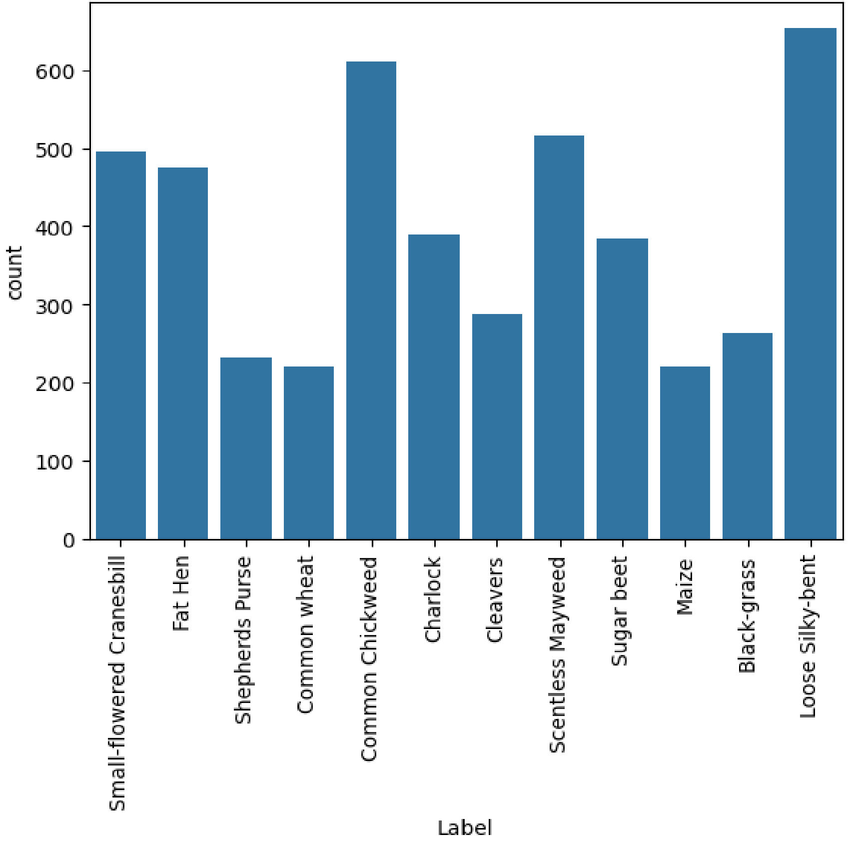
# EDA Results (cont)

## Class Distribution Analysis

**Insight-** Class imbalance evident, with Loose Silky-bent and Common Chickweed overrepresented.

Black-grass, Maize, Common Wheat & Shepherds Purse are underrepresented, affecting model bias.

**Observation-** Imbalance impacts model training, biasing predictions towards overrepresented classes.



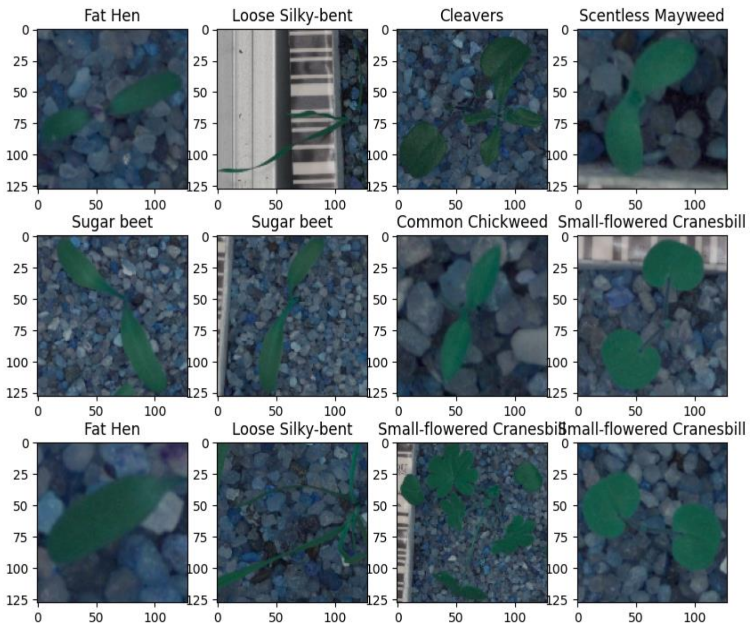
# EDA Results (cont)

## Visualization of Plant Seedlings

**Diversity Insight-** Notable variability in size, shape, and background among plant species.

**Challenge Insight-** Similar features among some species complicate classification due to visual variance. For Example: "Cleavers" and "Common Chickweed".

