Project

Plants seeding Classification

Date 7/01/2023

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Contents / Agenda

Executive Summary. Actionable insights.

Class Imbalance Management

Some classes like 'Black-grass' and 'Cleavers' showed lower precision and recall, indicating class imbalance issues. -> Implement more aggressive data augmentation for underrepresented classes or collect additional samples to balance the dataset.

Model Robustness

The model’s accuracy improved significantly with batch normalization and dropout layers, showing better generalization. -> Continue using these techniques in future models and explore additional regularization methods if necessary.

Learning Rate Adjustments

The use of ReduceLROnPlateau effectively improved the model’s convergence during training. -> Implement dynamic learning rate schedules in other projects to enhance model performance.

Validation Fluctuations

Validation accuracy showed fluctuations, indicating potential overfitting or noise in the validation set. -> Perform cross-validation and hyperparameter tuning to stabilize the model performance.

Executive Summary. Recommendations.

Enhance Data Collection

Increase the size and diversity of the dataset, particularly for underrepresented classes, to improve model accuracy and robustness.

Continuous Monitoring

Implement a monitoring system to continuously evaluate model performance on new data and retrain the model periodically to adapt to any changes.

Explore Advanced Architectures

Experiment with more complex architectures like transfer learning models (e.g., ResNet, Inception) which might capture more intricate patterns and improve accuracy further.

Deploy and Integrate

Deploy the model in a real-world agricultural setting and integrate it with existing systems to automate the seedling classification process, thereby saving time and reducing manual labor.

Business Problem Overview and Solution Approach

Problem Definition: The agriculture industry requires extensive manual labor to monitor and classify plant seedlings, leading to inefficiencies and potential errors. Despite technological advancements, there is a need for more effective methods to improve crop management and sustainability.

The agriculture industry, being a trillion-dollar sector, has a tremendous opportunity to benefit from technological innovations. These innovations can reduce the dependency on manual labor, increase efficiency, and potentially improve crop yields. By utilizing Artificial Intelligence (AI) and Deep Learning, the time and effort required to identify plant seedlings can be greatly reduced. This technological advancement not only makes the process more efficient but also more accurate than experienced manual labor.

Objective

The aim of this project is to build a Convolutional Neural Network (CNN) to classify plant seedlings into their respective categories. Accurate classification of seedlings is crucial for better crop management, leading to improved yields and more sustainable agricultural practices.

Solution approach

Data Collection and Preparation

The dataset includes images of plant seedlings from 12 species, provided by Aarhus University Signal Processing group. Images are in images.npy and labels in Labels.csv.

Data Preprocessing

Loaded from Google Drive, converted images from BGR to RGB using OpenCV, resized to 64x64 pixels, encoded labels using LabelBinarizer, and normalized pixel values.

Exploratory Data Analysis

Visualized species distribution with a count plot and displayed random images from each category to understand the dataset better.

Model Building and Training

Utilized a CNN for image classification. Built a sequential model with convolutional and pooling layers, dropout layers, and used Adam optimizer. Split data into training, validation, and test sets. Implemented data augmentation techniques to improve model performance. Used ReduceLRonPlateau callback to adjust the learning rate dynamically during training.

