

Plants' Bioelectrical Activity Communication in Green Infrastructures & Lab Experience

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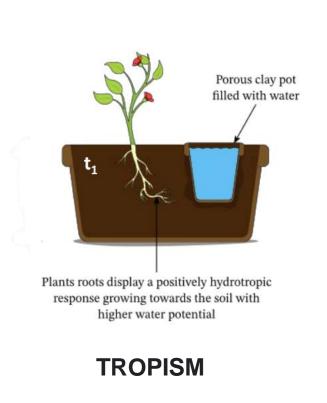
Work outline

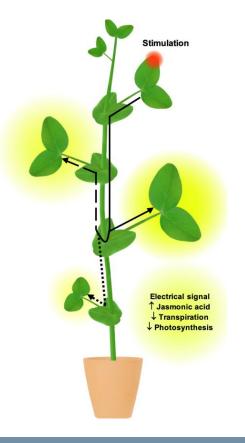
- 1. Introduction to Plant Bioelectrical Activity
- 2. Environmental Adaptation to Light Stimuli
- 3. Action Potentials in Plants
- 4. Literature Review
- 5. Data Analysis and Feature Analysis
- 6. Results and Conclusions

PLANTS'ADAPTABILITY

Plants are **sessile** organisms and so rely on their ability to **adapt** to the

environment to survive.

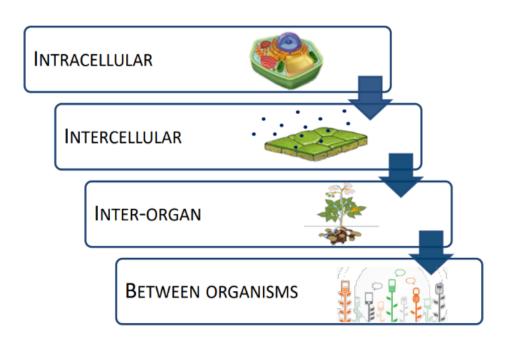


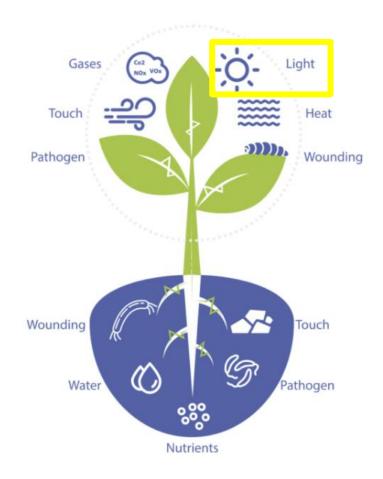


- Electrical signals
- · Chemical signals
- Etc.

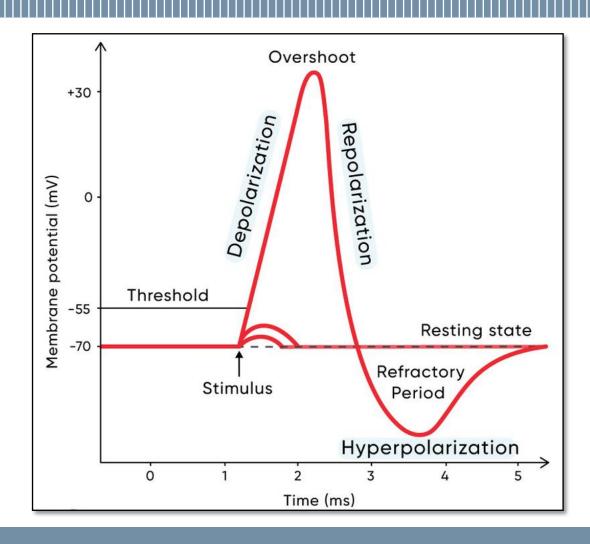
PLANTS' BIOELECTRICAL ACTIVITY

- Action Potential (APs)
- Variation Potential (VPs)
- Systemic Potential (SPs)





LIGHT-INDUCED APs



- 1. Resting State
- Rising phase (Depolarization)
- 3. Falling phase (Repolarization)
- 4. Undershoot

SYSTEM MODEL

It's the experimental design as in «Detecting Severe Plant Water Stress with Machine Learning in IoT-Enabled Chamber».

