PhytoNodes for Environmental Monitoring: Stimulus Classification based on Natural Plant Signals in an Interactive Energy-efficient Bio-hybrid System

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Abstract

Cities worldwide are growing, putting bigger populations at risk due to urban pollution. Environmental monitoring is essential and requires a major paradigm shift. We need green and inexpensive means of measuring at high sensor densities and with high user acceptance. We propose using phytosensing: using natural living plants as sensors. In plant experiments, we gather electrophysiological data with sensor nodes. We expose the plant *Zamioculcas zamiifolia* to five different stimuli: wind, temperature, blue light, red light, or no stimulus. Using that data, we train ten different types of artificial neural networks to classify measured time series according to the respective stimulus. We achieve good accuracy and succeed in running trained classifying artificial neural networks online on the microcontroller of our small energy-efficient sensor node. To indicate later possible use cases, we showcase the system by sending a notification to a smartphone application once our continuous signal analysis detects a given stimulus.

Keywords: phytosensing, biopotential, stimulus classification, neural networks

1 Introduction

The share of the human population living in cities is increasing. Estimates are that 68 % will live in cities by 2050.[4] Despite all the advantages of urban life (logistics, stimulated cultural life, etc.), it comes with the danger of increased exposure to pollution and subsequent health issues [West et al.(2016)]. While the primary goal should be to significantly reduce urban pollution, the other important means is to monitor the environment. State of the art in environmental monitoring are large, resource-hungry, and expensive measurement stations that cannot possibly scale well [Snyder et al.(2013)]. A paradigm change is required to reduce resource requirements and to allow for maximal scalability. Ideally, we require real-time data of high spatial sampling frequency to enable authorities to impose evidence-based policies. In the case of a health hazard, only rapid intervention can ensure protecting the citizens. Especially, these systems need to be greener to avoid the dichotomy of contributing to a city's pollution by measuring it. In our new EU-funded project 'WatchPlant' (2021-2024), we want to contribute to such a possible paradigm shift.

[1] Images retrieved from Vecteezy.com.

[4] https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html

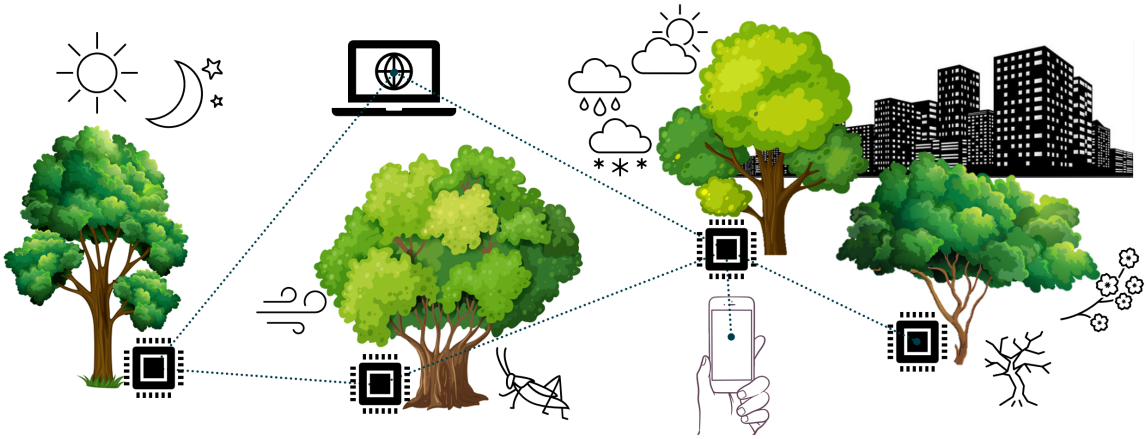

Fig. 1: Our vision for an interactive energy-efficient bio-hybrid system–where PhytoNodes interpret natural plant electric signals for environmental monitoring and notify closeby citizens.[2]

Our key idea is to use phytosensing [Volkov and Markin(2012), Chatterjee et al.(2015)], which is measuring environmental features via living natural plants. Plants planted in a city are exposed to the same air and air pollution as the citizens. Physiological reactions measured in natural plants may allow us to infer the causing stimulus, such as increased ozone concentrations or particulate matter. Medium-term stress reactions in the plants may even correlate with a few statistically identified health issues of citizens. Our goal is to miniaturize measurement stations by using plants as the primary sensor but necessarily combined with sensors on plants that measure their reactions. We expect significantly decreased costs and increased energy efficiency, while accuracy and reliability may be challenging.

