第十七屆農畜產品品質非破壞性檢測技術國際學術研討會

Non-destructive Detection for the Early Drought Stress Status of Tomato (*Solanum lycopersicum*) by Spectroscopy and Deep Learning

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農業部 MINISTRY OF AGRICULTURE

Personal information

Education

- Ph.D., Department of Agronomy, National Chung-Hsing University, Taiwan.
- M.S., Graduate Institute of Biochemical Science, National Taiwan University, Taiwan.
- B.S., Department of Science Education, University of Taipei, Taiwan.

Working Experience and Training

- 2023: Associate Researcher, Biotechnology Division, Taiwan Agricultural Research Institute.
- 2023: Summer School on Image Analysis for Plant Phenotyping. Wageningen University and Research. Nederland.
- 2018: Visiting Scholar. Australian Plant Phenomics Facility (APPF). Australia.
- 2017: Machine Learning for Big Visual Data. IEEE International Elite School. Taiwan.

Outline

- **Challenge of tomato (*Solanum lycopersicum*) cultivation.**
- **Aim**
- **Deep learning**
- **Experiment design:**
  - ✓ Greenhouse experiment
  - ✓ Model building and evaluation
- **Results**
- **Conclusions**

Challenge of tomato cultivation in Taiwan

To pr

Zhou *et al. BMC Plant Biology* (2017) 17:24
DOI 10.1186/s12870-017-0974-x

BMC Plant Biology

RESEARCH ARTICLE Open Access

Drought stress had a predominant effect over heat stress on three tomato cultivars subjected to combined stress

Rong Zhou[1,2,3†], Xiaqing Yu[3†], Carl-Otto Ottosen[4], Eva Rosenqvist[5], Liping Zhao[1,2], Yizhi Wang[1,2], Wenqui Xu[1], Tongmin Zhao[1,2*] and Zhen Wu[3*]

High Temp → **Heat stress** **Drought stress**

Plant height and leaf growth parameters of the three tomato cultivars under four days of control, drought, heat and combined stress. Different sub-graphs represent three tomato cultivars and phenotypes of 'Arvento', 'LA1994' and 'LA2093' under control, drought, heat and combined stress. The data represent mean values ± SE (n = 4). Different small letters above the bars indicate significant differences ($p < 0.05$)

Tomato drought stresses

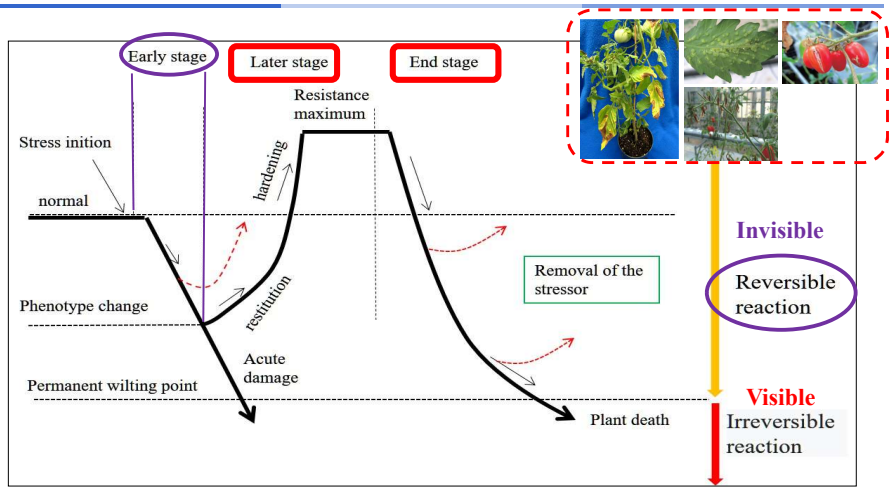
Weak growth

Flowers and fruits dropping

Fruit cracking.

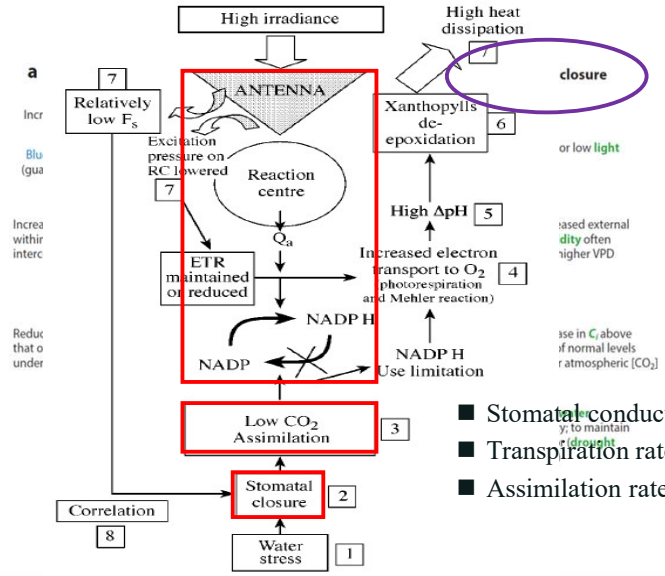
Odema

Early physiological status under drought stress



Physiological responses and state changes of plants after encountering drought stress. (modified from Lichtenthaler, 1998)。

Early physiological alteration under drought stress



- Stomatal conductance (g_s)
- Transpiration rate (E)
- Assimilation rate (A)

Medrano *et al.*, 2002

Physiological indicators of early drought status

- Stomatal conductance (g_s)
- Transpiration rate (E)
- Assimilation rate (A)