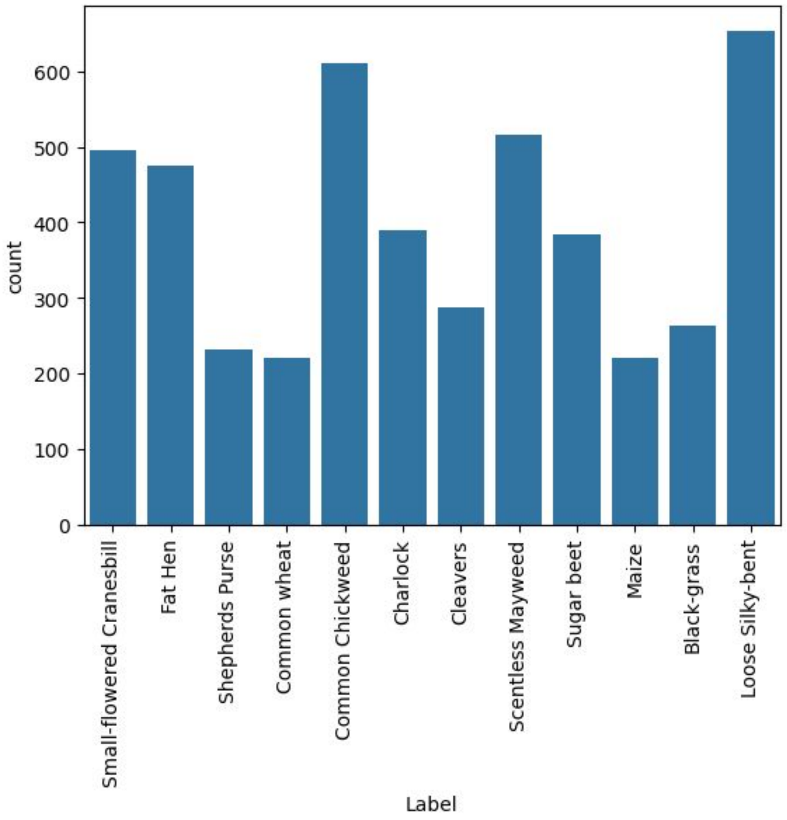
Model Evaluation

Evaluated model accuracy on the test set, plotted confusion matrix, and generated a classification report to assess detailed performance metrics.

Results and Insights

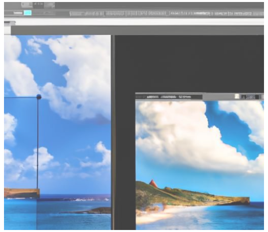
The model demonstrated high accuracy in classifying plant seedlings. Visualized predictions on test images showed effectiveness. Insights can automate and improve crop management.

EDA Results



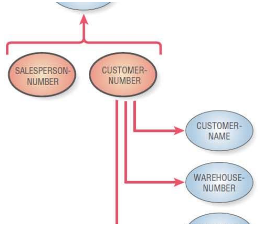
1. **Imbalanced Classes**:
   - 'Common Chickweed' and 'Loose Silky-bent' have the highest counts, over 600 and 500 respectively.
   - 'Shepherds Purse' and 'Common Wheat' and Maize have the fewest samples, below 250.
2. **Impact on Model Training**:
   - The model may perform better on classes with more samples and worse on underrepresented classes.
3. **Need for Balancing Techniques**:
   - Apply data augmentation or oversampling for underrepresented classes.
   - Use class weights during model training to balance learning.

Data Preprocessing



Resizing Images
Resizing images for reducing computational expense and standardizing input dimensions for the model.
We resize all images to 64x64 pixels. Method: Used OpenCV’s resize function

Encoding the Target Class labels is necessary for converting categorical labels into a numerical format that can be used by the model. Method: Use LabelBinarizer from sklearn.preprocessing to perform one-hot encoding on the target labels.



Data Normalization is for standardizing the pixel values of images to improve the convergence of the model training. Method: Scale the pixel values to the range [0, 1] by dividing by 255.

Model Performance Summary

- Overview of model and its parameters
- Summary of the final model for prediction
- Summary of key performance metrics for training and test data in tabular format for comparison

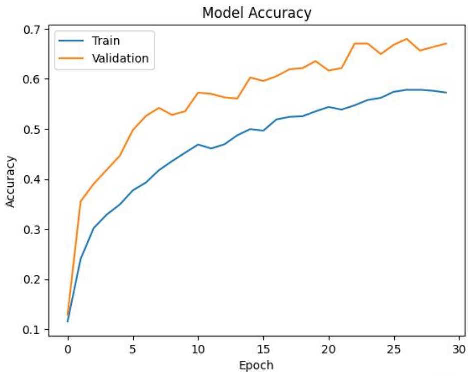
***Note**: You can use more than one slide if needed*

Model building. Overview.

