HyperStressPropagateNet: Time Series Modeling for Drought Stress Propagation in Plants using Hyperspectral Imagery

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HyperStressPropagateNet: Novelties

- It uses a convolutional neural network to classify the reflectance spectra at individual pixels as either stressed or unstressed to determine the temporal propagation of stress in the plant using hyperspectral imagery.
- A very high correlation between the soil water content (SWC) and the percentage of the plant under stress as computed by HyperStressPropagateNet on a given day demonstrates its efficacy.
- The algorithm has been used to illustrate the temporal propagation of stress both qualitatively and quantitatively.
- HyperStressPropagateNet has been evaluated on a dataset of image sequences of cotton plants captured in a high throughput plant phenotyping platform.
- The algorithm may be generalized to any plant species to study the effect of abiotic stresses on sustainable agriculture practices.

Materials and Methods

- The image sequences used for algorithm development and evaluation were obtained at the greenhouse of the University of Nebraska-Lincoln (Lincoln, Nebraska, U.S.) using High Throughput Plant Phenotyping Core Facilities (Scanalyzer 3D, LemnaTec Gmbh, Aachen, Germany).
- Plants were randomly divided into two groups of 10 corresponding to the two experimental groups (i.e., Experiments 1 and 2).
- Each experimental group was further split into two groups of 5 plants and assigned to treatment groups (control and drought stress).
- In Experiment 1, dry-down (DD1) was initiated 12 days after the onset of plant imaging and lasted for 8 days.
- A week later, a similar dry-down (DD2) was initiated for the second experimental group and lasted for 9 days.

- A hyperspectral image can be represented by a three-dimensional array of intensities, $H(x,y,\lambda)$, where (x,y) represents the location of a pixel and λ denotes the wavelength.
- It is, thus, often referred to as a hyperspectral cube.
- Intensity information at a specific location for all wavelengths can be represented by a spectral reflectance curve.

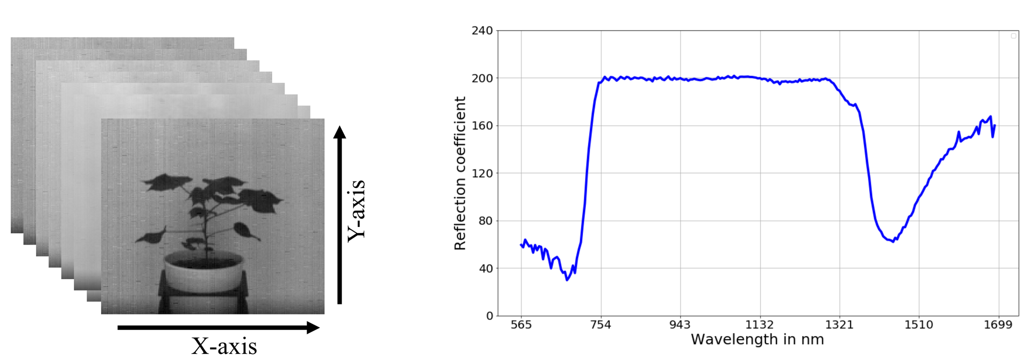

Fig. 1: (a) Hyperspectral cube; and (b) A sample spectral reflectance curve.

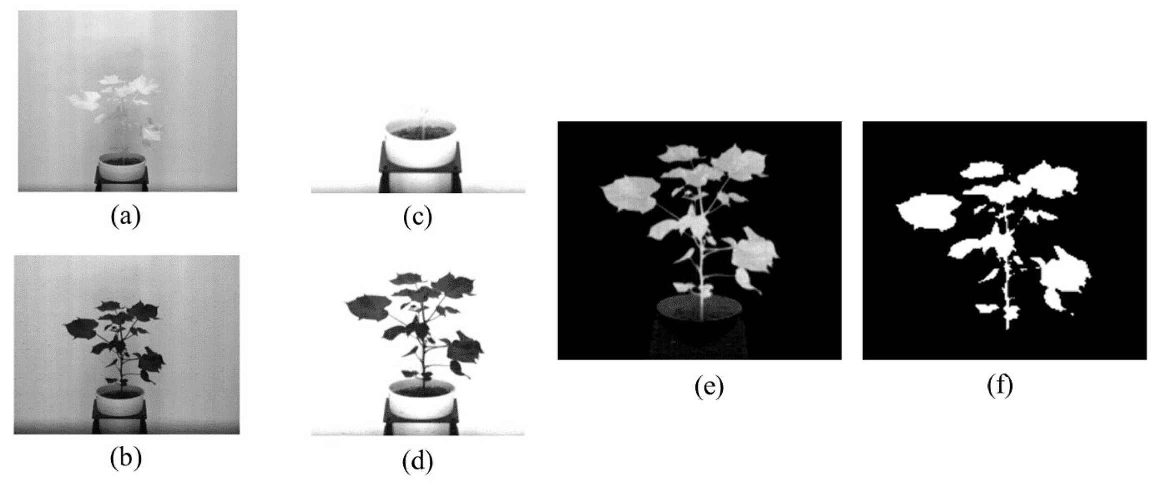

Fig. 2: Spectral band difference based segmentation.