Invisible
Reversible

Visible
Irreversible

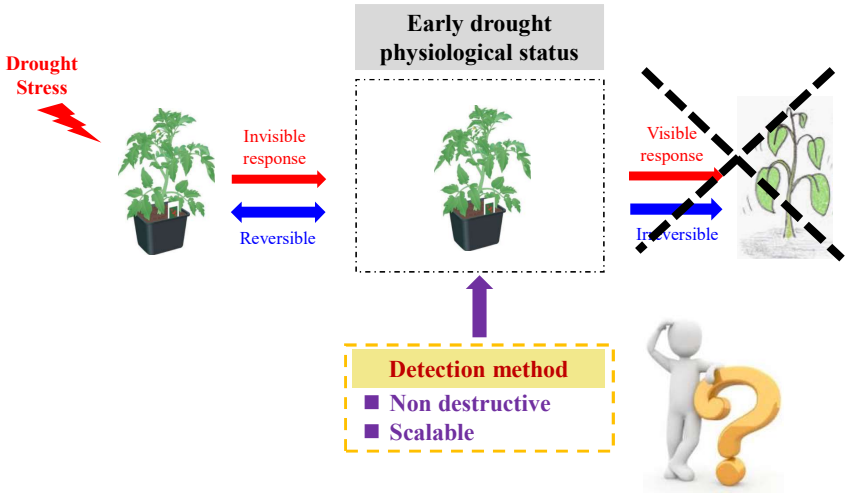
Early drought status | Middle and late

Drought stress

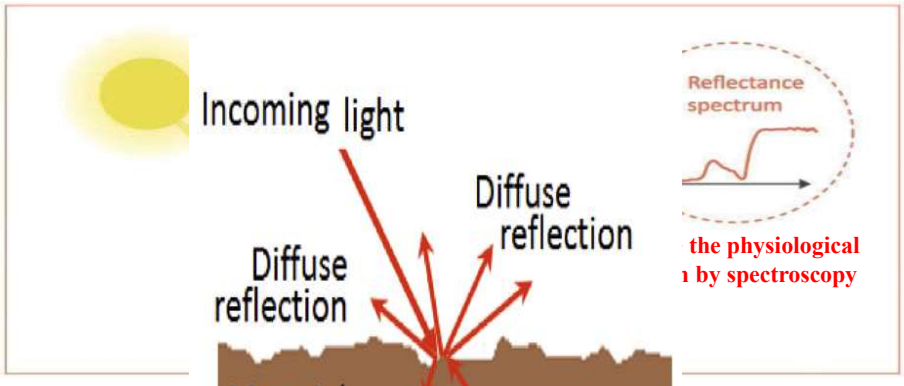
Drought treatment

Recoverable | Irrecoverable

Aim



Spectroscopy vs Physiological response

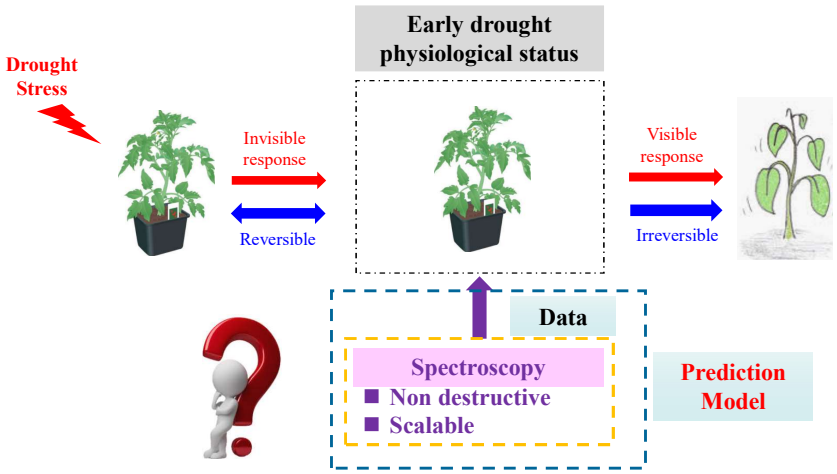


the physiological
by spectroscopy

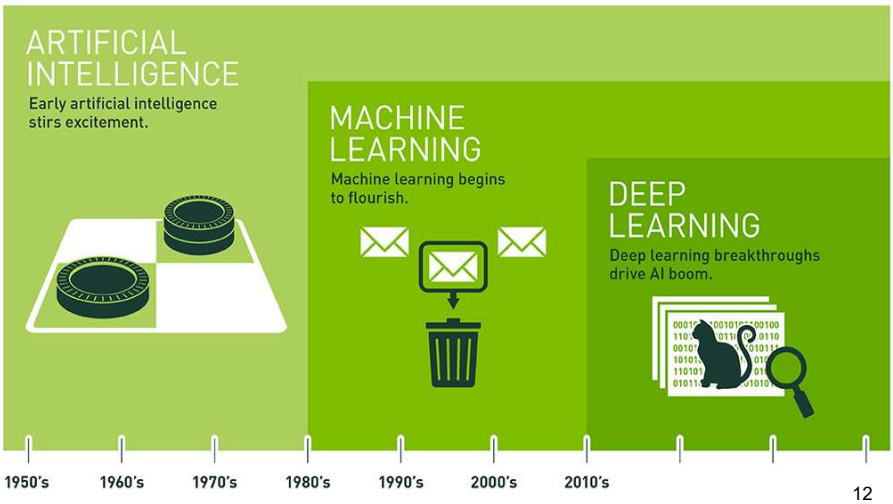
Biochemi
- Pigment typ
- Moisture co
- Cellular structure
- Organic compounds