Our main contributions in this paper are: (a) designed low-cost, energy-efficient sensor nodes for phytosensing called *PhytoNodes*, (b) a large set of plant experiments with different stimuli (wind, temperature, blue light, red light, no stimulus), (c) training and testing of ten different types of artificial neural networks (ANN) to classify the measurements in the plants according to the respective stimulus, (d) running a trained ANN on the microcontroller of our sensor nodes, and (e) partially showcasing the system's integration into a city's potential IT infrastructure by sending notifications to a smartphone application triggered by a successful online stimulus identification.

2 Related work

Over millions of years, plants have been exposed to dynamic environmental changes (e.g., varying temperature ranges and light conditions, air and soil pollution, drought, insect infestations, etc.). They have evolved to recognize, adapt to, and limit the damage resulting from such disturbances. Plants respond to external stimuli by producing chemical and electrical signals [Davies(2006), Harborne(1987)] that can be interpreted when coupled with electronics [Volkov and Markin(2012)]. The use of plants as sensors for environmental monitoring [Volkov and Ranatunga(2006)] is currently an attractive field of research. In WatchPlant [García-Carmona et al.(2021), Hamann et al.(2021)], we aim to contribute by developing a self-powered, energy-efficient network of electronic devices attached to plants for long-term detection and prediction of environmental conditions in urban settings.

Many recent research approaches follow similar ideas where natural plants and technology are combined in new ways. For example, the EU-funded project *flora robotica* [Hamann et al.(2015)] investigated the control of plant morphological growth (i.e., plant shaping) in response to external stimuli provided by

robotic elements for growing architectural artifacts. At the scale of individual plants, robotic controls were developed in *flora robotica* that direct plant growth toward desired targets [Wahby et al.(2018b), Wahby et al.(2016), Hofstadler et al.(2017), Hoffmann and Hüllermeier(2015)]. At the multi-plant scale, Wahby *et al.* have developed a decentralized robotic system that provides light stimuli to influence plant decision-making between multiple growth pathway options [Wahby et al.(2018a), Wahby et al.(2019)]. The EU-funded project PLEASED [Plants employed as sensing devices – project website(2015)] is an example closer to our vision of WatchPlant and the work we present here. In PLEASED, using plants as sensors was studied and Chatterjee *et al.* [Chatterjee et al.(2015)] implemented an approach to statistically classify external stimuli based on measured electrical responses. Another relevant and recent EU-funded project is I-Seed [Mazzolai et al.(2021)], which draws inspiration from the morphology and dispersal ability of plant seeds to develop self-deployable and biodegradable sensor nodes. The project's key idea is to use such nodes to monitor air and topsoil. Neal Stewart *et al.* [Stewart et al.(2018)] suggested a different but still relevant approach. They construct 'phytosensor walls' by equipping genetically engineered houseplants with electronics to detect harmful indoor microbiome. The engineered plants change the color of their leaves or activate LEDs to warn humans. Lu *et al.* [Lu et al.(2020)] developed a flexible device that monitors plant health via both leaf transpiration using a humidity sensor and the plant's environment using light and temperature sensors.

3 Methods

Our approach is to design PhytoNodes that are low-cost, energy-efficient phytosensing sensor nodes capable of running pre-trained ANN models to classify stimuli. We introduce our selected plant species, the hardware design of PhytoNodes, and our smartphone application for interacting with nearby citizens. We show our experimental setup that enables us to do a large number of data collection experiments with different stimuli (wind, temperature, blue light, red light, and no stimulus). With the collected data, we train ten ANN stimulus classifiers that we finally translate and implement using the programming language C to execute them on the PhytoNodes' microcontrollers.

3.1 Bio-hybrid living sensor

3.1.1 Plants

Our plant-electronic bio-hybrid setup integrates experimental protocols from two different scientific disciplines. The standard engineering laboratory is not designed to grow plants, and the standard plant biology laboratory is not designed to perform electronic experiments. Therefore, we selected the plant species *Zamioculcas zamiifolia* (family Araceae, a typical pot plant), see Fig. 2(a), for our bio-hybrid setup that grows reliably in an engineering environment, requires minimal maintenance, and exhibits strong electropotential responses to various stimuli. During experiments, we ensure uninterrupted applications of a single stimulus while keeping other environmental variables (e.g., temperature, light, etc.) within reasonable bounds.