- Two bands of specific wavelengths that have significant contrast in intensity are first identified (a-b).
- They are enhanced by multiplying a constant factor (c-d) and finally subtracted from each other to isolate the plant pixels, i.e., the foreground (e).
- The enhanced foreground image is then binarized using Otsu's automatic thresholding technique to generate a binary mask for the plant (f).
- The binary mask is used to segment the plant in all bands of a hyperspectral cube for subsequent analysis.

Training and Classification

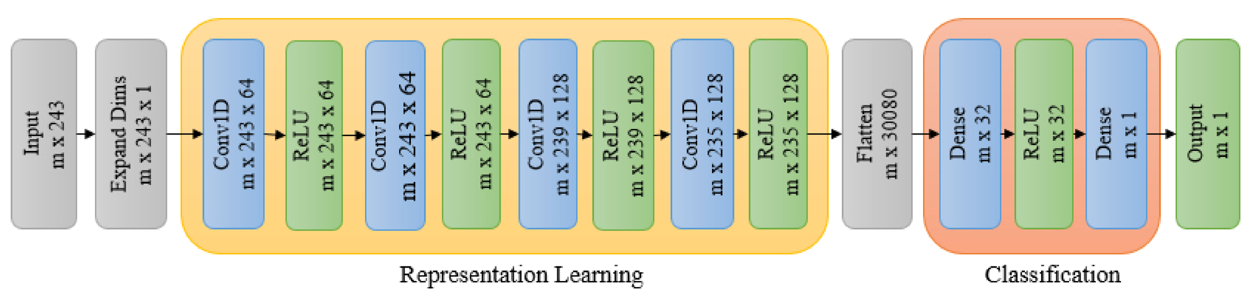

Fig. 3: CNN-based deep learning architecture for classification of stressed and unstressed pixels.

- 1D CNN is used to classify the reflectance spectra into two classes, i.e., stressed and unstressed.
- These convolutional layers learn from the representation learning component.
- The goal of representation learning is to learn the different features in the convolution layers and then use them in the subsequent dense layers for the final classification.

Fig. 4: (a) Training and validation loss vs number of epochs; and (b) training and validation accuracy vs number of epochs.

- The total number of epochs used during training is 30.
- From the two sets of graphs, it is evident that the validation loss and accuracy closely follow the training loss and accuracy, respectively.
- The model converges, and validation accuracy reaches above 95% within 10 epochs.

Results

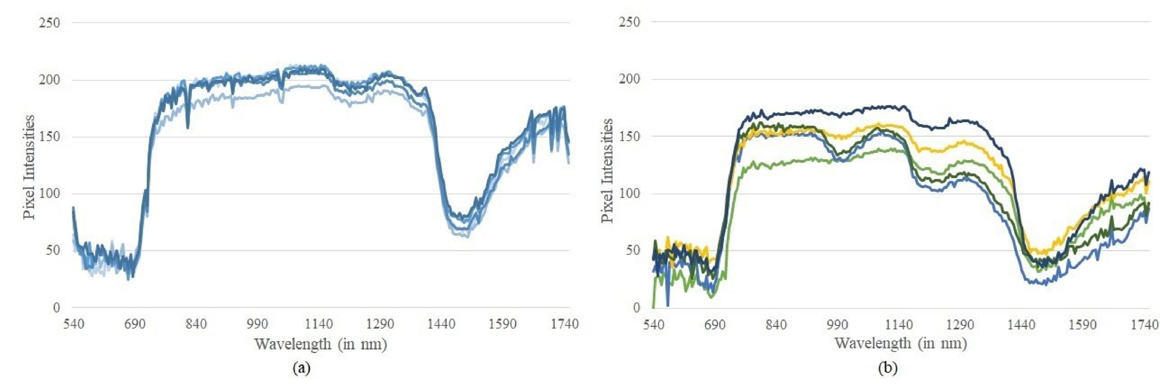

Fig. 5: Reflectance spectra generated at random pixels of a (a) controlled plant; and (b) stressed plant.