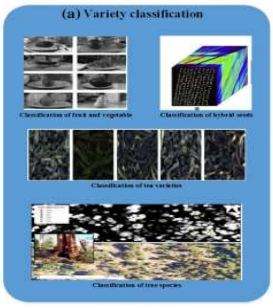
se
ent treatments
- …

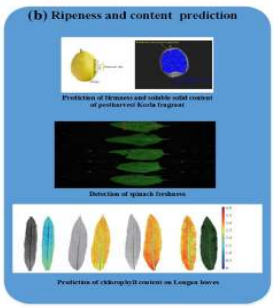
Aim

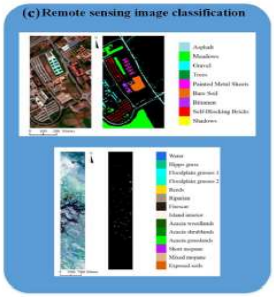


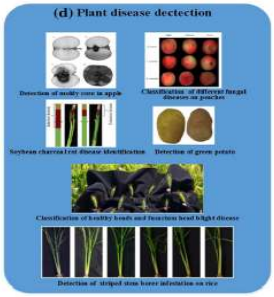
Deep learning











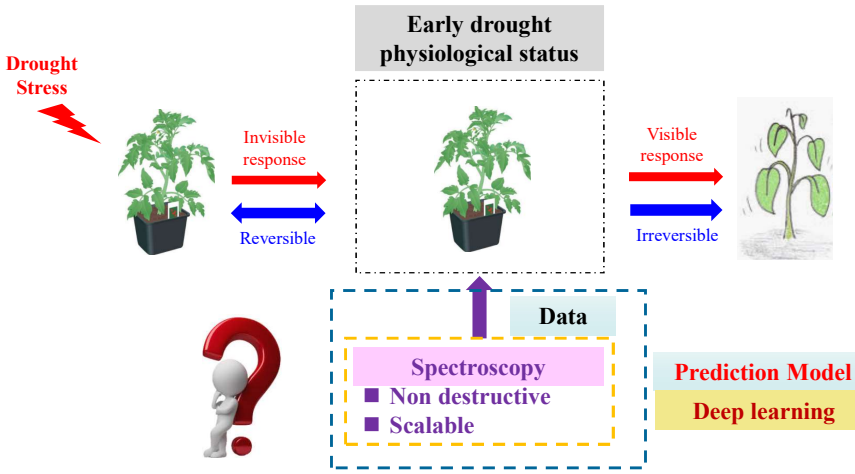
Deep learning in agriculture:

- Classification
- Prediction
- Detection
- Segmentation

Semantic segmentation of the fruits.

Maheswari et al., 2021; Wang et al., 2021

Aim



Experiment design

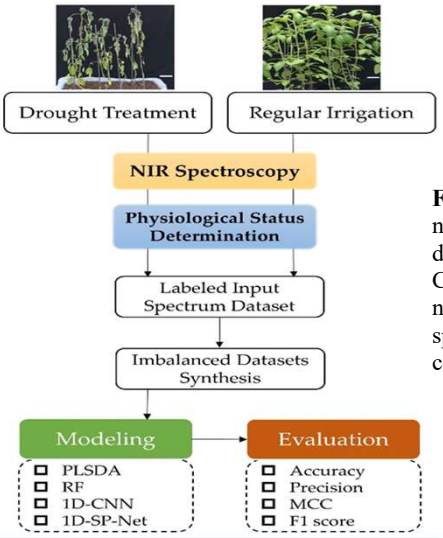


Figure 1. General workflow in this study. NIR, near infrared; PLSDA, partial least squares discriminant analysis; RF, random forest; 1D-CNN, one-dimensional convolutional neural network; 1D-SP-Net, one-dimensional spectrogram power net; MCC, Matthew's correlation coefficient.

Data collection

- Cherry tomato: '**Yu Nu**'.
- LI-6800 Portable Photosynthesis System.
- MS-720 Portable Spectroradiometer.
- WaterScout SM100.

Demonstration of environmental, physiological and NIR spectrum data collection by portable photosynthesis system LI-6800 (left) and spectroraidometer MS-720 (right).

Experiment design

Yu Nu

Drought treatment

Regular irrigation

label

Env parameters	Phy parameters	Spectrum
■ Temperature ■ Humidity ■ Soil water content (SWC) ■ Vapor pressure deficit (VPD)	■ Morphology ■ Leaf temperature ■ Net carbon dioxide assimilation rate (A) ■ Transpiration rate (E) ■ Stomatal conductance (g_s)	■ Visible and near infrared (Vis/NIR) spectroscopy

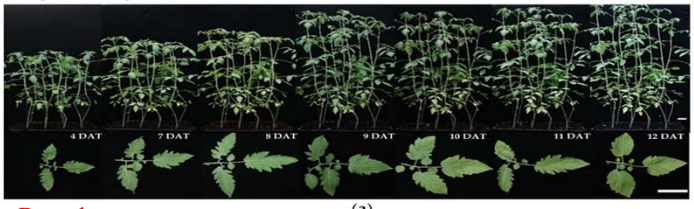
Determining the physiological status

Model building

Early drought status or normal status

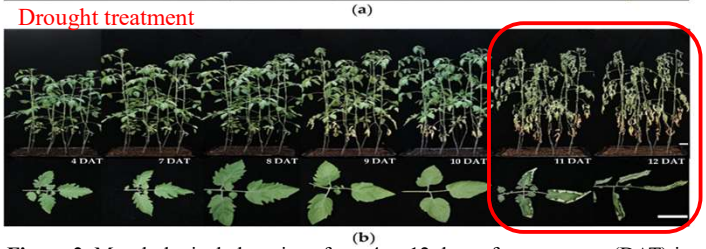
Results

Regular irrigation



(a)

Drought treatment



(b)

Significant branch softening and droping, leaves softened and heavily curled up with leaves.