3.1.2 PhytoNodes

The electronic part of our bio-hybrid sensors is based on the P-NUCLEO-WB55 dongle from STMicroelectronics. The dongle is an ultra-low-power, small-sized device (dimensions of 50 mm × 26 mm × 5 mm) that supports multi-protocol communication using Bluetooth Low Energy (BLE), Zigbee, Thread, and IEEE 802.15.4 protocols. It has a flash memory of 1 MB and a RAM of 256 kB. The device allows eight simultaneous Bluetooth connections, is designed for a communication range of 10 m, and allows up to 100 m. Its temperature range is between -40 °C and 105 °C allowing for outdoor applications. The device offers eight power supply modes that enable ultra-low power consumption from 2 nA to 7.48 mA in a voltage range of 1.7 V to 3.6 V. STMicroelectronics also offers an expansion package called X-CUBE-AI that enables automatic conversion of pre-trained Artificial Intelligence (AI) models to execute them on the device.

(a) *Zamioculcas zamiifolia* (b) PhytoNode

Fig. 2: Our bio-hybrid living sensor setup: (a) our plant species of choice (*Zamioculcas zamiifolia*), (b) our custom-designed PhytoNode sensor node prototype attached to the plant. Note the 3D printed attachment case in black.

We introduce phytosensing capabilities to the device by developing an expansion board with dimensions of 31 mm × 26 mm. The expansion board is equipped with an ADS122C04, a Texas Instruments 24-bit, four-channel, delta-sigma analog-to-digital converter (ADC). In this way, a PhytoNode can measure the electropotentials of a plant via needle-based electrodes inserted into the plant's stem and connected to one of the ADC channels, see Fig. 2(b). Currently, we use silver-coated copper wire electrodes, but we plan to switch to self-adhering surface electrodes [Meder et al.(2021)], which show more stable performance in the long term.

3.1.3 Phone app

A key part of WatchPlant's philosophy is to encourage citizen participation, both as beneficiaries of readily available environmental data and a rapid alert system and as active participants in collecting, processing, and distributing real-time measurements. In addition, a large active community would help raise awareness of the project and the need to monitor our urban environment.

As a proof of concept, we have developed a simple mobile application that communicates with PhytoNodes and displays their data in real-time. We envision a scenario where a citizen approaches our bio-hybrid sensor network, scans a QR code (or similar) to install the app, then grants it the necessary connection and notification permissions on the first run. With Bluetooth enabled, the app runs in the background, periodically searching for devices with specific Universal Unique Identifiers (UUID) defined by WatchPlant. When one of the PhytoNodes comes into range, a notification is displayed on the user's phone. When the user taps on the notification, the device connects to the sensor node and begins receiving data. The data represents the class name of the most likely stimulus that affected the plant in the last 10 minutes. Optionally, the user can also receive a notification when the value changes to a certain class of interest. For screenshots of the app in different operation phases see Fig. 3.

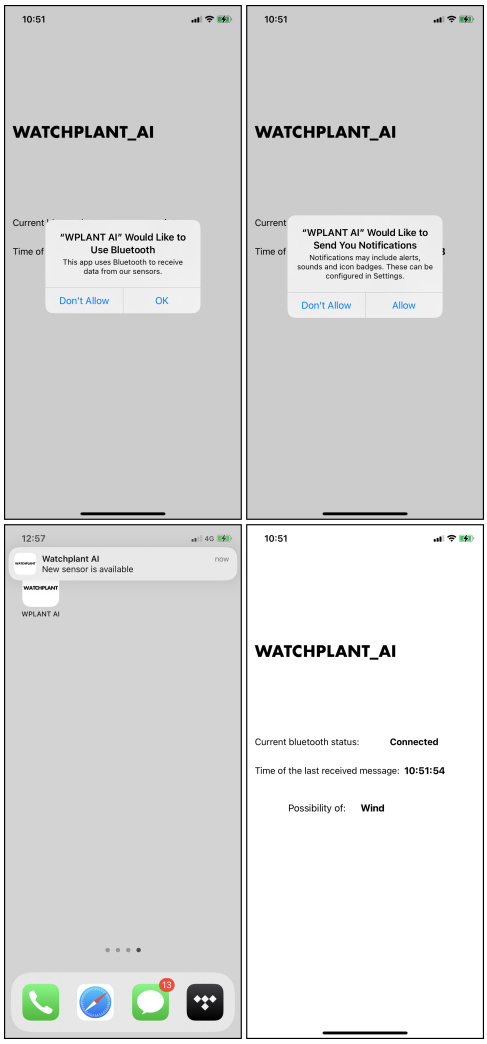

Fig. 3: Screenshots of our proof-of-concept mobile app displaying permission requests, the connection notification, and the classification result received from the PhytoNode. Screenshots were taken on iPhone 11 running iOS 15.6 Developer Beta operating system.