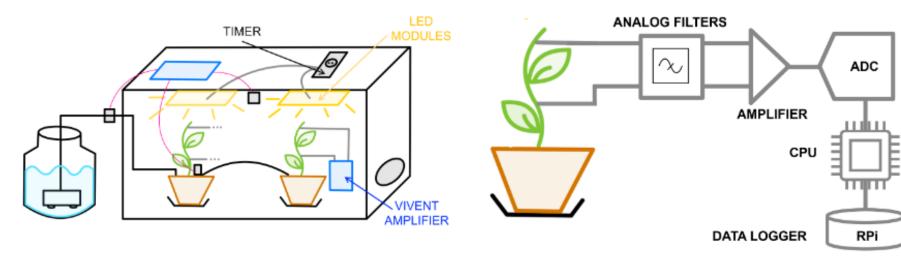
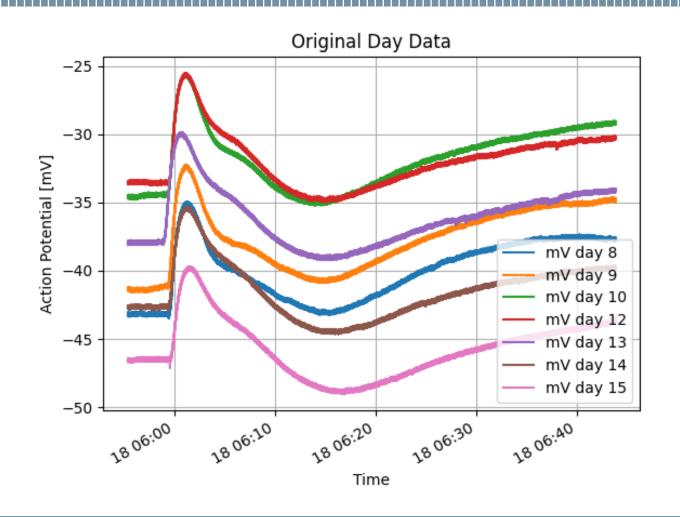


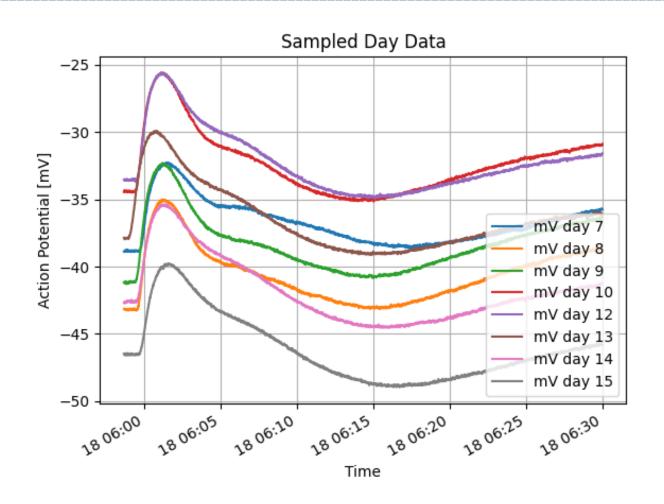
Fig. 3: Experimental set-up design scheme.

Fig. 4: Acquisition system.

RAW DATA – 256Hz



DOWN SAMPLE DATA – 1Hz



FEATURE EXTRACTION

These indicators are computed over raw data and sampled set of AP values:

- Minimum: The smallest value
- Maximum: The largest value

• Mean: The average value
$$Mean = \frac{\sum_{i=1}^n x_i}{n}$$

• Variance: Difference from the mean. $(\sigma^2) = \frac{\sum_{i=1}^N (x_i - \mu)^2}{N}$
• Standard Deviation: Amount of variation or spread. $(\sigma) = \sqrt{\frac{\sum_{i=1}^N (x_i - \mu)^2}{N}}$

$$\sigma(\sigma^2) = rac{\sum_{i=1}^N (x_i - \mu)^2}{N}$$

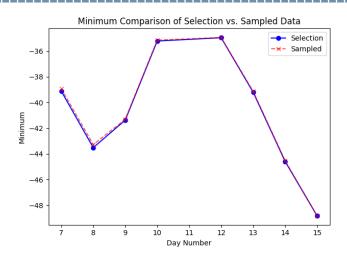
$$(\sigma) = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \mu)^2}{N}}$$

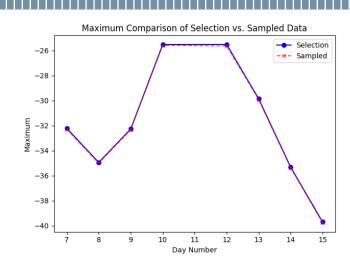
Variation Index: Relative variability.