Figure 2. Morphological alterations from 4 to 12 days after treatment (DAT) in different treatment groups: (a) regular irrigation treatment and (b) drought treatment (bar = 5 cm).

Results

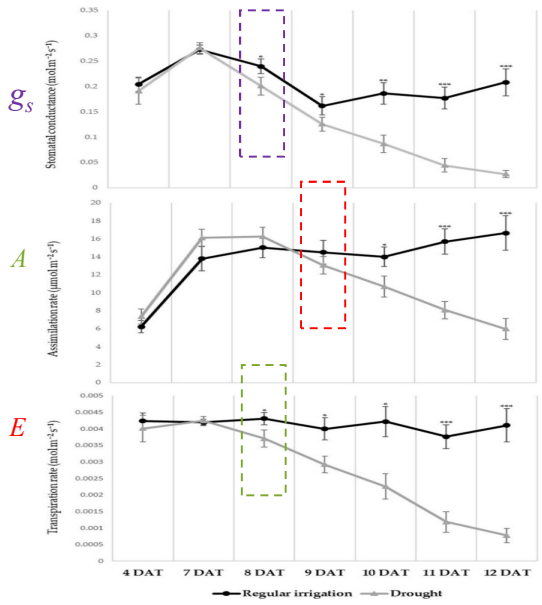


Figure 3. Stomatal conductance (*gs*), transpiration rate (*E*), and assimilation rate (*A*) changes under regular irrigation treatment and drought treatment from 4 to 12 DAT. Differences are represented as significant (*), highly significant (**), and extremely significant (***) at the 5%, 1%, and 0.1% levels, respectively, as determined by Student's t test. The error bar indicates the standard deviation.

Results

Regular irrigation

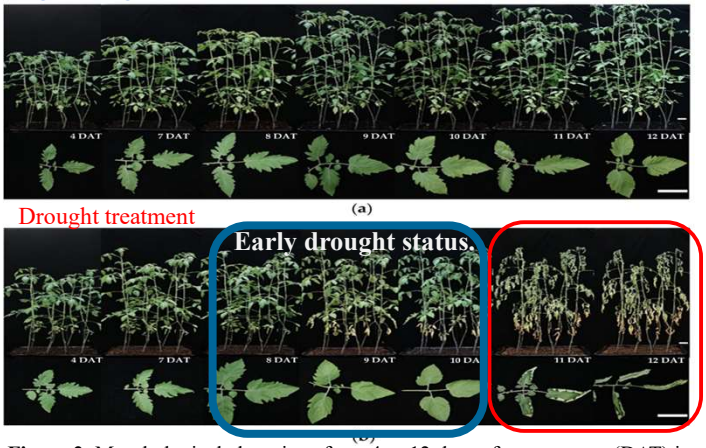


Figure 2. Morphological alterations from 4 to 12 days after treatment (DAT) in different treatment groups: (a) regular irrigation treatment and (b) drought treatment (bar = 5 cm).

Results

- Normal physiological status: There are **246** entries marked as '0‘
- Early drought status: **132** entries marked as '1'

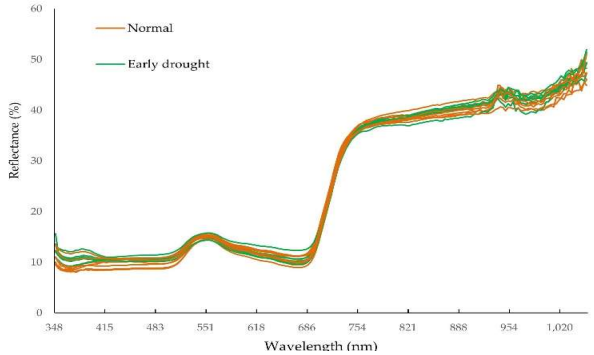
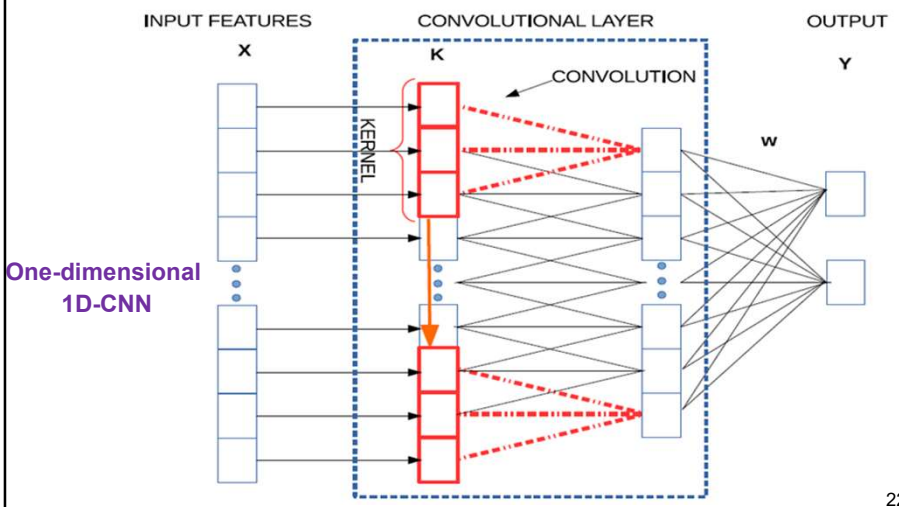


Figure 3. NIR spectra of “normal physiological status” (brown line) and “early physiological drought status” (green line) for the tomato variety “Rosada.” ◦

Tu *et al.*, 2022

Convolutional neural network (CNN)