3.2 ML-based classification

3.2.1 Experiment setup and data collection

As mentioned in Section 3.1.1, the experimental setup allows for uninterrupted long-term plant experiments. We expose the plant to either of four stimuli: wind, temperature, blue light, red light, or no stimulus as control. We apply only one stimulus at a time while the other environmental variables remain stable. For example, if we want to apply wind stimulus, we do not influence changes to other surrounding conditions (e.g., light, temperature, etc.). In addition, the whole setup exists in a grow box that eliminates uncontrolled external sources of air streams and reduces temperature effects, see Fig. 4. The grow box is equipped with a heating device (ROWENTA Mod.S02220F0) placed directly next to the plant. A fan (Nidec BETAV) is placed at a distance of 60 cm from the plant to enable the application of a wind stimulus. Also, six 45 W 'Erligpowht' LED growth lamps are placed above and around the plant to allow for applying light of different wavelengths. An 'Erligpowht' LED growth lamp contains 225 LEDs, 165 red and 60 blue ones, with maximum light emission at wavelengths of 650 nm and 465 nm, respectively. The blue LEDs are concealed in three growth lamps to emit only red light stimulus, and the red LEDs are concealed in the remaining three growth lamps to emit only blue light stimulus. One blue and one red lamp are placed above the plant, while the rest are placed on opposite sides around it. Programmable TP-Link HS 100 power sockets control the respective devices to trigger the required stimulus at predefined times. As we have developed the PhytoNode only recently, the data was collected using our previous setup using the CYBRES MU sensor[5] in combination with a Raspberry Pi 4 for information processing.

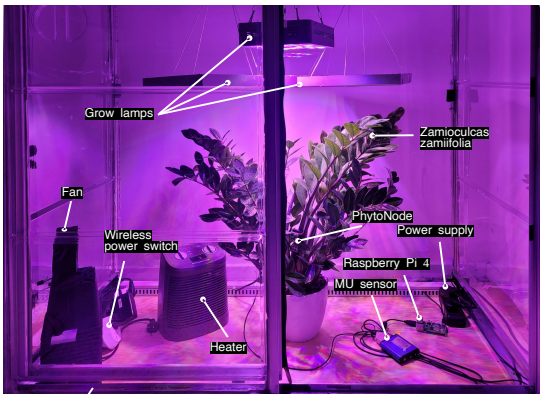

Fig. 4: The full experiment setup. It includes the PhytoNode attached to *Zamioculcas zamiifolia*, grow lamps, a fan, a heater, a wireless power switch, a Raspberry Pi 4, a CYBRES MU sensor, and a power supply.

An experiment lasts 130 minutes and is divided into three phases. The first phase prepares the stimulus application (prestimulus phase) and lasts one hour. In the second phase, a single stimulus is applied to the plant for ten minutes (stimulus phase). In the third phase (poststimulus phase), the stimulus application is terminated, and the plant is allowed to rest for another hour. The sensor measures the plant's electropotentials at a frequency of 1.5 Hz. In total, we performed 1320 experiments to collect data: 544 experiments of wind stimulus, 504 experiments of temperature stimulus, 134 experiments of blue light stimulus, and 138 experiments of red light stimulus. We use 544 examples of 10-min prestimulus phases and categorize them as 'no stimulus.'

[5] CYBRES MU sensor: http://cybertronica.co/?q=products/phytosensor

Tab. 1: Average accuracies for all ten classifiers in percent, first with two (wind & no stimulus), then three (+ temperature) and finally all five (+ red & blue light) classes. Required resources on the PhytoNode including flash, RAM and complexity. In addition, the relative loss of accuracy between the TensoFlow Lite and C-based model and the minimum compression required.

