Weed-Crop Recognition Using Deep Learning

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With chemical treatments providing threats to the environment and hand weeding being labor-intensive, the agriculture business faces substantial hurdles in controlling weeds (Qu & Su, 2024). By developing a deep learning model to identify weed crops accurately, we aim to help farmers boost their agricultural productivity. Using a convolutional neural network (CNN), this project will focus on classifying images of weeds and crops with high precision.

The initial model for this task will be a custom CNN designed to handle the variability in the visual characteristics of weeds and crops. Subsequently, we will use transfer learning with a pre-trained model like ResNet or MobileNet will be explored to enhance performance. The dataset used will contain images of crops and weeds under varying conditions, sourced from publicly available datasets or agricultural research databases.

Problem Definition

The goal of this project is to build a deep learning model capable of accurately classifying images into one of 7 classes: three crop classes (corn, lettuce, radish) and four weed classes (bluegrass, sedge, chenopodium album, cirsium setosum). The input will consist of images of agricultural fields that contain either one of the crop types or one of the weed types. The objective is to automate the identification process, helping farmers and agricultural systems to efficiently distinguish between crops and weeds.

Challenges to address include:

- **Visual Variability:** Differences in weed and crop shapes, colors, and sizes. Images captured under different lighting conditions, times of day, and stages of plant growth.
- **Environmental Noise:** Background interference like soil, stones, and other plants.
- **Imbalance in Classes:** Some classes might have more samples than others, leading to imbalanced training data, which can affect model performance.

Plan

Data Collection and Preprocessing

- Collect a balanced dataset containing labeled images of crops and weeds. We'll be using the dataset from this Github link, which contains images for the crops and weeds.
- Preprocessing Steps:
    - Resizing all images to a uniform size for efficient model training.
    - Normalization of pixel values to improve model convergence.
    - Data Augmentation to introduce variability and enhance model robustness, using techniques like rotation, horizontal/vertical flips, and brightness adjustments.

Model Selection and Architecture

- Custom Model: Develop a custom CNN using different hyperparameters and architecture.

- Baseline Model: Use ResNet or MobileNet as a baseline model, comprising:
    - Input Layer for the resized images.
    - Multiple Convolutional Layers with ReLU activation for feature extraction.
    - Max Pooling Layers to reduce dimensionality.
    - Fully Connected Layers for classification into the different types of crops and weed
    - Softmax Output Layer for final predictions.
- Transfer Learning / Fine-tuned Model: Using the base model as a pre-trained model, we can use different architectures and hyperparameters to fine-tune the weed and crop dataset.
- Optimization Techniques:
    - Different optimizers (e.g. adam, SGD) for efficient weight updates.
    - Dropout regularization or batch normalization to prevent overfitting.
    - Learning Rate Scheduler to adjust learning rates dynamically during training.

Training and Optimization

- Split Data into training, validation, and test sets (e.g., 70% training, 15% validation, 15% testing).
- Train both the custom CNN and the transfer learning model on the dataset, monitoring loss and accuracy.
- Use early stopping based on validation performance to prevent overfitting.
- Hyperparameter Tuning: Experiment with different batch sizes, learning rates, and number of epochs for optimal performance.

Evaluation and Comparison

- Evaluate all models using:
  - Accuracy: Overall correctness of classifications.
  - F1-score: Balance between precision and recall, particularly useful if there's an imbalance between weed and crop images.
  - Loss: Cross-entropy loss to assess model error.
- Compare the custom CNN with the transfer learning model based on the metrics above to determine the best-performing model.

Proposed Timeline

Timeline	Task	Description
September 29 - October 15	Data Collection & Preprocessing	Gather datasets, label data, perform preprocessing, and apply augmentation techniques.
October 16 - November 12	Model Development: Transfer Learning & Fine-Tuning	Build, train, and test the custom CNN model on the dataset. Implement and fine-tune the transfer learning model (ResNet/MobileNet).
November 8	Mid-Progress Meeting	Present the progress of the project, demonstrate preliminary results, and receive feedback for further adjustments.
November 13 - November 19	Optimization & Final Training	Optimize models by adjusting hyperparameters, regularization, and fine-tuning for improved accuracy.
November 20 - November 24	Evaluation & Analysis	Test models on the unseen test set, analyze results, and compare model performances.
November 25 - December 1	Further Improvements & Finalization	Apply feedback from the mid-progress meeting to enhance the model’s performance and finalize evaluations.
December 2 – December 6	Final Report & Presentation	Complete the documentation, analysis, and preparation of the final report and presentation for submission.

Evaluation Metrics

The models will be evaluated using the following metrics:

- Accuracy: The percentage of correct predictions across the test set.
- Precision and Recall: To evaluate the model's ability to correctly identify weeds (or crops) while minimizing false positives and negatives.
- F1-score: To provide a balanced evaluation of precision and recall, especially useful if a class imbalance exists.
- Confusion Matrix: To visually assess model performance on both classes and identify potential weaknesses in classification.

Results from the custom CNN will be compared against those from the transfer learning model, and the model demonstrating the best trade-off between accuracy, F1-score, and computational efficiency will be selected as the final solution.

References

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