**Feature Preprocessing-** Implemented robust methods to capture subtle differences, enhancing classification accuracy by changing to RGB and encoded target labels .



# EDA Results (cont)

## Key Observations- Overlap and Complexity

**Size Variance-** Different plant species exhibit varied leaf sizes. Models need to adjust for this to prevent bias toward larger leaves.

**Shape Features-** Variations like leaf serration in "Cleavers" versus smooth edges in "Common Chickweed" are crucial for classification.

**Color Analysis-** Species show various color patterns, necessitating RGB channel analysis to optimize feature detection.

**Background Elements-** Images include non-plant elements such as soil and rocks, suggesting the need for advanced image segmentation techniques.

**Imaging Conditions-** Fluctuations in lighting and background impact data consistency.

# EDA Results (cont)

## Key Observations (cont) -Implications for Classification

**Challenges-**

Increased classification complexity due to feature overlap and environmental variability. Background noise and overlapping features complicate model training, particularly for Fat Hen and Scentless Mayweed.

**Model Adjustments-**

Introduced batch normalization to improve model2 stability and adaptiveness to diverse inputs.

Adapted CNN architecture with less convolutional and maxpooling layers to enhance learning and prevent overfitting, focusing on essential features to improve model reliability and performance.

# Standardization

## Resizing Images

### Standardization

Uniformly resized all images to 64x64 pixels to match the neural network's input specifications, reducing computational load and accelerating processing time.

### Encoding the Target Class

Transformed categorical labels of plant species into numerical form, allowing the neural network to effectively process and learn from the data.

Image before resizing

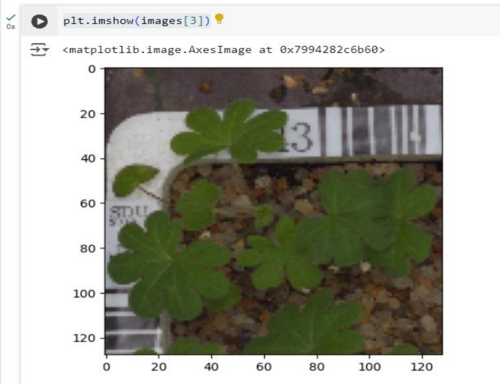



Image after resizing

# Data Preprocessing (cont)

## Conversion

**BGR to RGB**: Converted images from BGR to RGB color space to align with standard image processing norms, ensuring uniform color interpretation and analysis consistency.

## Data Normalization

**Scaling Pixel Values-** Normalized pixel values across all images to a range from 0 to 1, enhancing neural network training efficiency by facilitating faster convergence.

## Augmented Image Preprocessing

**Geometric Transformations-** Implemented rotations and scaling to diversify training examples and enhance the model's generalization capability by familiarizing it with plants viewed from different angles and scales.

# Model Performance Summary

## Model1 Progression

Starts at a training accuracy of 11.33% and validation accuracy of 14.72%, indicating initial struggle.

```
accuracy: 0.1133 - val_loss: 2.4269 - val_accuracy: 0.1472
```

Gradually improves to 61.94% training accuracy and 67.52% validation accuracy by the final epoch, showing steady learning.

```
accuracy: 0.6194 - val loss: 1.0181 - val accuracy: 0.6752
```

The maximum difference in accuracy between training and validation phases highlights potential underfitting concerns.

# Model Performance Summary (cont)

## Model1

**Architecture-** Basic CNN with three convolutional layers, three max pooling, one flatten, one fully connected, one dropout & one output layer with 128,828 trainable parameters.

