

Smart Plants: Low-Cost Solution for Monitoring Indoor Environments

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Abstract—Humans tend to spend most of their life indoors making the quality of indoor environments essential for human health and well-being. While several solutions for monitoring the indoor environment have been proposed, ranging from infrastructure-based monitoring solutions to cameras, these tend to require separate installation making the sensors difficult to maintain and upgrade. In this paper, we introduce the idea of using *smart plants* as an easy-to-deploy and affordable solution for monitoring the indoor environment. Plants are typically deployed close to humans and they increasingly are placed in containers that integrate sensors, such as soil moisture, temperature, humidity, and CO₂ sensors. We demonstrate how these sensors can be used as an alternative technology for monitoring – and enriching – indoor spaces without needing to install proprietary sensors or other technology. Specifically, we show how smart plants can be used to estimate overall CO₂ accumulation, occupancy information, and whether people use protective face masks or not. We also establish a research roadmap for the use of smart plants to monitor indoor environments.

Index Terms—Internet of Things, Pervasive Sensing, Air Monitoring, Smart Plants

I. INTRODUCTION

HUMANS tend to spend most of their time indoors [1] which makes the quality of indoor environment essential for human health and well-being. Indeed, the quality of indoor environments is linked with human health, productivity, comfort, and quality of life in general [2]. Ensuring the indoor environment is healthy and that it fosters productivity thus requires monitoring and offering feedback to the occupants on the current state of the environment. Current solutions for monitoring the indoor environment, such as proprietary indoor monitoring devices that integrate air quality sensors, infrared tracking and other sensors [3], [4] or occupancy monitoring solutions such as low-cost thermal arrays [5], are limited as they either require laborious deployments or capture limited information about the state of the environment. Indeed, both types of solutions need separate installation which requires deploying the sensors in the indoor space and often also additional wiring to ensure the devices are powered. Besides

being laborious and costly, the need for separate installation also makes maintaining and upgrading the sensors difficult.

The present paper contributes a novel approach for monitoring the indoor environments by re-purposing *smart plants* – plant containers that integrate sensors and micro-controllers. Plants are a common sight in residential and commercial spaces as they are used to decorate and improve the diversity of the environment. Plants also bring several benefits as they can be shown to improve the mental and emotional well-being of humans [6], support better cognitive performance [7], and help to improve the air quality of the space [8]. Thanks to advances in IoT garden and plant technology, plant containers increasingly integrate sensors, e.g., for monitoring the soil or the ambient environment. This information can then be used to optimise growth, detect potential issues, and to automate watering and other maintenance operations [9]. As plants are typically located close to the areas where humans perform activities, there is huge potential to re-purpose these sensors to also monitor the indoor environment. As the sensors are integrated directly into the containers, no laborious installation is needed and upgrading the sensors simply requires changing the containers rather than removing old sensors and installing new ones – including ensuring sufficient wiring is available. Indeed, the main benefits of smart plants are that they are affordable and easy to deploy. As a result, smart plants supplement existing techniques and offer an easy and cheap-to-deploy alternative, particularly for spaces that otherwise are difficult or costly to instrument.

We demonstrate the benefits and practical feasibility of smart plant sensing through extensive experiments that use CO₂, temperature and humidity sensors integrated with a plant container to demonstrate how plant sensors can provide insights into the overall indoor context. Specifically, we show that the sensors can be used to estimate overall CO₂ accumulation, occupancy information, and whether people use protective face masks. We also introduce other potential uses for smart plants as sensors – or even a sensing infrastructure – and establish a research roadmap for their use to monitor indoor environments. Taken together, our work paves the way toward establishing smart-plants as an affordable and easy to deploy sensing solution that can provide insights into human living conditions and ultimately improve the quality-of-life.

II. SMART PLANTS

Smart plants can supplement other forms of infrastructure by offering an easy to deploy solution that does not require separate installation and that is easy to maintain. We next

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briefly discuss different types of smart plant sensors, different application areas where they can be beneficial, and some key research challenges in adopting them as sensors for monitoring the indoor environment.