classifier	two classes [%]	three classes [%]	five classes [%]	flash [kB]	ram [kB]	complexity $\cdot 10^6$[MACC]	l2r [%]	compression [·]
CNN	89.07	89.13	77.16	11.83	10.82	0.12	$8.53 \cdot 10^{-5}$	0.00
Encoder	94.07	93.96	86.04	-	-	-	-	-
FCN	97.88	94.67	83.02	1010.00	601.58	105.52	-	1.01
Inception	97.78	93.63	82.31	1610.00	651.58	169.21	-	1.01
MCDCNN	89.83	88.96	80.28	574.36	13.96	0.66	$1.22 \cdot 10^{-1}$	3.91
MCNN	57.20	34.17	28.70	2470.00	369.52	13.684	-	1.22
MLP	91.69	87.92	77.58	702.24	5.49	0.71	$2.32 \cdot 10^{-1}$	3.94
ResNet	98.14	95.21	82.91	1910.00	601.58	201.18	-	1.01
t-LeNet	97.52	90.88	78.15	209.20	2.52	0.07	$5.11 \cdot 10^{-7}$	0.00
TWIESN	73.14	55.17	42.06	-	-	-	-	-

3.2.2 Classifier training

We aim to classify the measured electrical signals according to the applied stimulus. The electrical activity of plants is generally sensitive to many factors, subject to noise, and depends on the plant's physiological state as well as many environmental features. Therefore, we cannot just rely on single electrical measurements at single moments in time. Instead, we need to perform a time series classification (TSC), allowing us to examine changes and patterns over a longer period of time during or after a stimulus application phase. As described in Section 3.2.1, one experiment runs for 130 minutes with stimulus application for ten minutes. Since we record at a frequency of 1.5 Hz, we obtain a time series of 400 electrical potentials for each experiment during stimulus application. To prepare the data sets for classification, Z-score normalization is performed for each experiment: $x_{\text{norm}} = (x - \mu_x)/\sigma_x$, where μ is mean and σ is standard deviation of the unnormalized experiment. Z-score normalization removes any shift or scaling of the data and is required to compare different experiments from different plants without an inherent bias [Rakthanmanon et al.(2013)].

Given the success of deep learning in recent years [LeCun et al.(2015)], we decided to use a deep learning framework developed by Fawaz *et al.* [I. Fawaz et al.(2019)] for TSC. The framework includes ten different deep classifiers: Multi-Layer Perceptron (MLP), Fully Convolutional Neural Network (FCN), Residual Network (ResNet), Encoder, Multi-scale Convolutional Neural Network (MCNN), Time Le-Net (t-LeNet), Multi-Channel Deep Convolutional Neural Network (MCDCNN), Time Convolutional Neural Network (CNN), Time Warping Invariant Echo State Network (TWIESN), and Inception. We train all ten previously mentioned classifiers in three settings, five iterations each. In the first setting, we train two-class classifiers (wind and no stimulus). In the second setting, we train three-class classifiers (wind, temperature, and no stimulus). In the third one, we train five-class classifiers (wind, temperature, red light, blue light, and no stimulus). In all three settings, we use 70 % of the experiment data in each class for training and the remaining 30 % for testing. To evaluate the performance of the different classifiers, we record four metrics: accuracy, precision, recall of classifiers, and training time in seconds.

3.2.3 Classifiers on STM nodes

Our goal is to classify the measured electrophysiological responses of plants using the PhytoNodes. This allows the classification results to be sent directly to BLE-enabled devices, such as mobile phones of passing citizens. We use the toolchain provided by STMicroelectronics, consisting of STM32CubeMX (v. 6.3.0) and STM32CubeIDE (v. 1.7.0) in combination with the extension package X-CUBE-AI (v. 1.13.3)[6] for artificial neural network applications. The first step is to convert the trained neural networks into TensorFlow Lite[7] format to allow further processing on the microcontroller and X-Cube-AI. Then, the TensorFlow Lite format is converted into an ANN model based on the programming language C to be executable on the microcontroller. X-Cube-AI enables initial analysis and validation of the neural networks. We analyze the networks trained on five stimuli concerning their resource utilization, including the required RAM and flash memory, as well as their complexity in Multiply And Accumulate operations (MACC) (see Table 1). The MACC can be used to estimate the required clock cycles per classification. For the STM32 Arm® Cortex®-M4 CPU used, this corresponds to approximately 9 cycles per MACC. If the ANNs exceed the available RAM or flash memory, a compression of fully connected layers is possible using weight-sharing-based K-means clustering. Transforming the trained ANN to a C-based model and its compression can result in a decrease in classification accuracy. For this reason, the relative loss of accuracy (l2r) between the TensorFlow Lite and the C-based models is calculated. The l2r is only determined for the classifier with five stimuli that do not exceed the available memory. The classification results of the two models are compared and checked for equality. We evaluate the best classifier of the five independent iterations and analyze them on the lowest possible compression (see next section).