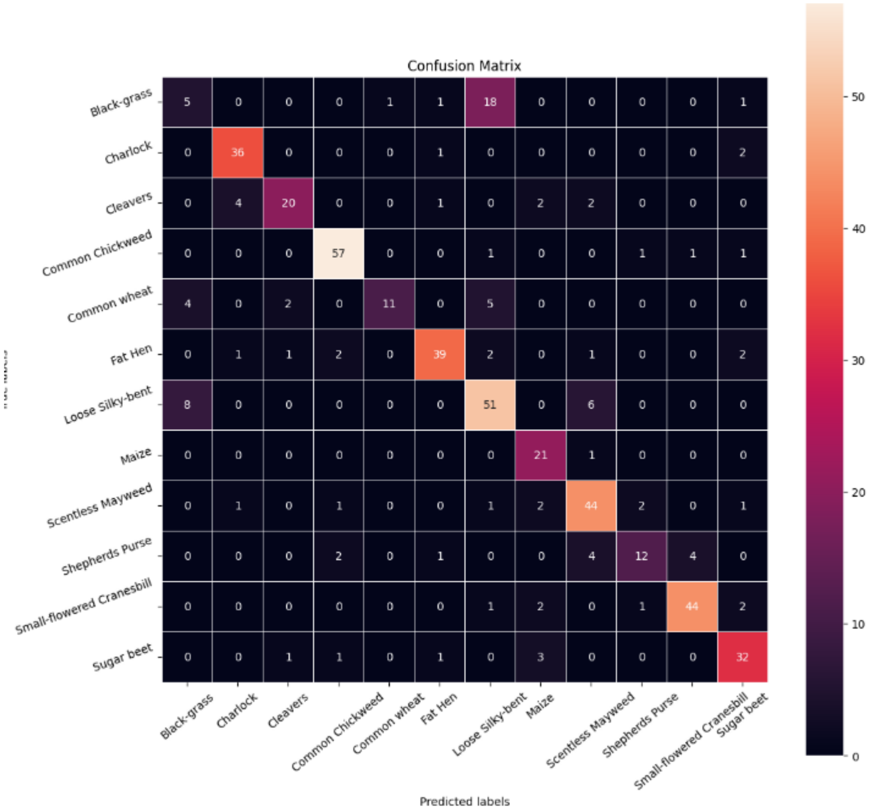
```
model1.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 64, 64, 128)       3584

 max_pooling2d (MaxPooling2  (None, 32, 32, 128)       0
 D)

 conv2d_1 (Conv2D)           (None, 32, 32, 64)        73792

 max_pooling2d_1 (MaxPoolin  (None, 16, 16, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 16, 16, 32)        18464

 max_pooling2d_2 (MaxPoolin  (None, 8, 8, 32)          0
 g2D)

 flatten (Flatten)           (None, 2048)              0

 dense (Dense)               (None, 16)                32784

 dropout (Dropout)           (None, 16)                0

 dense_1 (Dense)             (None, 12)                204

=================================================================
Total params: 128828 (503.23 KB)
Trainable params: 128828 (503.23 KB)
Non-trainable params: 0 (0.00 Byte)
```

# Model Performance Summary (cont)

## Model1

### Confusion Matrix Highlights

High misclassification rates between classes such as Black-grass and Loose Silky-bent.



# Model Performance Summary (cont)

## Model1

**Accuracy-** Achieved an overall accuracy of 65% on the test data.

**Precision and Recall-**
Best performance- Common Chickweed with a precision of 81% and recall of 82%.
Weakest performance- Black-grass with both low precision and recall, indicating difficulty in distinguishing this class.

**F1-Score-** Varied significantly across classes, demonstrating some imbalance in the dataset.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.00 | 0.00 | 0.00 | 26 |
| 1 | 0.81 | 0.64 | 0.71 | 39 |
| 2 | 0.59 | 0.76 | 0.67 | 29 |
| 3 | 0.81 | 0.82 | 0.81 | 61 |
| 4 | 0.50 | 0.05 | 0.08 | 22 |
| 5 | 0.60 | 0.56 | 0.58 | 48 |
| 6 | 0.54 | 0.98 | 0.70 | 65 |
| 7 | 0.73 | 0.50 | 0.59 | 22 |
| 8 | 0.59 | 0.67 | 0.63 | 52 |
| 9 | 0.80 | 0.35 | 0.48 | 23 |
| 10 | 0.81 | 0.84 | 0.82 | 50 |
| 11 | 0.57 | 0.66 | 0.61 | 38 |
| accuracy | | | 0.65 | 475 |
| macro avg | 0.61 | 0.57 | 0.56 | 475 |
| weighted avg | 0.63 | 0.65 | 0.62 | 475 |

# Model Performance Summary (cont)

## Model2 Progression

Begins with higher initial accuracies of 24.95% (training) and 25.47% (validation), indicating a better starting fit.

