Automated Plant Seedling Classification Using Deep Learning

1. Introduction

1.1 Objective

The aim of this project is to develop a deep learning model capable of accurately identifying different species of plant seedlings based on their images. This automated classification system can help in improving agricultural efficiency by aiding farmers and researchers in managing crops more effectively.

1.2 Motivation

Efficient identification of plant species at early stages is crucial for disease control and crop management. An automated system can significantly reduce manual labor and improve accuracy, leading to better decision-making in agricultural practices.

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2. Dataset

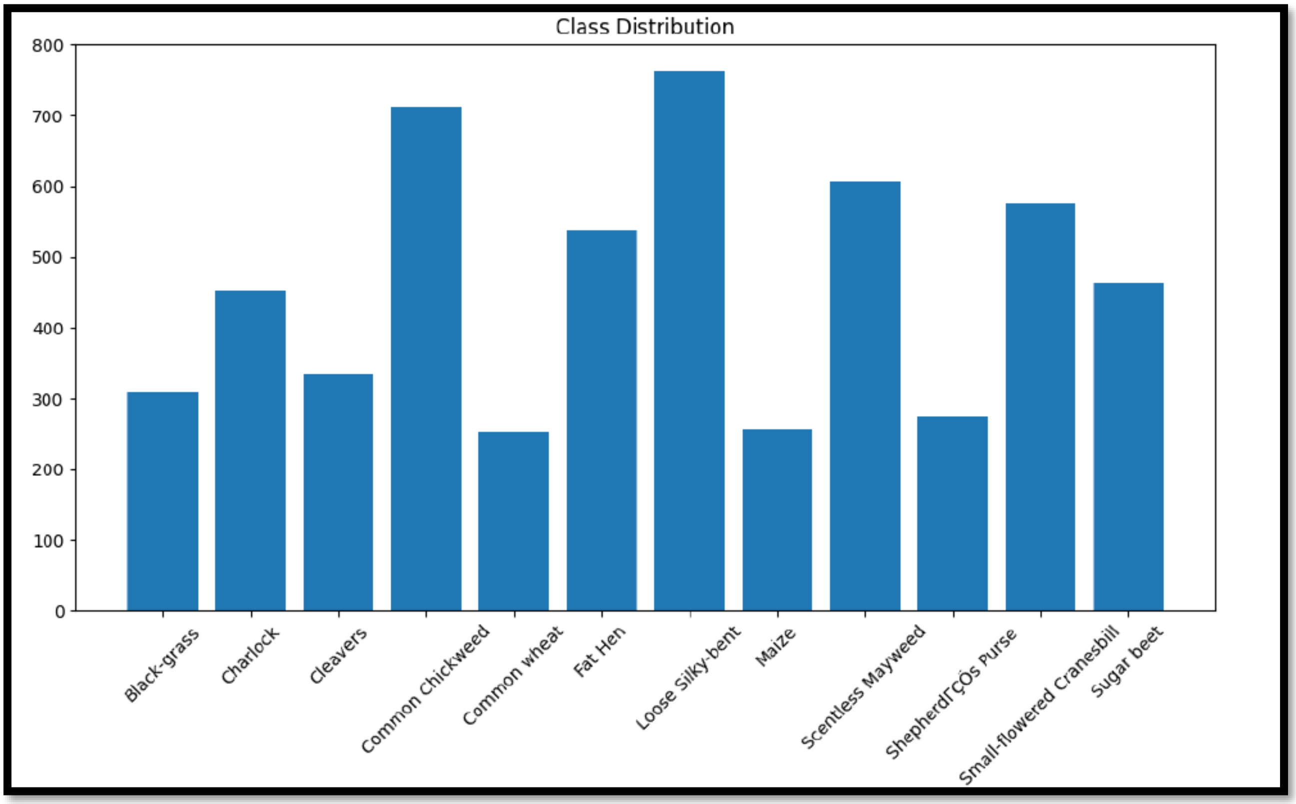
2.1 Source

- Dataset obtained from **Kaggle**: V2 Plant Seedlings Dataset
- The dataset consists of **12 classes** of plant seedlings.

2.2 Data Overview

- **Total Images**: 5,533 images after cleaning
- **Class Distribution**: (Refer to the Class Distribution chart)

Figure 1: Class Distribution



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3. Data Preprocessing and Augmentation

3.1 Preprocessing Steps

- **Resizing**: All images were resized to 224x224 pixels for compatibility with the ResNet18 model.
- **Normalization**: Pixel values were normalized to the range [0, 1].
- **Data Augmentation**: Applied random cropping, horizontal flipping, and random rotations to increase dataset diversity.