A. Sensors and Hardware

Smart plant sensors generally come in two main forms. First, plant sensors have been designed for monitoring individual plants and they capture moisture, and potentially also the nutrient levels in the soil, and provide feedback to users on when to water the plants. These sensors can either be directly integrated into the container or be ground-mounted on the soil. The main purpose of these devices is to monitor irrigation and to automate or facilitate watering [10] or to detect plant diseases [11]. Greenhouses, gardens, and grow rooms, in turn, typically use more advanced sensors that combine soil monitoring with atmospheric parameters, including temperature, humidity, luminosity and CO₂, as these are essential for optimising the growth conditions [12]. For indoor monitoring, the best option is to integrate CO₂ and temperature sensors with the plant containers as these provide the most direct way to measure human occupancy. As miniaturisation of sensors continues, we expect the gap between plant and garden sensors to close. Hence plant sensors are likely to integrate most of the sensors that garden devices incorporate in the near future. Alternatively, luminosity changes can be used to estimate human presence and changes in humidity have been shown to have a strong correlation with CO₂ [13]. Hence, it is also possible to use other sensors as a proxy when CO₂ sensors are unavailable.

B. Application Domains

Thermal comfort, the subjective comfort with the thermal properties of the environment, is a key parameter for well-being. A high thermal comfort level can also benefit cognitive functions, e.g., the error rate and productivity of workers has been shown to be higher in environments that have high thermal satisfaction [14]. Plants usually are placed close to sunlight and thus the luminosity values they capture reflect also sunlight intensity instead of merely capturing the strength of ambient light. Comfort in turn can be estimated using temperature and humidity sensors as cold environments cause shivering which increases both oxygen and CO₂ exhalation [15], whereas too hot environments increase sweat exertion which correlates with increased humidity [16].

Workplace productivity requires avoiding burn-out, an emotional and physical state of exhaustion that reduces productivity. Companies are looking at non-intrusive monitoring solutions that aid employees so that it is possible to preserve a healthy cognitive state and to sustain productivity in the long-term. Plants are typically located in desk places to improve well-being. As these deployments are close to users, they can be used to provide cues about stress and cognitive load [17] through monitoring the temperature and breathing characteristics (e.g., variance of exhaled CO₂). Prolonged stress and a high cognitive load over time (beyond the average of 4 and

half hours typical productivity [18]) can provide warnings of the potential of suffering burn-out.

Non-Pharmaceutical Interventions (NPIs) refer to non-medical countermeasures for slowing down the spread of illnesses. Mask use and social distancing are two powerful ways to slow down disease spread, particularly in case of respiratory diseases that spread in close physical contact [19]. CO₂ sensors can be used to estimate occupancy as well as crowding of spaces [4] and hence they can serve as proxy a for social distancing. Face mask use, in turn, results in higher accumulation of CO₂ [20] and can even present a health risk in vulnerable people if the indoor temperature and humidity are high [21]. Hence sensors integrated into smart plants can provide insights into how well NPIs are followed.

C. Research Challenges

Sensing Challenges. Smart plant sensors are prone to the same issues as what CO₂ sensors generally face as an occupancy monitoring solution [3]. Namely, the CO₂ values accumulate slowly and the values are mediated by the monitoring context. Indeed, the accumulation of CO₂ depends on the total number of individuals within close proximity, the body mass of the individuals, the distance of the sensor from the individuals, the air ventilation in the environment, and many other factors. Thus, smart plant sensors are better at capturing *relative* differences in environments rather than detecting absolute differences. These issues can potentially be alleviated by learning different models for different kinds of environments and using model selection techniques to select the best fitting model for a given environment [22].

Programmability. Smart plants are an emerging area for IoT technology and the ecosystem is still in its infancy. Indeed, while plant containers that integrate sensors are becoming increasingly common, the access to sensors is typically closed or heavily constrained and all interactions take place through a companion app. The goal of our work is to show that offering access to these sensors can offer significant benefits to facilitate monitoring the environment and it is highly likely that the programming access to the devices will improve in the near future.