Accuracy improves , achieving 76% training accuracy and 78% validation displaying rapid adaptation and efficient learning.

Smaller accuracy gaps between training and validation suggest enhanced generalization capabilities, likely due to effective implementation of various advanced data augmentation techniques and batch normalization.

```
accuracy: 0.2495 - val_loss: 2.4059 - val_accuracy: 0.2547

accuracy: 0.7621 - val_loss: 0.6931 - val_accuracy: 0.7897
```

# Model2 (Augmented CNN)

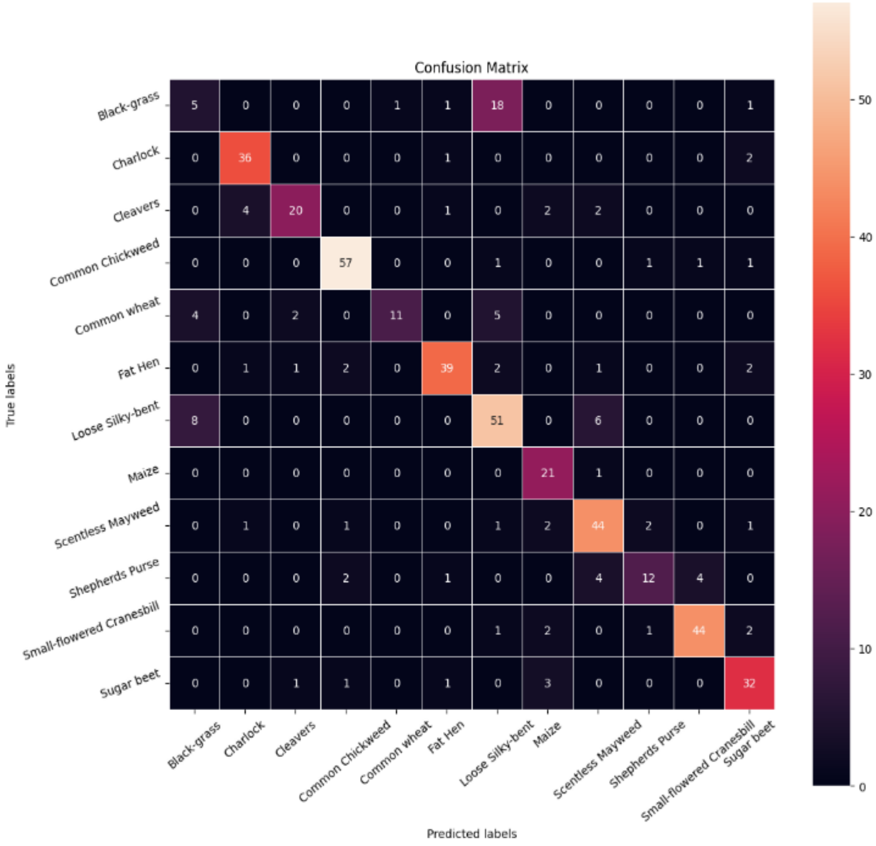
**Architecture-** Enhanced CNN architecture that includes data augmentation techniques like rotation to improve generalization. Two convolutional layers, two max pooling, one batch normalization, one flatten, one fully connected, one dropout & one output layer with 151,612 trainable parameters.

```
model2.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 64, 64, 64)        1792

 max_pooling2d (MaxPooling2  (None, 32, 32, 64)        0
 D)

 conv2d_1 (Conv2D)           (None, 32, 32, 32)        18464

 max_pooling2d_1 (MaxPoolin  (None, 16, 16, 32)        0
 g2D)

 batch_normalization (Batch  (None, 16, 16, 32)        128
 Normalization)

 flatten (Flatten)           (None, 8192)              0

 dense (Dense)               (None, 16)                131088

 dropout (Dropout)           (None, 16)                0

 dense_1 (Dense)             (None, 12)                204

=================================================================
Total params: 151676 (592.48 KB)
Trainable params: 151612 (592.23 KB)
Non-trainable params: 64 (256.00 Byte)
```

# Model Performance Summary (cont)

## Confusion Matrix Highlights

Reduced misclassifications overall, especially for minority classes, showcasing the augmented model's ability to better distinguish between similar-looking species.