3.2 Dataset Split

- **Training Set**: 70%
- **Validation Set**: 20%
- **Test Set**: 10%

Figure 2: Random Sample Images from Dataset

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4. Model Architecture

4.1 Transfer Learning with ResNet18

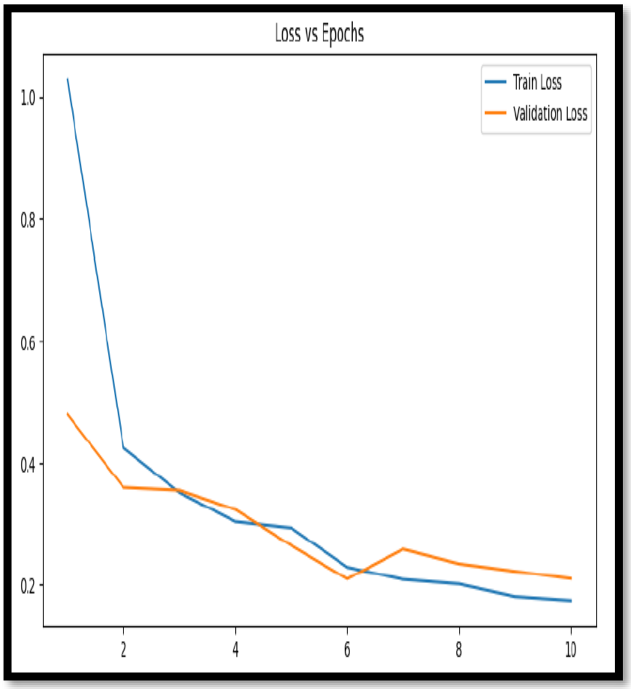
We utilized a pre-trained **ResNet18** model, fine-tuning the final layer to output predictions for 12 classes.

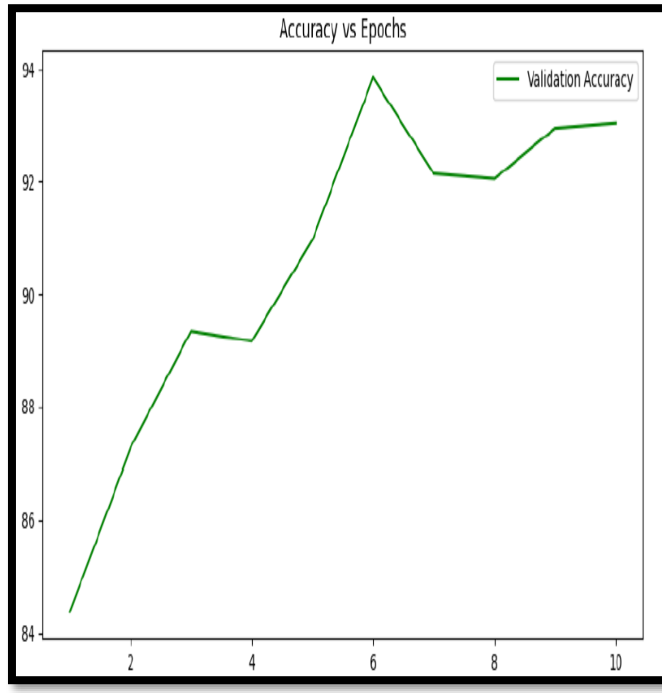
4.2 Training Parameters

- **Loss Function**: CrossEntropyLoss
- **Optimizer**: Adam with a learning rate of 0.0001
- **Epochs**: 10
- **Batch Size**: 32