In addition, we have created a BLE GATT-based profile that allows data exchange between PhytoNodes and any other device that uses BLE. The electrical activity of a natural plant is measured once the device is connected to a power supply. With each new reading, a Z-score normalization is performed over the previous 400 readings. The modified array of 400 entries serves as input to the inserted ANN, as described in Section 3.2.2. The PhytoNode continuously scans for incoming connection requests from other BLE devices to establish a connection. The classification results are sent to the remote peer once a successful connection occurs.

4 Results

Our obtained classifier accuracies as functions of class numbers representing the different stimuli, as described in Section 3.2.2, are summarized in Table 1. The highest accuracies are achieved in TSC with two classes. ResNet outperforms the classifiers with an accuracy of 98.14 %, while all classifiers achieve an average accuracy of 88.63 %. The more classes, the lower the accuracy as expected. For three classes, the average accuracy drops to 82.37 %. ResNet still achieves the highest accuracy, but only at 95.21 %. The lowest average accuracy of all classifiers with 71.82 % is achieved for five classes. Here, the Encoder achieves the highest accuracy with 86.04 %. MCNN achieves lowest accuracy in all runs.

Only four out of ten classifiers can operate on the PhytoNode. Both the Encoder and TWIESN cannot be converted to a TensorFlow Lite format due to incompatible data formats, preventing further analysis. FCN, Inception, MCNN, and ResNet exceed the available RAM and flash with maximal compression factors of 1.01 and 1.22. Only CNN and t-LeNet are supported without compression, while MCDCNN and MLP require compression factors of at least 3.91 and 3.94, respectively. The lowest complexity of PhytoNode-compatible neural networks is achieved by t-LeNet with $0.07 \cdot 10^6$ MACC, while MLP has the highest complexity with $0.71 \cdot 10^6$ MACC. The network complexities of these networks are significantly lower than FCN, Inception, MCNN and ResNet, which require excessive memory. Despite transformation

[6] Find user information at: https://www.st.com/en/embedded-software/x-cube-ai.html

[7] TensorFlow Lite is a mobile library for deploying machine-learned models on mobile, microcontrollers, and edge devices.

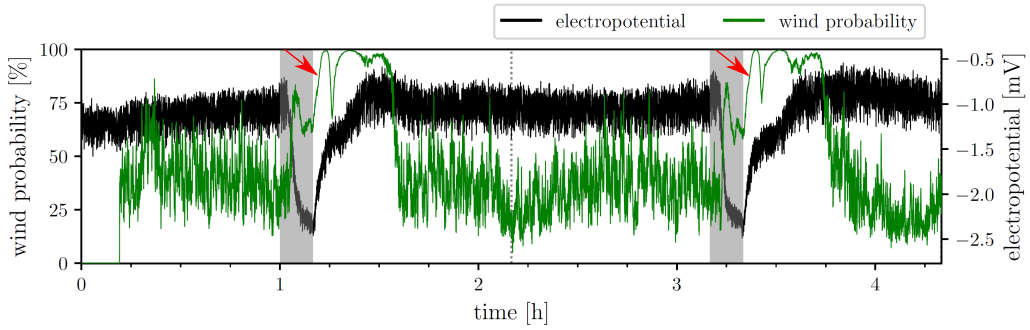

Fig. 5: Two consecutive 120 min experiments with wind as stimulus. The dashed vertical line indicates the end of the poststimulus of the first application and the beginning of the prestimulus interval of the second application. The black line shows the measured electropotential while the gray areas represent the application of a wind stimulus for 10 min. The green line illustrates the classification probability of wind at each time step as a function of the last 400 measured potentials. The red arrows indicate the first time step at which the probability rises above 90 % (i.e., wind stimulus detection event).

and compression, a maximal relative accuracy loss of 0.23 % (MLP) was observed, indicating that roughly the same classification results can be expected.