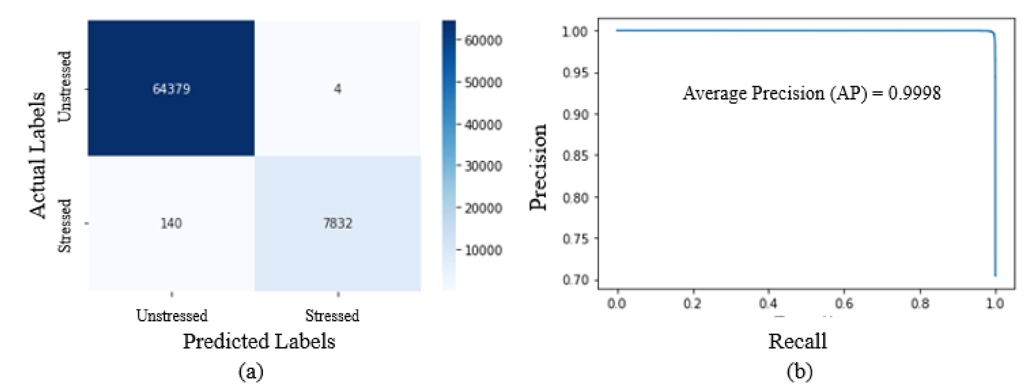

Fig. 6: Performance metrics for HyperStressPropagateNet: (a) confusion matrix; and (b) precision-recall curve.

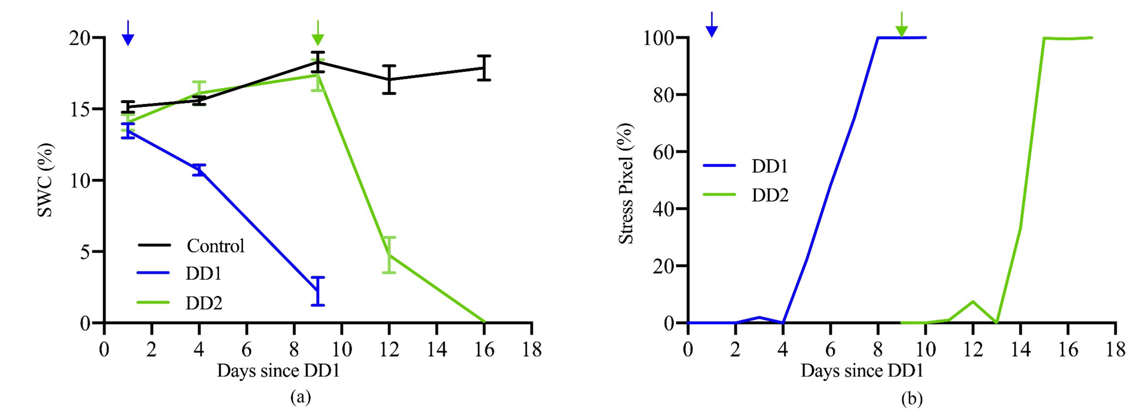

Fig. 7: (a) SWC (%) for the control and the two dry-down groups (DD1, Plant A and DD2, Plant B); and (b) stress pixel (%) over days since DD1 for the same plants.

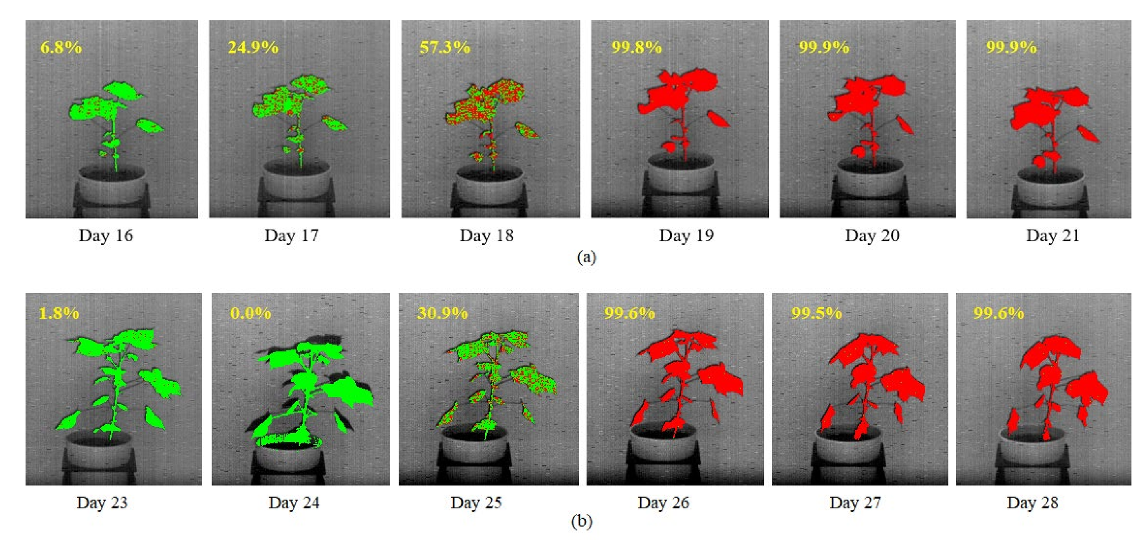

Fig. 8: Illustration of qualitative and quantitative temporal propagation of stress using Plant A (DD1 group) and Plant B (DD2 group).

- Pixels classified as stressed and unstressed are shown in red and green, respectively.
- The percentage of stressed pixels to the total plant pixels are shown at the top-left corner of each image.
- The study shows a high correlation between the SWC and the percentage of stress pixels in the plants.

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