1. **Backend Clearing & Seed Fixing**:
   - Ensures reproducibility.
   - Clears previous models/data.
2. **Model Initialization**:
   - Sequential model setup.
3. **Layers Added**:
   - **Conv Layer 1**: 128 filters, 3x3 kernel, ReLU, padding='same', input_shape=(64, 64, 3)
   - **MaxPooling 1**: 2x2 pool size, padding='same'
   - **Conv Layer 2**: 64 filters, 3x3 kernel, ReLU, padding='same'
   - **MaxPooling 2**: 2x2 pool size, padding='same'
   - **Conv Layer 3**: 32 filters, 3x3 kernel, ReLU, padding='same'
   - **MaxPooling 3**: 2x2 pool size, padding='same'
   - **Flatten**: Converts 3D output to 1D vector.
   - **Dense Layer**: 16 neurons, ReLU.
   - **Dropout**: 0.3 rate.
   - **Output Layer**: 12 neurons, Softmax.
4. **Compilation**:
   - Optimizer: Adam
   - Loss Function: Categorical Crossentropy
   - Metric: Accuracy

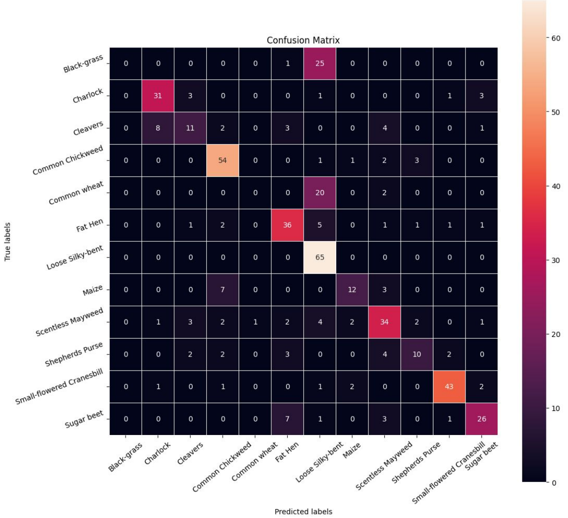
Model accuracy plot and confusion matrix

- **Training and Validation Accuracy**:
  - The model's training accuracy steadily improves, reaching approximately 57% by the end of 30 epochs.
  - The validation accuracy also improves, peaking around 67%, indicating good generalization to unseen data.
  - **Observation**: A consistent gap between training and validation accuracy suggests slight overfitting, but the model is relatively well-tuned.



Confusion Matrix

- **Class-wise Performance**:
  - **Loose Silky-bent**: The model performs best on this class with 65 correct predictions.
  - **Common Chickweed**: Another strong class with 54 correct predictions.
  - **Black-grass** and **Cleavers**: The model struggles with these classes, showing few correct predictions and many misclassifications.



Classification report highlights

Precision, Recall, and F1-Score:

- **High Precision**: Classes like **Loose Silky-bent** (0.53) and **Common Chickweed** (0.90) have high precision, indicating fewer false positives.
- **High Recall**: Classes such as **Loose Silky-bent** (1.00) and **Common Chickweed** (0.86) also show high recall, indicating the model correctly identifies most true positives.
- **Low Scores**: Classes like **Black-grass** and **Cleavers** have low precision, recall, and F1-scores, indicating poor performance.

Overall Accuracy:

- The overall accuracy of the model on the test set is 67.79%.

	precision	recall	f1-score	support
0	0.00	0.00	0.00	26
1	0.76	0.79	0.77	39
2	0.55	0.38	0.45	29
3	0.77	0.89	0.82	61
4	0.00	0.00	0.00	22
5	0.69	0.75	0.72	48
6	0.53	1.00	0.69	65
7	0.71	0.55	0.62	22
8	0.64	0.65	0.65	52
9	0.62	0.43	0.51	23
10	0.90	0.86	0.88	50
11	0.76	0.68	0.72	38
accuracy			0.68	475
macro avg	0.58	0.58	0.57	475
weighted avg	0.63	0.68	0.64	475

Model performance Improvement

1. Reducing the Learning Rate

- **Technique**: Used ReduceLROnPlateau to decrease the learning rate if validation accuracy plateaued.
- **Benefit**: Helps the model converge better by taking smaller optimization steps when needed

2. Data Augmentation

- **Technique**: Applied data augmentation to increase training data variability.
- **Benefit**: Improves the model's ability to generalize to new data by providing diverse training examples.

3. Improved Model Architecture

- **Changes**:
  - Added Batch Normalization.
  - Modified convolutional layers and included dropout 0.3 for regularization.
- **Benefit**: Enhanced model robustness and performance.

4. Training the Improved Model

- **Approach**: Trained the model with augmented data and reduced learning rate.
- **Outcome**: Achieved better accuracy and generalization.

Model2 accuracy plot and confusion matrix

- **Training and Validation Accuracy**:

The improved model shows steady improvement in both training and validation accuracy over the epochs. The final training accuracy reaches around 75%, and the validation accuracy reaches approximately 77%.