4.3 Training and Validation Curves

Figure 3: Loss vs Epochs
Figure 4: Accuracy vs Epochs





5. Evaluation

5.1 Performance Metrics

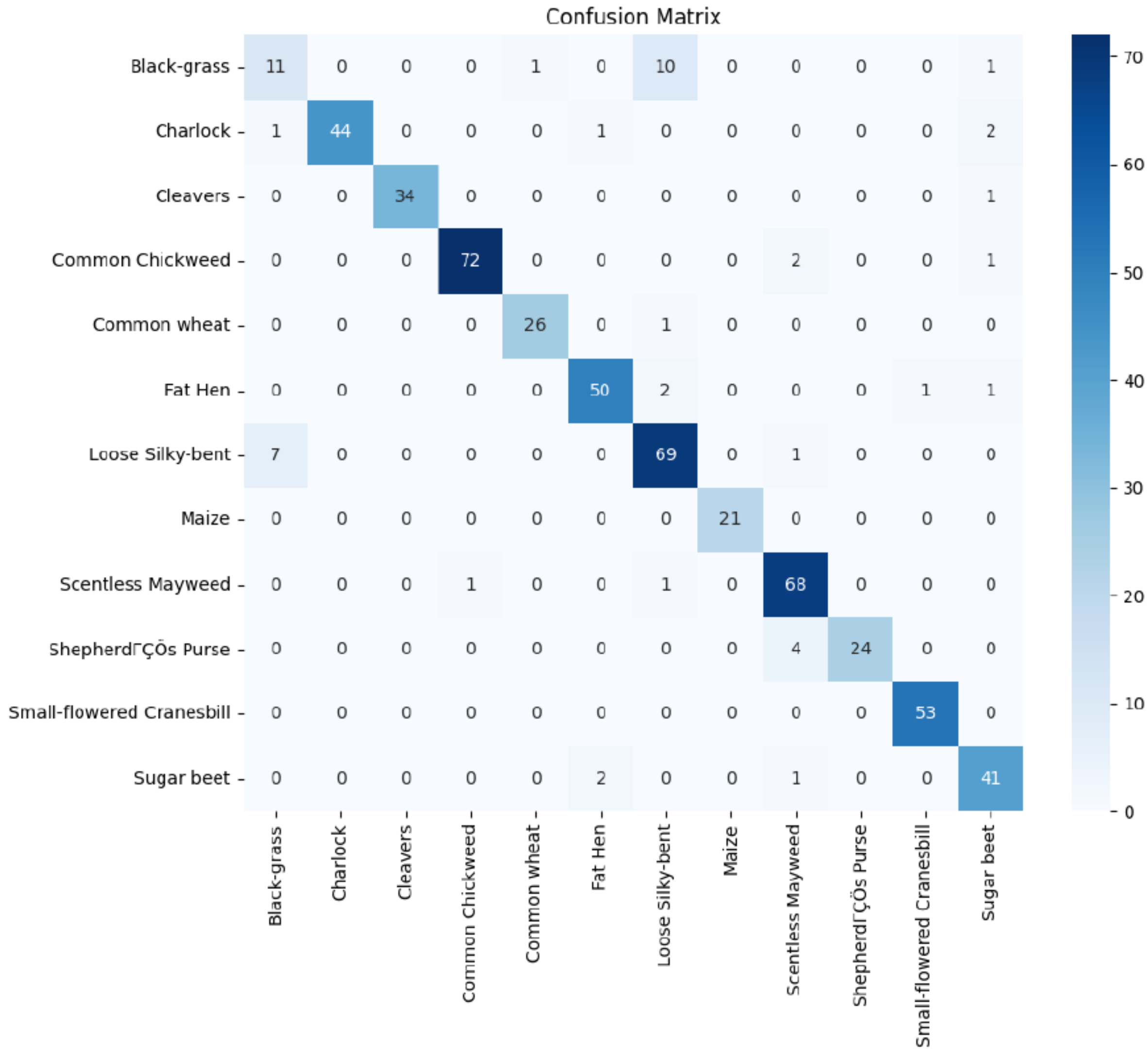
The model was evaluated using precision, recall, F1-score, and accuracy on the test dataset.

Classification Report:

Class	Precision	Recall	F1-score	Support
Black-grass	0.58	0.48	0.52	23
Charlock	1.00	0.92	0.96	48
Cleavers	1.00	0.97	0.99	35
Overall Accuracy			**92%**	555

5.2 Confusion Matrix

Figure 5: Confusion Matrix



5.3 Correct and Incorrect Predictions

Figure 6: Sample Correct and Incorrect Predictions

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6. Conclusion

6.1 Key Findings

- The model achieved an accuracy of **92%** on the test dataset.
- Transfer learning with ResNet18 was effective, achieving high precision and recall scores.
- Data augmentation helped prevent overfitting and improved model robustness.

6.2 Challenges

- **Class Imbalance**: Certain classes, such as "Black-grass", had fewer samples, resulting in lower precision and recall.
- **Visual Similarity**: Some classes, like "Loose Silky-bent" and "Black-grass", were visually similar, leading to misclassifications.

6.3 Future Work

- Experiment with more advanced models like EfficientNet.
- Collect additional data for underrepresented classes to address class imbalance.
- Implement a weighted loss function to handle class imbalance better.

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7. References

- Kaggle Dataset
- PyTorch Documentation