NEURAL NETWORK-BASED HIGH THROUGHPUT FIELD PHENOTYPING OF HORTICULTURAL CROPS USING HYPERSPECTRAL UAV IMAGERY

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Introduction

- Integration of Unmanned Aerial Vehicle (UAV) and deep learning techniques has helped advanced the High Throughput Field Phenotyping (HTFP) by robust estimation of crop biophysical parameters. HTFP is becoming a major front in precision-ag, which can potentially help farmers continuously gauge crop-health in a single UAV flight and strategic decisions for agronomic practices, targeted irrigation and the effective use of fertilizers.
- Chlorophyll content measurement (Chl-a) is essential in agriculture to gain valuable insights into plant health, growth and yield.
- Stem water potential (SWP) is one of the most accurate measurements for water stress in horticulture crops which helps growers to avoid any water stress conditions in cultivations.

Objectives

- Predicting water stem potential and chlorophyll content in melon and tomato using 50 and 150 bands acquired by hyperspectral camera and linking it to yield production.
- To assess if there is a significant difference in performance when using 50-band product as compared to the 150-band product.

Materials and Methods

Location: The experiment was carried out at the Tenuta di Alberese farm (42.6935º N, 11.1425º W) owned by Terre Regionali Toscane in Tuscany Region (Italy) in 2021, within the DATI project (EU PRIMA).

Experimental design and data collection: Two crops, melon and tomato (Figure 1a) were monitored with 9 replicates.

Fig 1. a) Experimental design and b) UAV system used

- Two field campaigns were carried out on 06/23/2021 and 08/02/2021. A Senop HSC-2 hyperspectral camera mounted on a DJI Matrice Pro Hexacopter UAV platform (Figure 1b) was used for the flight measurements and, in the same days, Chl and SWP ground measurements were collected using a dualex sensor and a Scholander pressure chamber.
- The flights were performed at a speed of 1.8 m/s at a height of 30 m above ground level (AGL) providing spectral images with a ground sampling distance (GSD) of approximately 2 cm/pixel.
- Reflectance hypercubes were processed with 50 and 150 spectral bands (500-900nm) and a Full Width at Half Maximum of about 8 nm.
- A supervised region-of-interest (ROI) procedure was used for the hyperspectral data extraction from each replicates and date, to perform the post-processing dataset as input of the Neural Network model.

Materials and Methods Cont.

- Number of training data points: 18
- To resolve the issue of less data points, Leave-Out-CrossValidation method was implemented as shown in figure 2 below

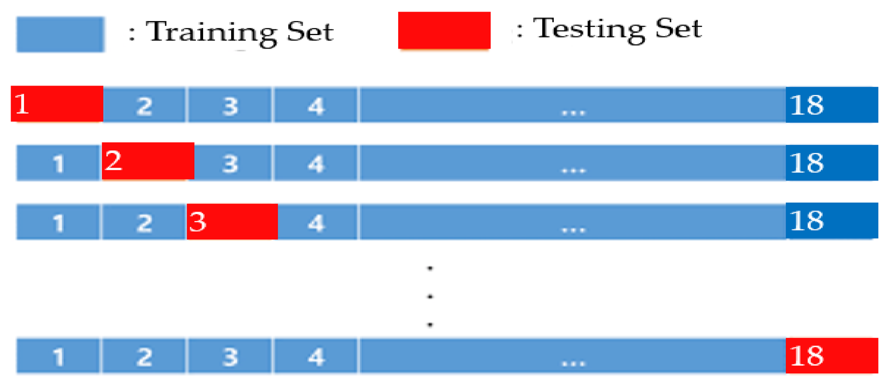

Fig 2. Implementation of Leave-Out-Cross Validation to repeatedly fit model that contains (18-1=17) observations

- A Simple Sequential Neural Network with an input layer, a dense hidden layer and an output layer was built. Model architecture is shown in figure 3 below and table 1 shows training set up

