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Engineering, Built Environment and IT
Department of Computer Science

Introduction to Deep learning
COS 801

Homework 1

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Convolutional Neural Network and SVM Classification

Over the past decade, Convolutional Neural Networks (CNNs) have achieved remarkable success in image recognition, face detection, object classification, and image segmentation, establishing themselves as a foundational technique in computer vision [1, 2]. These advancements have led to impactful applications across diverse sectors, including robotics, unmanned aerial vehicles (UAVs), military surveillance, and medical diagnostics, among others [3].

Building on this success, an important research question arises if CNN-based deep learning models can be adapted—with different convolutional strategies and architectures—to effectively distinguish between weeds and crop seedlings in agricultural settings? Developing such a system could significantly enhance automated crop monitoring and precision farming, contributing to increased agricultural productivity and sustainability.

This line of inquiry aligns closely with the United Nations Sustainable Development Goal (SDG) 2: Zero Hunger, which aims to ensure food security and promote sustainable agriculture by 2030 [4]. Leveraging CNNs to tackle weed-crop classification holds promise not only for reducing manual labour and herbicide use but also for promoting environmentally conscious farming practices [5]. It could also be used to yield better crops and stewardship of the environment.

Common chickweed	Black grass	Fat Hen
Shepherd's purse	Charlock	Loose silky-bent
Scentless mayweed	Cleavers	Maize & Sugar beet

Table 1: Description of Species

One of the key objectives of this assignment is to develop a system capable of identifying and differentiating weeds from crop seedlings—a task that highlights the strength of CNNs in feature extraction when compared to traditional machine learning approaches. This challenge serves as an excellent opportunity to showcase the effectiveness of CNNs in handling complex visual classification tasks in agriculture.

The Table 1 below provides a summary of the dataset, which includes both a training set and a test set comprising images of plant seedlings at various stages of growth. Each image is labelled with a unique identifier (filename), and the dataset covers 12 distinct plant species. The overarching goal is to build a robust classifier capable of accurately predicting the species of a plant based on a given image. This not only aids in automated weed detection but also contributes to precision agriculture and supports efforts toward food security.

The list of species included in the dataset is as follows:

1. Problem description

   - Feature Extraction with CNNs and SVM Classification

     Implement an hybrid model where a CNN to extract intensive feature in the input data, and feed the final layer with Support Vector Machine (SVM) to differentiate a weed from a crop seedling?
     Specifically:

     – Construct a CNN with a fully connected (dense) layer over a Softmax function with Support Vector Machine (SVM) [6] as your classifier and report the evaluation matrices as stated below?
     – Extract the output from the last or second-to-last layer of your trained Convolutional Neural Network (CNN) model to use as feature representations. Then, train the extracted features on XGBoost classifier [7] and evaluate its performance.
     – You are required to report on the following by compare the performance of three different models
       (a) CNN + SVM: Extract features from the last or second-to-last CNN layer and use them to train an SVM classifier.
       (b) CNN + XGBoost: Similarly, extract features from your CNN and train an XGBoost classifier
       (c) Baseline CNN: Evaluate the performance of your original CNN model.
       Instructions:

* Implement each model and report the evaluation metrics (e.g., accuracy, F1-score, precision, recall, and ROC-AUC if applicable).
* For the CNN model, experiment with different configurations of filters, strides, and max-pooling operations.
* Clearly state the hyper-parameters you chose (e.g., number of filters, kernel size, stride length, pooling size) and justify your choices based on model performance or computational efficiency.
* Experiment by replacing the activation function (e.g., ReLU) with several alternative activation functions in order to gain insights into the impact of different activations at various levels of abstraction (e.g., adjust the settings to observe the impact on the feature maps) and report your findings accordingly.
* Provide a comparison table or plot summarizing the results across the three approaches.
* Reflect on which combination performs best and why, considering aspects such as model complexity, generalization, and training time.

2. Evaluation

You are expected to submit your results along with an evaluation of your implementation using appropriate performance metrics. Specifically, you should:

- Calculate the mean F-score, such as the micro-averaged F1-score, to assess overall classification performance.

- Generate and include a plot of the ROC (Receiver Operating Characteristic) curve [8] to visually evaluate the trade-off between true positive and false positive rates across different thresholds.

Given positive/negative rates for each class k, the resulting score is computed this way:

$$\text{Precision}_{micro} = \frac{\sum_{k \in C} TP_k}{\sum_{k \in C} TP_k + FP_k}$$

$$\text{Recall}_{micro} = \frac{\sum_{k \in C} TP_k}{\sum_{k \in C} TP_k + FN_k}$$

The F1-score is calculated as the harmonic mean of precision and recall:

$$F1 - score = 2 \times \frac{Precsion(P) \times Recall(R)}{Precsion(P) + Recall(R)}$$

This metric provides a single, balanced measure that accounts for both false positives and false negatives, making it especially useful in scenarios where one class may dominate.

3. Dataset Description

The dataset is described as follows and download here.

- **train.csv** – This file contains the training data, which is the images of plant seedlings in the dataset folders on the Google drive and it can be used to train the propose model.
- **test.csv** – This file contains the test data, which is the images of plant seedlings in the dataset folders on the Google drive and it can be used to test/evaluate the propose model.

References

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