One-dimensional
1D-CNN

Acquarelli et al. 2017

Model building – 1DCNN

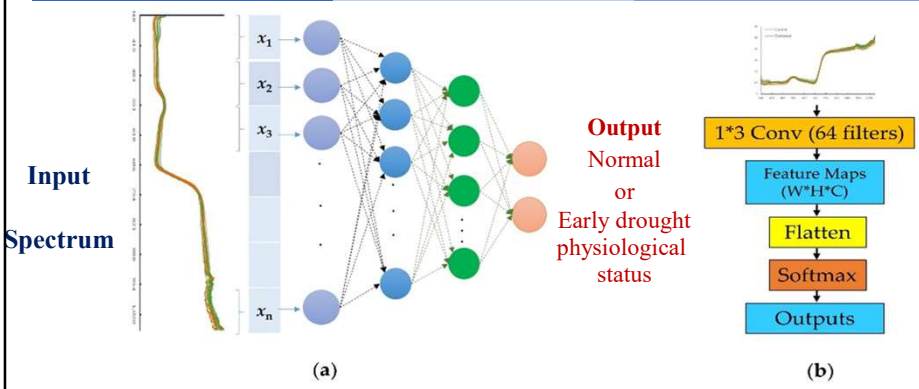


Figure 4. Illustration of the 1D-CNN (**one-dimensional convolutional neural network, 1D-CNN**): (a). The network comprised an input layer (light purple circles) transformed from the input spectra (far left), a feature layer (blue circles), a fully connected layer (green circles) and an output layer (orange circles) that represented the classification results ("normal" or "early drought stress" physiological status); (b). hierarchical layer flow of the 1D-CNN model. W, H and C represent the width, height, and number of channels of the feature map, respectively.

Model building – 1D-SP-Net

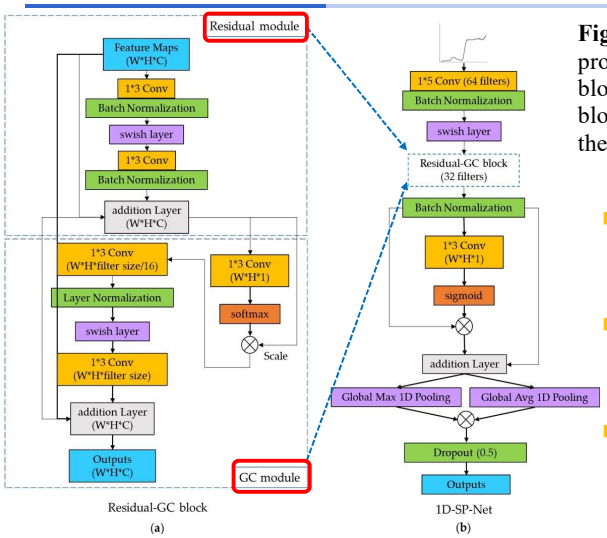


Figure 5. Architecture of the proposed 1D-SP-Net: (a) residual block and global context (GC) block; (b) hierarchical structure of the 1D-SP-Net.

- The **Residue module** has the characteristics of reducing training errors and simplifying the operation process (He et al., 2016)
- The **GC module** has the feature of self attention learning, which can enhance the ability to extract global and local features.
- Zhao et al. (2021) demonstrated that the prediction accuracy of the CNN model can also be improved to 96.0%

Results

Table 1. Comparison of predictive performance for PLSDA, RF, 1D-CNN, and 1D-SP-Net models by accuracy, precision, MCC, and F1 score metrics.

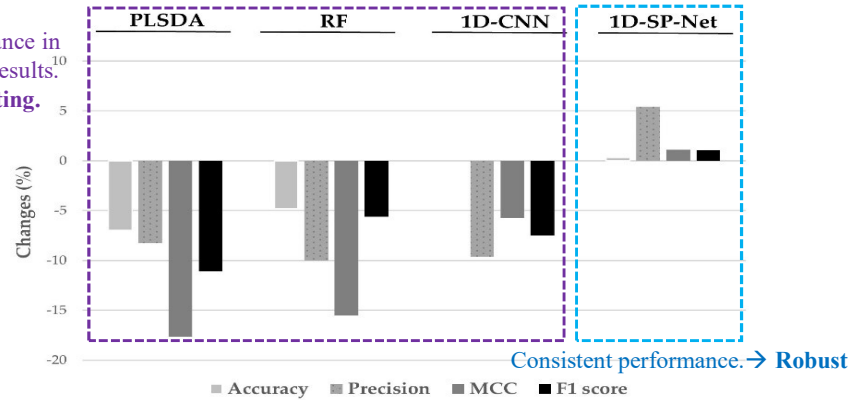
Model	Training				Testing			
	Accuracy (%)	Precision (%)	MCC	F1 score	Accuracy (%)	Precision (%)	MCC	F1 score
PLSDA	93.2	90.4	0.85	0.90	86.7	82.9	0.70	0.80
RF	81.1	75.6	0.58	0.71	77.2	68.4	0.49	0.67
1D-CNN	90.0	88.0	0.79	0.87	90.0	80.0	0.74	0.80
1D-SP-Net	**96.0**[a]	**93.1**	**0.91**	**0.94**	**96.3**	**98.0**	**0.92**	**0.95**

[a] Bold characters represent the highest values for a respective metric among the models.