# Model Performance Summary (cont)

**Accuracy-** Improved overall accuracy to 78%, reflecting the effectiveness of augmentation in handling varied inputs.

**Precision and Recall-**
'Common Chickweed' precision improved to 90% and recall in 'Loose Silky-bent' improved to 81%, showing better handling of these classes after augmentation. Improved handling of 'Fat Hen' with a precision of 65%, indicating better feature learning.

**F1-Score-** Improvement across almost all classes, with notable enhancements in previously underperforming classes.

**Model2** shows a clear improvement over **Model1** in almost all metrics. The augmentation techniques adopted in Model2 effectively addressed underfitting, which was an apparent issues in Model1.
The use of advanced data augmentation in Model2 not only helped in achieving higher accuracy but also ensured more balanced precision and recall across the classes, which is critical for practical deployment scenarios where all species are equally important.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.29 | 0.19 | 0.23 | 26 |
| 1 | 0.86 | 0.92 | 0.89 | 39 |
| 2 | 0.83 | 0.69 | 0.75 | 29 |
| 3 | 0.90 | 0.93 | 0.92 | 61 |
| 4 | 0.92 | 0.50 | 0.65 | 22 |
| 5 | 0.89 | 0.81 | 0.85 | 48 |
| 6 | 0.65 | 0.78 | 0.71 | 65 |
| 7 | 0.70 | 0.95 | 0.81 | 22 |
| 8 | 0.76 | 0.85 | 0.80 | 52 |
| 9 | 0.75 | 0.52 | 0.62 | 23 |
| 10 | 0.90 | 0.88 | 0.89 | 50 |
| 11 | 0.78 | 0.84 | 0.81 | 38 |
| accuracy | | | 0.78 | 475 |
| macro avg | 0.77 | 0.74 | 0.74 | 475 |
| weighted avg | 0.78 | 0.78 | 0.78 | 475 |

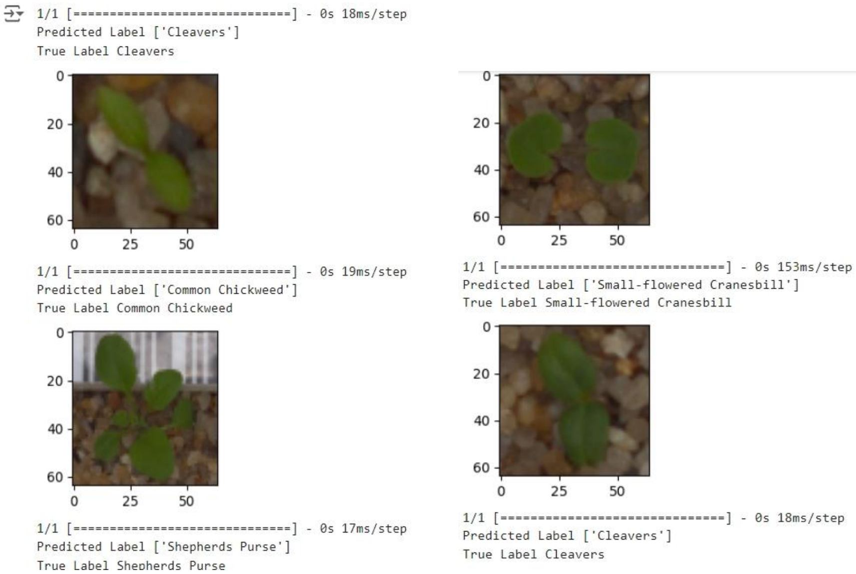
# Model Performance Summary (cont)

## Model Predictions: Successes and Challenges

**Effective Classification-** Model2 accurately identifies distinct plant species like "Small-flowered Cranesbill" and "Common Chickweed," showcasing its strength in differentiating subtle differences.

**Misclassification Issues-** Demonstrates challenges with similar species such as "Cleavers" and "Shepherds Purse," highlighting the need for improvements in feature extraction additional training.

**Visual Proof of Model Performance-** The images serve as practical evidence of how well the model can both succeed and struggle with real-world data, reflecting its overall efficacy and areas for enhancement.



# Model Performance Summary (cont)

## Model Overview and Parameters

**Architecture-** Both models utilize a basic CNN architecture comprising convolutional, max pooling, dropout layers and fully connected layers enhancing feature extraction through layers of minimized depth and adding normalization.