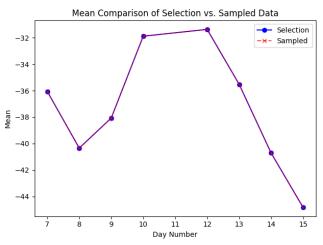
$$VI = \frac{Standard\ Deviation}{Mean}$$

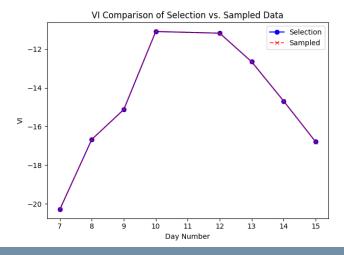


RAW DATA VS. SAMPLED DATA

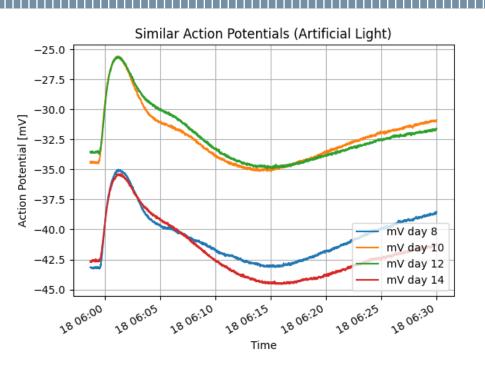


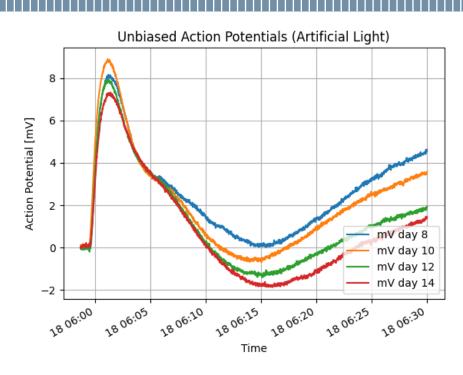




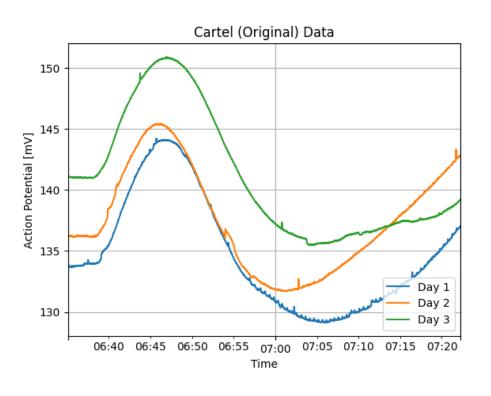


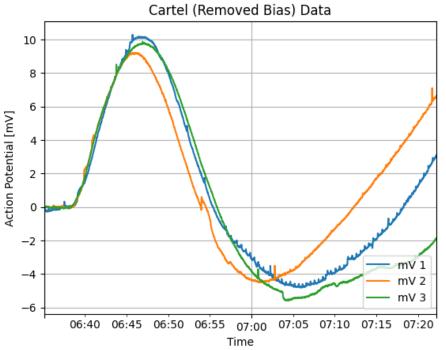
DATA NORMALIZATION





... AND IF THE LIGHT WAS NATURAL?