1D-SP-Net > PLSDA = 1D-CNN > RF

Results

Lower performance in testing results. **Overfitting.**



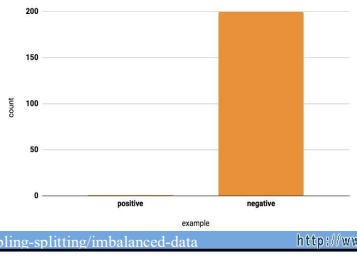
Consistent performance. → **Robust**

Figure 6. Changes (%) of performance in accuracy, precision, MCC (Matthew's correlation coefficient) and F1 scores between training and testing results of the PLSDA (partial least squares discriminant analysis), RF (random forest), 1D-CNN (one-dimensional convolutional neural network) and 1D-SP-Net (one-dimensional spectrogram power net) models.

Issue of class imbalance

→ A classification data set with skewed class proportions.

- Negative to model performance (Lee *et al*., 2017).
- CNN models have been applied to deal with classification imbalanced data sets (Buda *et al*., 2018; Ding *et al*., 2017; Nemoto *et al*., 2018).
- Khan et al. (2018) confirmed that the model constructed by CNN has better predictive ability.



https://developers.google.com/machine-learning/data-prep/construct/sampling-splitting/imbalanced-data

Issue of class imbalance

$$\text{Imbalance ratio (IR)} = \frac{\text{Number of major class (Normal physiological status)}}{\text{Number of minor class (Early drought status)}}$$

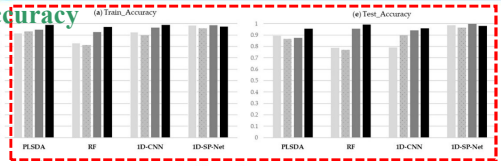
Table 2. Extent of the imbalance in the data sets used in this study.

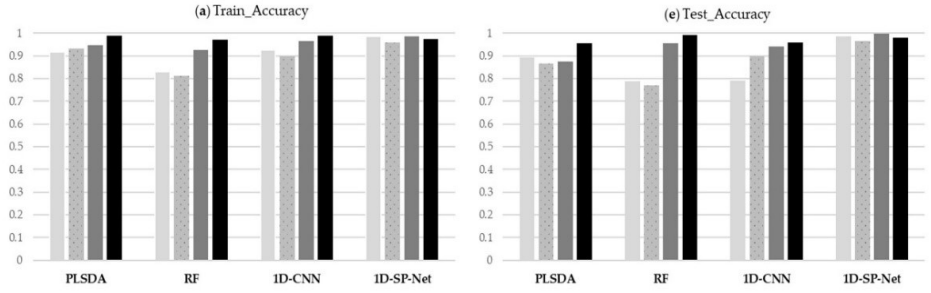
Dataset	Type	Imbalance Ratio	Major class [b]	Minor class [c]
IR1	Synthetic [a]	1	189	189
IR2	Original dataset	2	246	132
IR10	Synthetic	10	340	38
IR50	Synthetic	50	370	8

[a] Synthetic data set was established by random sampling from the original data set.
[b] Number of observations that were classed as "normal physiological status.
[c] Number of observations that were classed as "early physiological drought status.

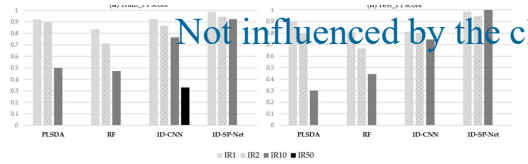
Results

Accuracy





Not influenced by the class imbalance



Tu *et al*., 2022

Accuracy paradox

- Valverde-Albacete *et al*. (2014) explained that the **accuracy** evaluation index is used to measure the model to predict the unbalanced data set, and cannot actually reflect the predictive performance of the model.
- The **MCC** and **F1 score** evaluation indicators can more faithfully reflect the prediction performance of the model in predicting different imbalanced data sets under the condition of using imbalanced data sets (Chicco *et al*., 2021; Pillai *et al*., 2017)

Distributed unequally

		True condition	
		Positive	Negative
Predicted condition			
	Positive	0	0
	Negative	10	990

Acc = (0+990)/(0+0+10+990) = **99%**

Distributed equally

		True condition	
		Positive	Negative
Predicted condition			
	Positive	9	90
	Negative	1	900

Acc = (9+900)/(9+90+1+900) = **90.9%**

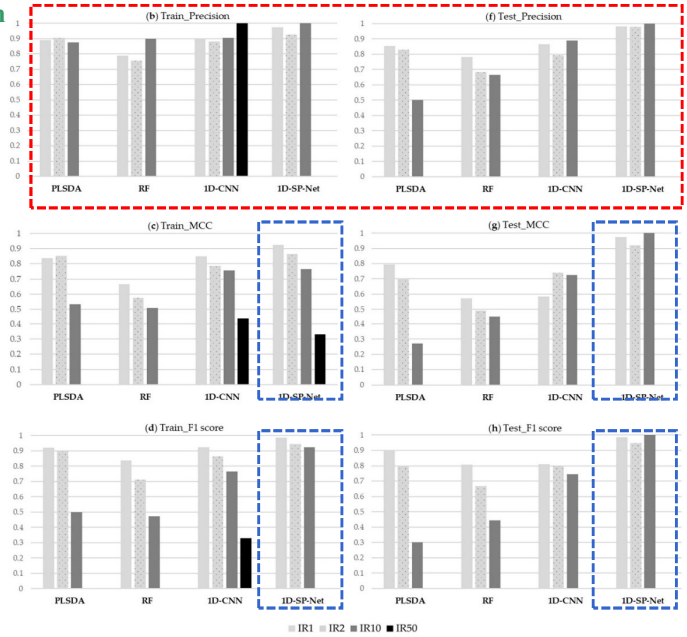
https://www.linkedin.com/pulse/class-imbalance-classification-headache-gonzalo-ferreiro-volpi

