Mining Intelligent Patterns using SVAC for Precision Agriculture and Optimizing Irrigation (Student Abstract)

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Abstract

The ability to leverage the advances in precision agriculture, computer vision, and edge devices can immensely benefit sustainable agriculture yield. Utilizing the available resources to their maximum requires reliable and intelligent real-time insights to optimize and automate the current agriculture infrastructure. In some countries with low internet penetration rates, such systems need offline and extremely efficient edge deployments. We propose a framework that attends to the trifecta of (i) predicting crop water requirements and irrigating the land appropriately, (ii) providing intelligent insights from aerial images and sensor data for crop management that is fully offline, and (iii) effective post-training quantization and model pruning that leverage the lottery ticket hypothesis - an arbitrarily instantiated network containing a subnetwork that when trained independently will perform as well as the original full network, trained for a similar number of cycles for shrinking the machine learning models and improving latency on the edge.

Introduction

Conventional sustainable agricultural practices involve much human intervention and introduce several inefficiencies in farm management, implementing archaic practices, or suboptimal resource usage. We propose an end-to-end framework that uses different variables such as the rainfall data, publicly available historical crop yield data, soil moisture sensor data, and Hyperspectral and RGB images taken from drones to provide intelligent insights.

Automating irrigation requires historical crop water requirement patterns, region-specific rainfall pattern data, and real-time sensor data such as soil moisture, soil pH, nutrient levels, and temperature sensors strategically deployed at regular intervals. To obtain these values in real-time, we have developed a unique minimal hardware system consisting of one Raspberry Pi 3 as a parent node, several NodeMCUs, and a custom edge-module with several sensors to obtain real-time data for each of the required variables for our predictive algorithm to reliably predict the irrigation requirement specific to the plant.

We use aerial RGB images from cameras mounted on drones/UAVs for land mapping, crop monitoring, and counting the yield. The mounted optical sensor also captures the soil reflectance and chlorophyll content, which gives us all the required information to fully manage the entire crop cycle using just our predictive models and the crop management application for the user.

We use post-training quantization to reduce the model size and experiment with the lottery ticket hypothesis (Frankle et al. 2018) to prune the model to make it sparser. We try to exploit the expressivity of batchnormalization to reduce further the model size deployed on the parent node to process the data in real-time and perform the required actions. The predictions control the motor and determine the time interval at which to fulfil the irrigation requirements.

Approach

In order to predict the crop water requirement, we use real-time data from various sensors to obtain (a) air temperature, (b) dew point temperature, (c) relative and specific humidity, (d) precipitation amount, (e) soil moisture, (f) soil pH, (g) nutrient level, (h) LAI (Leaf Area Index) from the RGB drone images and (i) OSAVI vegetation index from the optical sensors capturing the reflectance information. An efficient implementation of the Partial Least Square Regression is trained on all the listed data features. The efficient implementation and the higher efficiency aids comprehensive hyperparameter tuning. The predicted irrigation values from the PLSR model have been tested at farm sites in India.

We fine-tune the YOLOv4 algorithm (Bochkovskiy, A et al. 2020) to count the ripe crop yield by fine-tuning onto our dataset of cabbage crops annotated from the farm images.