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 128)               7040
_________________________________________________________________
dense_1 (Dense)              (None, 256)               33024
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 257
=================================================================
Total params: 40,321
Trainable params: 40,321
Non-trainable params: 0
_________________________________________________________________
```

Fig 3. Neural Network Model Architecture

Frameworks	Tensorflow
Optimizer	Adam
Loss Function	Mean Squared Error
Epochs	300

Table 1: Training set up with 300 epochs

Results

- For both crops, the 50-band product as well as the 150-band product was used to model Chl-a and SWP respectively. Table 2 shows the summary of all permutations with their respective RMSE values.
- It can be noted that all the RMSE values are appreciatively very low. This indicates that even for a small dataset, a sequential and a dense neural network can determine the non-linear relationships that might exist among the bands and the target quantities of Chl-a and SWP.

Crop	No. of Bands	Parameter	RMSE	R^2
Tomato	50	Chl-a	0.560	0.851
Tomato	150	Chl-a	0.453	0.902
Tomato	50	SWP	0.033	0.936
Tomato	150	SWP	0.034	0.941
Melon	50	Chl-a	1.084	0.948
Melon	150	Chl-a	0.858	0.968
Melon	50	SWP	0.015	0.936
Melon	150	SWP	0.102	0.941

Table 2: Summary of results with 50 and 150 bands for Chl-a and SWP of Tomato and Melon crops respectively

Results Cont.

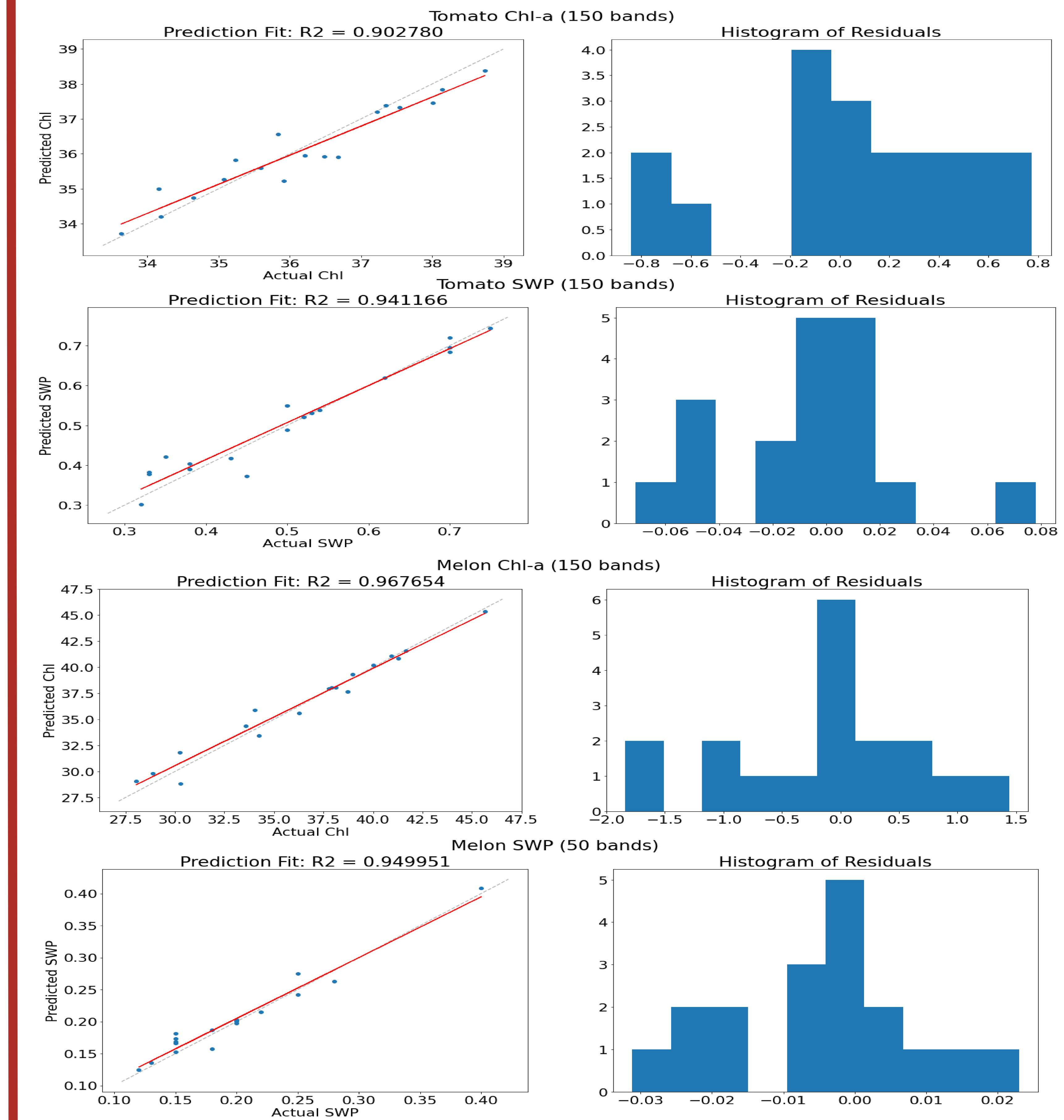

Figure 4. R-squared values of the best performing models

- For tomato, Chl-a was best explained by the 150-band product with an R2 of 90%, and SWP was also best explained by the 150-band product with and R2 of 94%.
- For Melon, Chl-a was best explained by the 150-band product with an R2 of 96%, and SWP was best explained by the 50-band product with an R2 of 94%.
- This indicates that there isn't much difference in the 50-band and 150-band product's influence on modelling Chl-a and SWP for the two crops. Both carry orthogonally the same amount of information.

Discussion & Conclusion

- We also experimented with conventional machine learning algorithms and our results showed that conventional machine learning algorithms such as gradient boosting, decision tree, linear regression perform poorly on this dataset characterized by with fewer data points.
- Sequential Dense Neural Networks were able to fit the dataset with fewer datapoints because their dense nature (high number of nodes in the hidden layer), allows to model underlying non-linear relationships more easily.
- High R-square indicate good scalability of the models and the potential to be deployed on UAVs to give one-flight crop information to farmers.