Observation: The validation accuracy fluctuates but generally follows the training accuracy, indicating a better generalization capability compared to the initial model.

Evaluation on Test Data

- **Test Accuracy**: The improved model achieves a test accuracy of 76.84%, a significant improvement over the previous model.
- **Test Loss**: The test loss is 0.7565, indicating a better fit on the test data.

Confusion Matrix

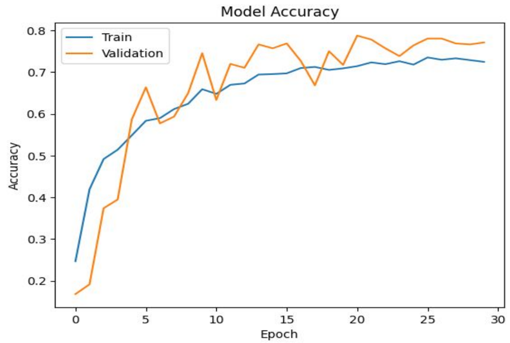
- **Class-wise Performance**:

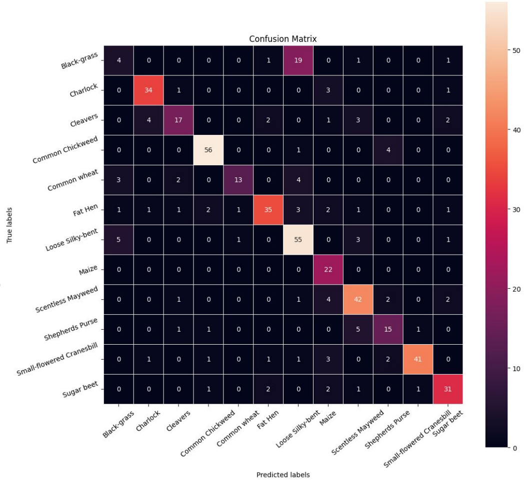
Loose Silky-bent: Still performs well with 55 correct predictions.
Common Chickweed: Continues to perform strongly with 56 correct predictions.
Black-grass: Shows improvement with 4 correct predictions, but still has significant misclassifications.

- **Improved Misclassifications**:

Black-grass still show room for improvement, but their performance has improved compared to the initial model.
Misclassifications are reduced across several other classes.

- **Impact of Data Augmentation and Learning Rate Reduction**:
  - The overall distribution of correct and incorrect predictions is more balanced.
  - Classes with fewer samples have shown improvement, highlighting the effectiveness of the applied techniques.






```
15/15 - 0s - loss: 0.7565 - accuracy: 0.7684 - 217ms/epoch - 14ms/step
```

Classification report highlights

- **Precision, Recall, and F1-Score**:
  a. **High Precision and Recall**: Classes like **Common Chickweed** (0.92 precision and recall) and **Loose Silky-bent** (0.65 precision, 0.85 recall) show high performance.
  b. **Improved Scores**: Classes that previously had low scores (e.g., **Black-grass**, **Cleavers**) have seen improvements.
  c. **Consistent Performance**: The model shows consistent performance across most classes with high precision, recall, and F1-scores.
- **Overall Accuracy**:
  a. The overall accuracy of the model on the test set is 76.84%.
- **Macro and Weighted Averages**:
  a. **Macro Average**:
     i. Precision: 0.74
     ii. Recall: 0.73
     iii. F1-score: 0.73
  b. **Weighted Average**:
     i. Precision: 0.77
     ii. Recall: 0.77
     iii. F1-score: 0.76

	precision	recall	f1-score	support
0	0.31	0.15	0.21	26
1	0.85	0.87	0.86	39
2	0.74	0.59	0.65	29
3	0.92	0.92	0.92	61
4	0.87	0.59	0.70	22
5	0.85	0.73	0.79	48
6	0.65	0.85	0.74	65
7	0.59	1.00	0.75	22
8	0.75	0.81	0.78	52
9	0.65	0.65	0.65	23
10	0.95	0.82	0.88	50
11	0.79	0.82	0.81	38
accuracy			0.77	475
macro avg	0.74	0.73	0.73	475
weighted avg	0.77	0.77	0.76	475

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macro avg	0.74	0.73	0.73	475
weighted avg	0.77	0.77	0.76	475