**Parameters-**

**Convolutional Layers-** Utilize 3x3 filters for effective spatial feature extraction.

**Max-Pooling-** A 2x2 pool size reduces data dimensionality while retaining important features.

**Dropout-** A 0.3 rate helps by randomly disabling neurons.

**Fully Connected Layers-** Compile features to classify images into 12 distinct categories.

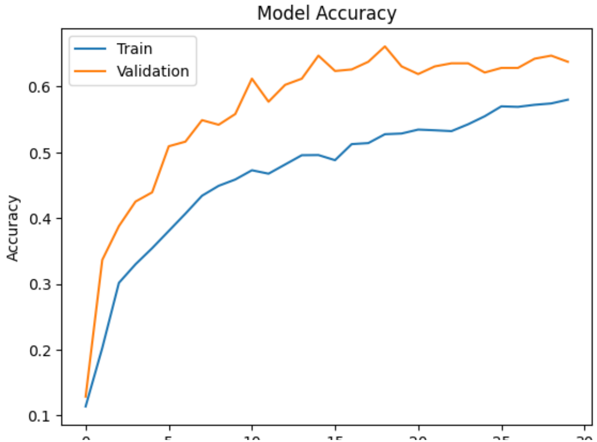
**Performance-** Model1 achieved a training accuracy of 61% and a validation accuracy of 67%, indicating potential underfitting. Model2, on the other hand, improved upon this with a training accuracy of 76% and a validation accuracy of 78%, suggesting generalization capabilities.

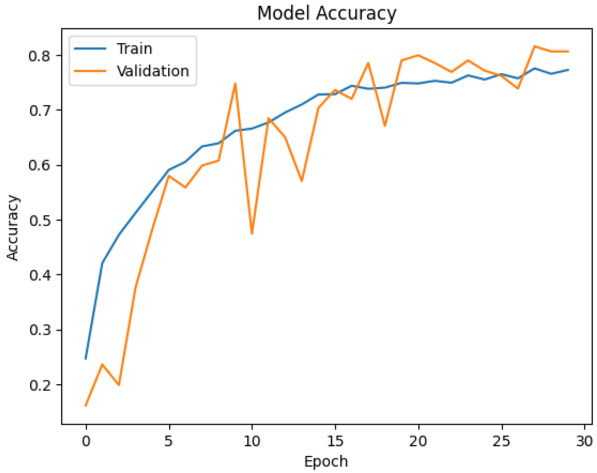
# Model Performance Summary (cont)

## Model Training Dynamics

**Model1 Insight-** Reaches a training accuracy of 61%, showing potential underfitting with a 67% validation accuracy.

**Model2 Insight-** Displays more consistent performance with a peak training 76% and validation accuracy of 78%, indicating convergence.



# Model Performance Summary (cont)

## Augmented Model Performance

**Data Augmentation Techniques-** Techniques included random rotations up to 20 degrees which diversified the training data and mimicked various real-world conditions. Batch normalization and dropout layers are integrated into the models to reduce overfitting by randomly deactivating neurons during training, ensuring the model remains effective across different scenarios without memorizing specific features.

**Augmented Model Performance-** Achieved a significant accuracy improvement to 78% after implementing the augmentation techniques. Notable improvements in class-specific precision and recall were observed, demonstrating the model's enhanced learning and predictive abilities due to a more robust and diverse training dataset.

# Model Performance Summary (cont)

## Model 1 vs. Model 2 Performance Comparison- TEST

**Overall Accuracy-** Model1 has an accuracy of 65%, while Model2 improves significantly to 78%.

**Macro Average Precision-** Model1 stands at 61% compared to Model 2's 77%, indicating better overall precision in Model2.

**Macro Average Recall-** Model1 has a recall of 57% against Model2's 74%, showing Model2's superior ability to correctly identify positive instances across all classes.