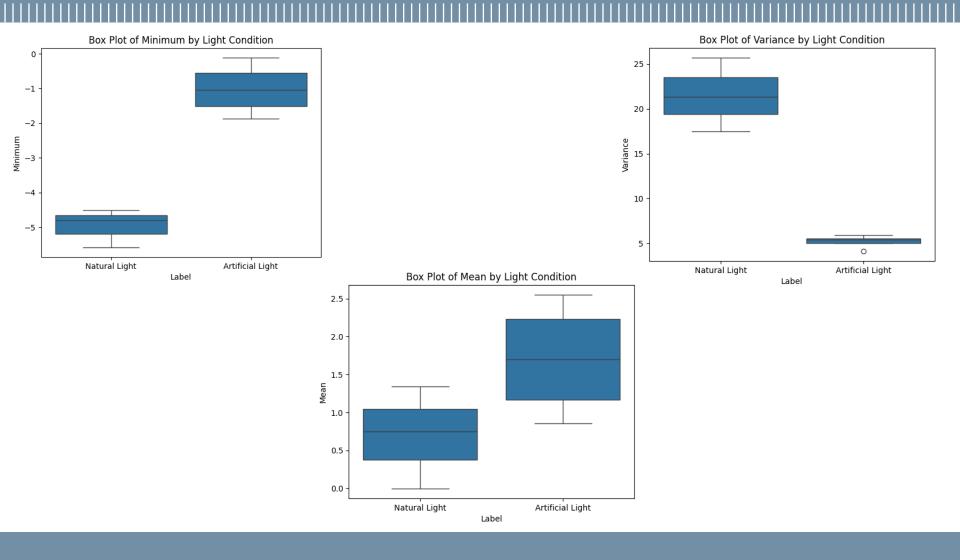




FEATURE ANALYSIS

	Day	Minimum	Maximum	Mean	Standard Deviation	VI	Variance	Label
0	1	-4.8107	10.2809	0.7491	4.6155	0.1623	21.3027	0
1	2	-4.5143	9.2124	1.3407	4.1809	0.3207	17.4800	0
2	3	-5.585	9.8577	-0.0035	5.0685	-0.0007	25.6902	0
0	8	-0.114	8.1573	2.5501	2.0318	1.2551	4.1283	1
1	10	-0.6936	8.8906	2.1187	2.308	0.918	5.3268	1
2	12	-1.3997	7.9071	1.2737	2.3353	0.5454	5.4536	1
3	14	-1.8759	7.3167	0.8559	2.4278	0.3526	5.8940	1

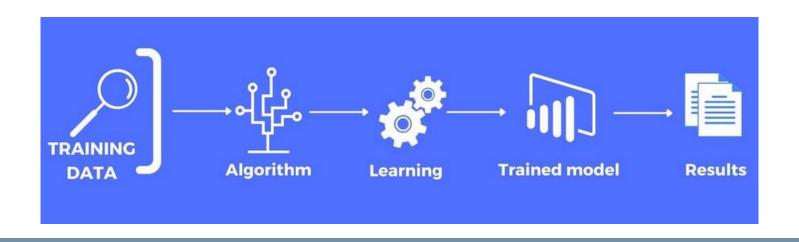
SPLITTER FEATURES



SOME EXPERIMENTS WE DID!

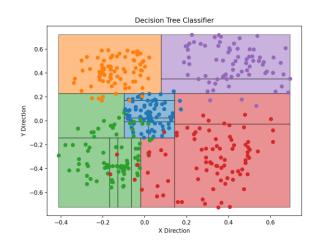
MACHINE LEARNING MODELS

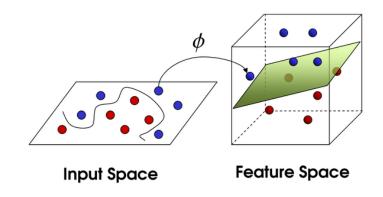
- Achieve real-time response detection to stimuli in plants
- Novel insights into the plant monitoring methodologies
- ML is a field of AI that enables algorithms to learn from data and make decisions.

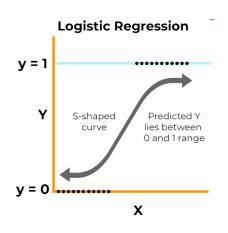


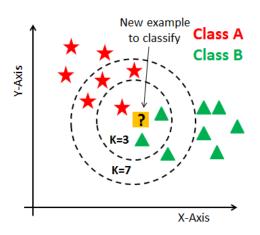
MACHINE LEARNING MODELS

- Support Vector Machine
- K-Nearest Neighbors
- Logistic Regression
- Decision Trees









OUR FICTITIOUS RESULTS

ML Model	Accuracy
Logistic Regression	100%
KNN	100%
SVM	100%
Decision Trees	85.71%

	Day	Minimum	Maximum	Mean	Standard Deviation	VI	Variance	Label
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Important Considerations:

- 1. There are only 7 samples and 6 features.
- 2. The features are highly based on each other.
- 3. The samples are significantly recognizable.
- The models are trained and tested using Leave-One-Out Cross-Validation (LOOCV)

CONCLUSION

- The ML models were effective in distinguishing between the classes under study.
- Visual analysis of the signals revealed clear differences between artificial and natural light classes.
- The approach must be validated under true field conditions where unregulated factors could impact results.
- The obtained accuracy is not valid until we have more samples.



References

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- [9] https://byjus.com/biology/