We use the MCDCNN trained on two classes (wind and no stimulus) to test our concept. Although MLP and t-LeNet have higher accuracy in the two-class case, MCDCNN shows less loss of accuracy with increased class number. MCDCNN has higher accuracy in the five-class case and is the most promising classifier for the case of multiple stimuli. For our evaluation, we use a dataset that was neither included in the test set nor the training set to emulate a realistic use case. The evaluation has a duration of about 4.3 hours and includes two applications of the wind stimulus after 1 h and 3.2 h. In Fig. 5 we give the measured electropotential (black line) and the output of the MCDCNN that indicates the probability of currently observing a wind stimulus. The two wind applications (marked in gray) are recorded at the same intervals as in the training data. We have two consecutive sequences of the three phases as described earlier: 1-h prestimulus phase, 10-min stimulus phase, and 1-h poststimulus phase. The electropotential readings show an evident change during the two applications of the wind stimulus. At the same time, the output of the MCDCNN increases to values consistently above 50 %. An initial local maximum of about 80 % is reached 3 minutes into the wind application. Since the neural network classifies a time series covering the last 10 min, the output wind classification probability of over 90 % is detected only after the end of the application. Sending a notification for possible stimulus detection to the citizens' mobile devices should only take place when a high classification probability is obtained. Our trained classifiers output a probability per class (i.e., a stimulus likelihood), therefore, we only allow a wind notification if the likelihood probability is greater than 90 %. The wind causes a potential drop from $\approx -1mV$ to $\approx -2.5mV$, see Fig. 5. This drop is again restored during the poststimulus phase. Given that probabilities of more than 90 % are still found even 20 minutes after application. This interestingly indicates that portions of poststimulus data were still highly relevant for the classifier. Similar behavior is observed for the second application. The first maximum of 84.45 % is reached 3.75 min after the start of the application. Probabilities of more than 90 % are obtained again after the application and persist for up to 22 min.

All collected datasets and trained classifiers as well as the code for the experiment and data collection setup, the code for STM-based PhytoNodes and for the phone app are available online [Buss et al.(2022)].

5 Conclusion and Future work

By developing a BLE and AI-enabled PhytoNode, we have laid the foundation for an interactive plant-electronic bio-hybrid network. We created a dataset of electrophysiological responses of *Zamioculcas zamiifolia* to five different stimuli. Using this dataset, we successfully trained ten different deep learning networks to classify time series, achieving accuracies of up to 98.14 %. Four of the ANNs can operate on the PhytoNode's microcontroller with accuracy losses of less than 1 %. Due to the BLE capability of the PhytoNode, we can communicate directly with nearby civilians via mobile phones. In this way, the civilian is informed about the current environmental conditions based on the plant's biopotentials. We have enabled this by developing a mobile application that allows exchanging data with PhytoNodes via BLE. However, during our tests for online classification on-board the PhytoNode, we realized that the classification accuracy is not as high as achieved on the test dataset. We believe this is because the data collection occurred in a different season, during different environmental conditions leading to different electrophysiological responses. A possible solution to this issue would be collecting enough data to include the plant's electrophysiological responses throughout all seasons and growth stages. One more aspect we can improve is the balance of the training dataset. We performed fewer data collection experiments for the blue and red light stimuli than those for the other three stimuli. This can lead to the well-known biasing issue in the trained classifiers. Despite the two issues mentioned above, we provide a complete framework that enables training classifiers of high accuracy, which can run on our lightweight, energy-efficient sensor nodes. We would like to utilize the maximum potential of our newly developed bio-hybrid sensors. Therefore, in the future, we plan to train classifiers for different plant species and also expand our classification classes to include further stimuli. Currently, we have only studied the temporal pattern of the signals, but some of them are transmitted throughout the plant. Spatial analysis of the signal distributed over the plant (e.g., adding more electrodes at different branches and stem positions) may lead to further insights that can provide information about the plant and thus about the stimulus. We have designed a sensor node based on hardware that allows us to keep the required energy to a minimum. The energy needed depends on the scenario, the classification task, and the chosen duty cycling of the sensor node. For example, if a lot of data needs to be collected, one of the requirements is to achieve the highest possible data throughput with minimal power consumption. In another scenario, where only rarely occurring events need to be detected, we may need to guarantee a long network lifetime and possibly switch between different modes to communicate an event through the network. In future work, we will also investigate possibilities of energy harvesting on the PhytoNode, for example, via solar cells. PhytoNodes are not limited to monitoring only the electrical activity of plants using electrodes. By adding more phytosensing nodes, we can create heterogeneous networks of multi-modal PhytoNodes that will lead to a better understanding of plant physiology, the plants' environment, our own environment, living spaces, urban pollution, and ultimately our future growing cities.

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