Comparison

Metric	Initial Model	Improved Model
Accuracy	68%	77%
Macro Average		
Precision	0.58	0.74
Recall	0.58	0.73
F1-score	0.57	0.73
Weighted Average		
Precision	0.63	0.77
Recall	0.68	0.77
F1-score	0.64	0.76

Class	Metric	Initial Model	Improved Model
Black-grass (0)	Precision	0	0.31
	Recall	0	0.15
Charlock (1)	Precision	0.76	0.85
	Recall	0.79	0.87
Cleavers (2)	Precision	0.55	0.74
	Recall	0.38	0.59
Common Chickweed (3)	Precision	0.77	0.92
	Recall	0.89	0.92
Common Wheat (4)	Precision	0	0.87
	Recall	0	0.59
Fat Hen (5)	Precision	0.69	0.85
	Recall	0.75	0.73
Loose Silky-bent (6)	Precision	0.53	0.65
	Recall	1	0.85
Maize (7)	Precision	0.71	0.59
	Recall	0.55	1
Scentless Mayweed (8)	Precision	0.64	0.75
	Recall	0.65	0.81
Shepherds Purse (9)	Precision	0.62	0.65
	Recall	0.43	0.65
Small-flowered Cranesbill (10)	Precision	0.9	0.95
	Recall	0.86	0.82
Sugar beet (11)	Precision	0.76	0.79
	Recall	0.68	0.82

Summary of key improvements

- Learning Rate Reduction: Improved convergence and generalization by adjusting the learning rate during training.
- Data Augmentation: Enhanced model's ability to generalize and handle class imbalance through techniques like rotation, flipping, and scaling.
- Improved Architecture: Added batch normalization and dropout layers to improve performance and reduce overfitting.
- Better Training Strategy: Resulted in significant improvements in accuracy and overall model performance through refined training approaches.

Conclusion

The final model selected for plant seedling classification is a CNN designed with improved architecture and trained using data augmentation and learning rate reduction techniques. This model has demonstrated improvements in accuracy and generalization compared to the initial model.

Key Improvements in the Final Model:

- Reduced Learning Rate: Applied `ReduceLROnPlateau` to help the model converge better.
- Data Augmentation: Enhanced the training dataset variability to improve generalization.
- Improved Architecture: Added batch normalization and dropout layers to enhance robustness and reduce overfitting.
- Training Strategy: Achieved a final test accuracy of 76.84% with a reduced loss.

Model Summary

- Architecture:
  - Convolutional layers with filters of 64 and 32.
  - MaxPooling layers to reduce the spatial dimensions.
  - Batch normalization for stable and faster training.
  - Dense layers with dropout for regularization.
  - Softmax output layer for multi-class classification.
- Training Results:
  - Test Accuracy: 76.84%
  - Improved metrics across all classes: Higher precision, recall, and F1-scores.

Key improvements of the final model

76.84%	Applied	Enhanced	Added BN & Dropout
Test Accuracy	Reduced Learning Rate	Data Augmentation	Improved Architecture

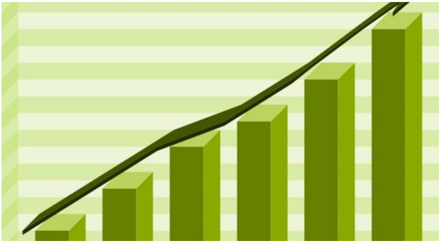
Conclusion

Sample Outputs:

- **Image 1**: **Predicted Label**: Small-flowered Cranesbill **True Label**: Small-flowered Cranesbill
- **Image 2**: **Predicted Label**: Cleavers **True Label**: Cleavers
- **Image 3**: **Predicted Label**: Common Chickweed **True Label**: Common Chickweed
- **Image 4**: **Predicted Label**: Shepherds Purse **True Label**: Shepherds Purse

Conclusion

The final model exhibits robust performance with substantial improvements in accuracy and generalization. The combination of learning rate reduction, data augmentation, and an enhanced CNN architecture has resulted in a reliable classifier for plant seedling categories. The model's predictions on test images align closely with the true labels, showcasing its effectiveness in real-world scenarios.



By incorporating these advanced techniques and refining the model architecture, we have achieved a high-performing model capable of aiding in agricultural technology and improving efficiency in plant seedling classification.