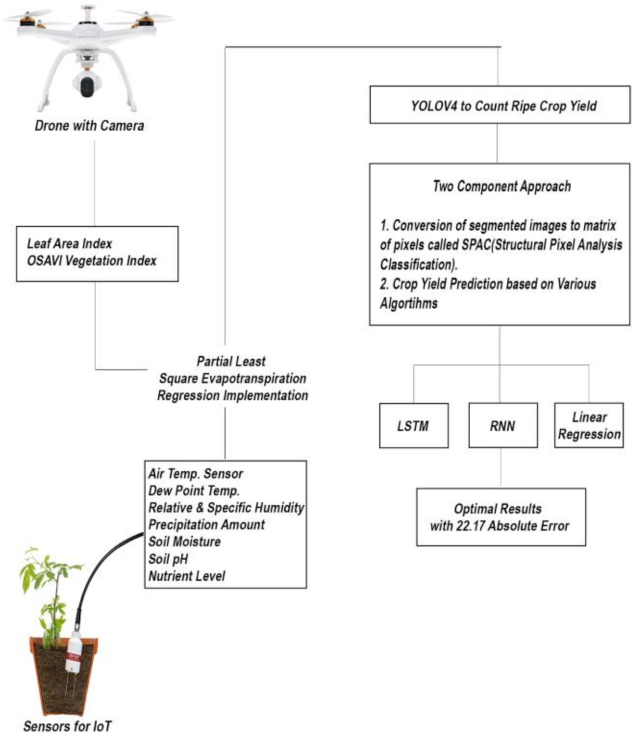

Figure 1: Architecture of the precision agriculture system.

We fine-tune the model for the ripe cabbage crops from a model trained on the global wheat head dataset. These fine-tuned models are deployed on the parent node and efficiently discern the crops and count them from the drone RGB images obtained from the camera mounted on the drone. The optical sensor, on the other hand, captures the Near-IR and mid-infrared wavelengths of reflectance values. This aids in crop area mapping and identifying the index values, such as for chlorophyll.

The crop management makes use of two distinct components: (i) image segmentation and localization of crops from drone RGB images to map the harvest regions and (ii) prediction of crop yield from the historical data available for various locations from publicly available datasets to validate our machine learning model's output. We also propose the Stratified Pixel Analysis Classification (SPAC) algorithm to detect and segment crops from drone images that help in the crop detection in that it helps identify and reduce soil compaction and does away with the requirement of heavy machinery. The drone RGB images are transformed into a matrix format with each pixel value representing geospatial data. We then select the corresponding pixels for the crops whose yield has to be computed and based on their predicted probability values, match them with the different classes.

The hardware system developed includes the Raspberry Pi 3 as the parent node that controls all the NodeMCUs and the custom board, including all of the sensors required for our PLSR model. These nodes provide the parent node with sensor data at regular intervals. They are responsible for controlling the valves, and motor connected through a micro-drip irrigation system for delivering water to the crops based on the predicted irrigation requirements and custom model made using Partial Least Square Regression where we make use of the evapotranspiration coefficient of the crop. This moisture-sensitive parameter is unique for each crop. This provided optimal results for determining the crop's water requirements as verified for one cabbage crop cycle. The equation customized from Partial Least Square Regression is as follows: the daily reference crop evapotranspiration (ET_0):

$$ET_c = K \,.\, ET_0 \qquad (Eq. 1)$$

Where K_c is the crop coefficient and depends on multiple factors, namely, the crop type, climate, crop evaporation, and soil growth stages.

$$Y = XW_h C'_h + ET_c$$

$$Y = XW_h (P'_h W_h)^{-1} C'_h + ET_c \qquad (Eq. 2)$$

Y is the matrix of dependent variables, X is the input feature matrix, and we calculate the residuals in the form of evapotranspiration coefficient, while P and W are the matrices generated by PLSR.

Results

The output from the segmentation of multispectral images is verified by validating the findings by predicting the region's crop produce from historical data available. We use the data provided by the Government of India, with Season, Area, Year, and their Production parameters. The rainfall and temperature readings from our designed system and historical data to enhance the model we use as our final dataset. We have used the Recurrent Neural Networks (RNN), a simple Long Short Term Memory (LSTM), and a Robust Linear Regressor (RANSAC) as our baseline models. The data is non-linear by nature, which is evident from the optimal performance of the RNN as compared to other baselines, and the results were as expected, with RNN having a minimal mean absolute error of 34.16 and LSTM having 22.17 for the crop yield produced. Additionally, the YOLOv4 algorithm for cabbage crop yield counting from RGB images has obtained a precision of 0.8241 and an F1-score of 0.8042. The results have been validated at Nagalpur farms, Gujarat.

References

Bochkovskiy, A., Wang, C.Y. and Liao, H.Y.M., 2020. YOLOv4: Optimal Speed and Accuracy of Object Detection. arXiv preprint arXiv:2004.10934.

Frankle, J. and Carbin, M., 2018. The lottery ticket hypothesis: Finding sparse, trainable neural networks. arXiv preprint arXiv:1803.03635.