Results

Precision

MCC

F1 score



Tu *et al.*, 2022

Taiwan Agricultural Research Institute

Conclusions

- The 1D-SP-Net is a promising model that can determine the early drought status of tomato seedlings in a noninvasive manner.
- The 1D-SP-Net is more robust and resistant to the effects of imbalanced data sets than PLSDA, RF, and1D-CNN models.
- **Key feature bands?**

http://www.tari.gov.tw/

Experiment design

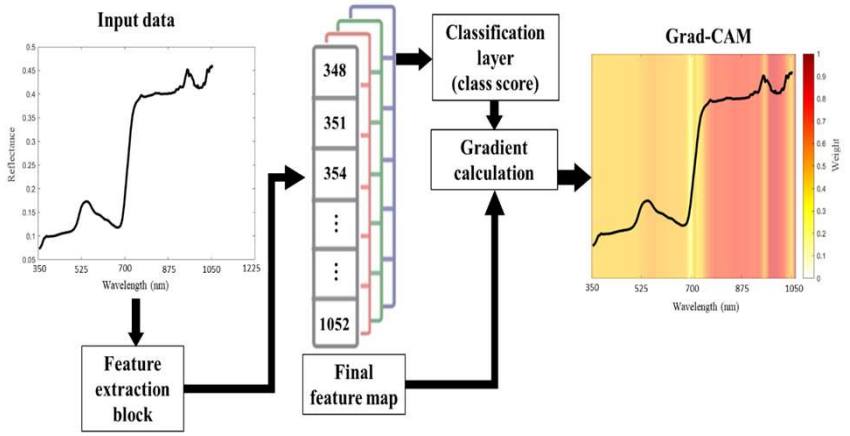
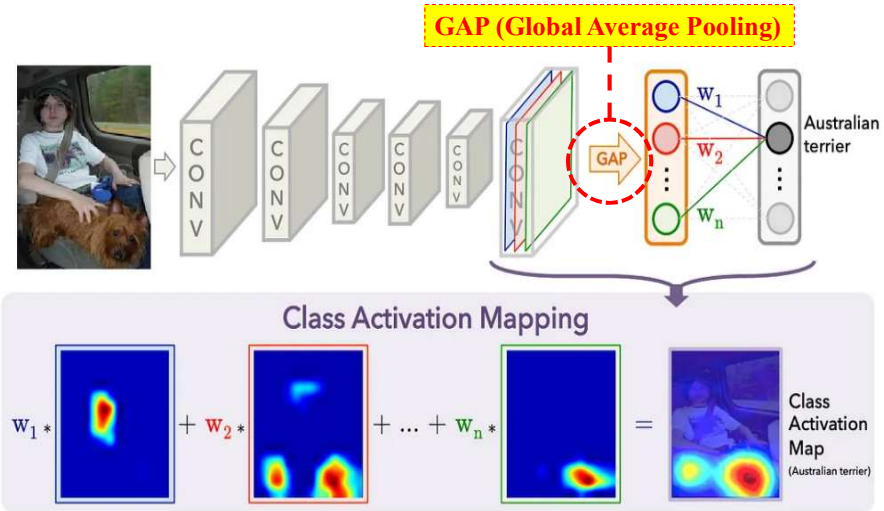


Figure. 8. Flowchart of Grad-CAM (Gradient-weighted class activation mapping) mechanism for extracting feature bands of spectroscopic data.

Kuo *et al.*, 2023

Gradient-weighted class activation mapping (Grad-CAM)



Zhou *et al.*, 2015

Results

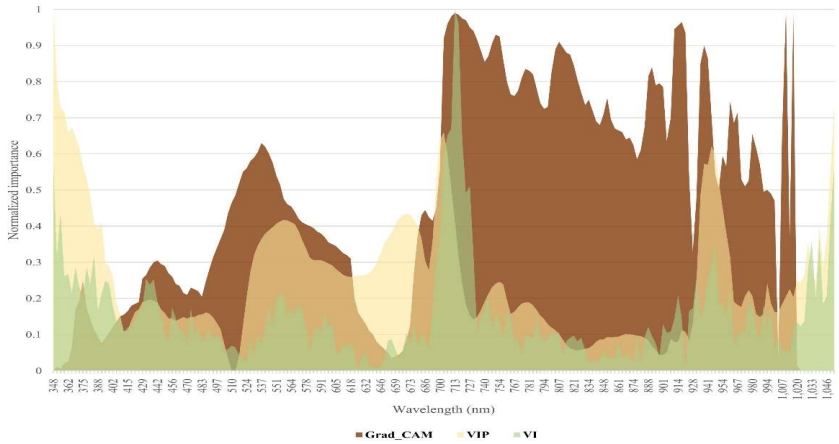


Figure 9. Normalized importance of feature bands for PLSDA (variable importance projection, VIP), RF (variable importance, VI), and 1D-SP-Net (Gradient-weighted class activation mapping, Grad-CAM).

Results

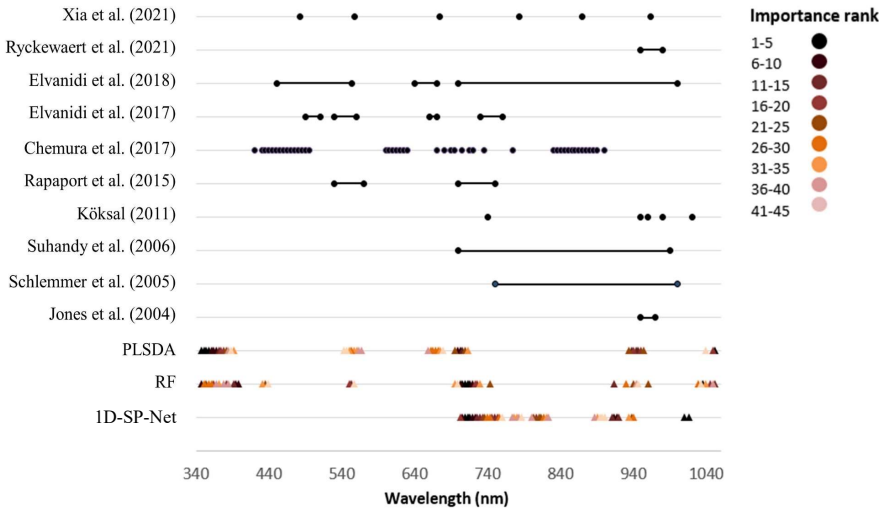


Fig. 10. Distribution of the top 45 ranked feature bands for PLSDA, RF, and 1D-SP-Net. The results of this study are compared with those of previous studies.