**Macro Average F1-Score-** Model1 records a macro average F1-score of 56%, whereas Model2 achieves a higher F1-score of 74%, suggesting more balanced precision and recall in Model2.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.00 | 0.00 | 0.00 | 26 |
| 1 | 0.81 | 0.64 | 0.71 | 39 |
| 2 | 0.59 | 0.76 | 0.67 | 29 |
| 3 | 0.81 | 0.82 | 0.81 | 61 |
| 4 | 0.50 | 0.05 | 0.08 | 22 |
| 5 | 0.60 | 0.56 | 0.58 | 48 |
| 6 | 0.54 | 0.98 | 0.70 | 65 |
| 7 | 0.73 | 0.50 | 0.59 | 22 |
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| 2 | 0.83 | 0.69 | 0.75 | 29 |
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| 10 | 0.90 | 0.88 | 0.89 | 50 |
| 11 | 0.78 | 0.84 | 0.81 | 38 |
| accuracy | | | 0.78 | 475 |
| macro avg | 0.77 | 0.74 | 0.74 | 475 |
| weighted avg | 0.78 | 0.78 | 0.78 | 475 |

# Model Performance Summary (cont)

## Final Model Selection and Rationale

**Selected Model-** Augmented CNN Model2 due to its improved robustness and balanced performance.

**Metrics**:

Overall Precision: Improved to 77%.

Overall Recall: Improved to 74%.

**Validation-** Demonstrated reduced misclassification rates, particularly for typically underrepresented classes like 'Black-grass', confirming the model's effectiveness in real-world scenarios.

# Conclusion

## Analysis and Future Recommendations

### Performance Analysis

**Identified Disparities-** Some class performance variations requiring advanced tuning to enhance accuracy and manage underfitting.

### Advanced Balancing Techniques

**Algorithmic Strategies-** Implementation of cost-sensitive learning to prioritize underrepresented classes and potential use of SMOTE for synthetic sample generation.

### Agricultural Impact

**Automation and Decision-Making-** Deep learning reduces manual labor and improves decision-making in agriculture through more accurate seedling classification.

**Sustainability and Productivity-** Enhanced classification accuracy aids in optimal resource application, promoting sustainability and increased agricultural productivity.

# APPENDIX

# Appendix

## Model Training Details

**Epochs**- 30 training epochs implemented.

**Layer Configuration-** Consists of multiple convolutional layers with increasing filter depth (32, 64, 128), followed by max-pooling layers and dropout rates of 0.3 to reduce overfitting.

**Hyperparameters**- Used ‘ReducedLROnPlateau’ to decrease the loss at a smaller learning rate and used Adam optimizer; various batch sizes used for efficient training.

## Visual Comparisons of Predictions

See "Model Training Dynamics" for graphs of training versus validation accuracy.

# Appendix (cont)

## Case Studies on Model Predictions

Examples of correct predictions showcase the model2 ability to accurately identify 'Common Chickweed' and ‘Cleavers’.

Incorrect predictions highlight challenges with underscoring areas needing improvement.

## Technical Insights

Use of augmented image preprocessing techniques such as rotation adjustment to enhance model robustness.

# Appendix (cont)

## Specific Class Performance Insights

**Class 0 ("Black-grass") Precision:** Model1 struggles with 0% precision, while Model2 shows some improvement at 29%.

**Class 3 ("Common Chickweed") Recall:** Model1 achieves a high recall of 82%, with Model2 also performing well at 93%.

**Class 10 ("Sugar beet") F1-Score:** Model1 scores an F1-score of 82%, which is one of its best performances, nearly matched by Model2's 89%.

# Data Background and Contents

The dataset for this project was provided by the Aarhus University Signal Processing group in collaboration with the University of Southern Denmark. It contains a collection of images aimed at facilitating the development of machine learning models capable of identifying and classifying plant seedlings at various growth stages.

## Dataset Composition

**Images-** The dataset, packaged as images.npy, includes several thousand images of seedlings from 12 different plant species, capturing a wide variety of growth stages and conditions.

**Label-** Accompanying labels for these images are stored in Labels.csv, where each label corresponds to one of the 12 plant species which include species such as Black-grass, Charlock, Cleavers, and Common Chickweed.

# Data Background and Contents (cont)

## Image Details

**Resolution**- Images are provided in high resolution, which were later resized to 64x64 pixels to standardize the input size for neural network processing.

**Color Space**- Initially presented in BGR color format, images were converted to RGB to align with standard image processing practices used in model training.

## Unique Challenges Presented by the Data

**Variability**- The dataset showcases considerable variability in terms of lighting, background, and plant positioning, reflecting real-world conditions under which agricultural imaging systems must operate.

**Class Imbalance**: Some species are more prevalent than others, presenting a typical challenge of class imbalance in machine learning, which necessitates strategic approaches in training phase like data augmentation.

Great Learning

# Happy Learning !