Results

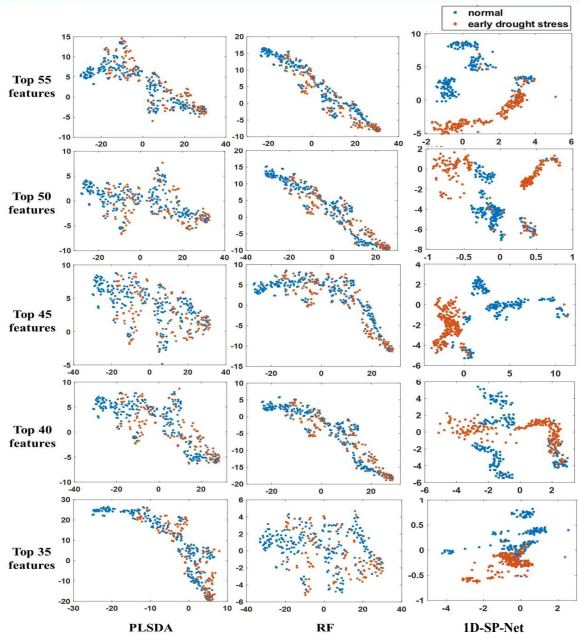


Figure. 11. t-SNE (t-distributed stochastic neighbor embedding) maps of various feature groups by ranking (top 55 to top 35 in groups of 5). X axis: feature bands found by VIP of PLS, VI of RF and Grad-CAM of 1D-SP-Net; y axis: number of ranked feature bands.

Results

Figure 12. Performance of PLSDA, RF, and 1D-SP-Net models when different numbers of features were used. X axis: number of ranked feature bands; y axis: accuracy metric.

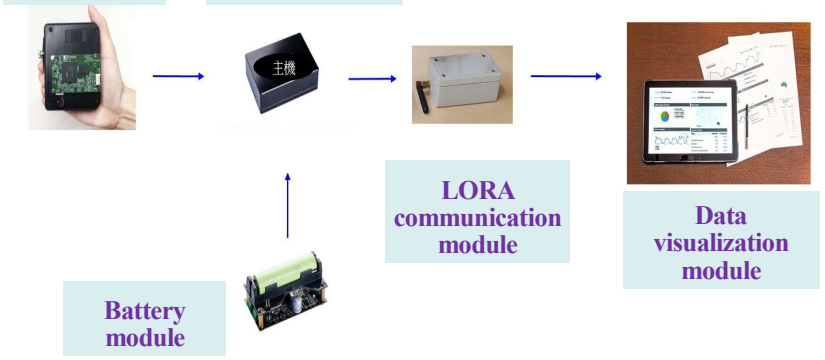
Conclusions

- The 1D-SP-Net is a promising model that can determine the early drought stress status of tomato seedlings in a noninvasive manner
- The 1D-SP-Net is more robust and resistant to the effects of imbalanced data sets than PLSDA, RF, and1D-CNN models.
- Key feature bands in the Vis/NIR spectroscopic data for 1D-SP-Net were identified using Grad-CAM.
- 1D-SP-Net constructing by less number of feature bands maintain a higher performance.

Ref

- C.E. Kuo, **Y.K. Tu**, S.L. Fang, Y.R. Huang, H.W. Chen, M.H. Yao and B.J. Kuo. Early detection of drought stress in tomato from spectroscopic data: A novel convolutional neural network with feature selection. 2023. Chemometrics and Intelligent Laboratory Systems 293:104869. (Sci) **(Co-First author)**
- S.L. Fang, **Y.K. Tu**, L. Kang, H.W. Chen, T.H. Chang, M.H. Yao and B.J. Kuo. CART model to classify the drought status of diverse tomato geontypes by VPD, air temperature, and leaf-air temperature difference. 2023. Scientific Reports 13:602. (Sci) **(Co-First author)**
- **Y.K. Tu**, C.E. Kuo, S.L. Fang, H.W. Chen, M.K. Chi, M.W. Yao and B.J. Kuo. A 1D-SP-Net to determine early drought stress status of tomato (*Solanum lycopersicum*) with imbalanced Vis/NIR spectroscopy data. 2022. Agriculture 12(2):259. (Sci)
- **Y.K. Tu**, H.W. Chen, M.K. Chi, S.L. Fang, M.W. Yao and B.J. Kuo. Establishment of the Early Prediction Model of Water Deficit Stress for Cherry Tomato Using Hyperspectral Data. 2022. J. Taiwan Agric. Res. 71(2):87-99.
- **Y.K. Tu**, H.W. Chen, S.L. Fang, M.H. Yao and B.J. Kuo. Establishment of early discrimination methods for drought stress of tomato grown in greenhouse by using environmental parameters and NIR spectroscopy. 2020. Acta Hortic. 1311:501-512.

Future work



Thanks for listening.
Any comment or question?