Privacy and Security. Any sensors installed in indoor environments present privacy and security challenges [23], and sensors integrated into plant containers are no different. People occupying the space need to be made aware of the sensors, and access to the data needs to be restricted to ensure it is not used for malicious purposes. For example, having remote access to CO₂ could be used to infer whether the owners of an apartment are at home. Ensuring sufficient level of privacy and security requires sufficient sophistication from the micro-controllers operating the sensors and can increase the cost of the containers. Thus, optimally the sensors would integrate with a smartphone or a smart space hub that is responsible for providing the required privacy and security functionality.

III. EXPERIMENTS

We demonstrate the potential of using sensors in plant containers for monitoring indoor environments through ex-

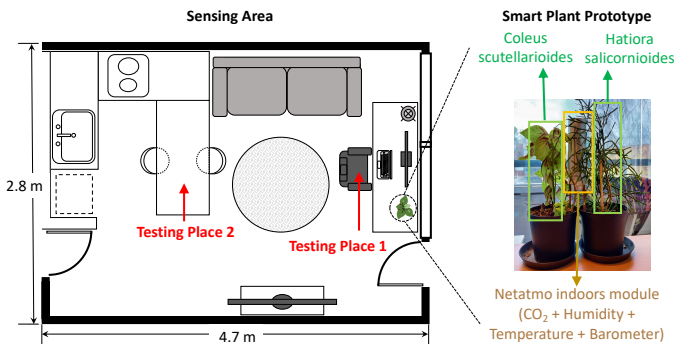


Fig. 1: Experimental Setup of Smart Plant Prototype.

tensive experiments that consider overall CO₂ accumulation estimation, occupancy detection, and face mask use detection as representative examples of applications that can be implemented by re-purposing smart plant sensors. We next describe our experimental setup and measurements in detail.

Plants. We consider plants that are common and representative of ornamental plants for indoor spaces: (i) coleus scutellarioides (common name: painted nettle, average height: 45 cm, hardiness: USDA Zone 10-11, water needs: moderate to high) and (ii) hattoria salicornioides (common name: bottle cactus, average height: 40 cm, hardiness: USDA Zone 10-11, water needs: low). Both plants are easy to grow and care, their size facilitate placing them as potted desk plants. The greenery was planted into separated pots (11.5 cm x 11 cm). The plants covered the sensors used for monitoring to ensure a realistic monitoring context, and the height of the plants from the top of the pot was: coleus, scutellarioides: 22.5 cm, hattoria salicornioides: 26.5 cm.

Apparatus. We built a simple prototype container that integrates a Netatmo portable weather station with a plastic plant container. The size of the weather station is 15.5 cm x 4.5 cm and it uses a dedicated power supply via a Mini-USB interface. WiFi connection is required for device configuration and downloading the samples on a smartphone. We rely on the weather station as it allows accessing the measurements through a separate app and a web dashboard as most commercial off-the-shelf plant containers do not currently offer separate programmable access.

Sensors. Indoor air quality was measured through the Netatmo station. The weather station collects sensor measurements for carbon dioxide (CO₂, range: 0 to 5,000 ppm, accuracy: ± 50 ppm), temperature (T, range: 0°C to 50°C, accuracy: ± 0.3 °C), barometric pressure (P, range: 260 mbar to 1.260 mbar, accuracy: ± 1 mbar) and relative humidity (RH%, range: 0 to 100%, accuracy: ± 3 %) sensors. The sensors were properly calibrated following the manufacturer's guidelines before each test.

Environment. The sensing area corresponds to a space with dimensions 2.8 m x 4.8 m inside a studio (one room) apartment; see Figure 1(a) for an illustration. The characteristics of the area are representative of common living or office space. The smart plant prototype comprises of the plants and the weather station (see Figure 1(b)). The station was covered

and placed between the desk plant container (pot) providing air quality measurements around the plants. The location of the persons during the sampling included two places with different distances relative to the plant: (i) a work desk at 80 cm distance (position 1) and (ii) a dining table at 380 cm distance (position 2). We also separately characterise the levels of CO₂ when the room is empty. We denote the mean value of the space when it is unoccupied as L_i and consider this value as a reference point. Between experiments, we include a minimum break of 30 minutes and ensured the CO₂ level stabilises to the reference value L_i before further measurements are collected. Having a minimum gap of 30 minutes ensures that the mean CO₂ level is within the reference value with a 97.5% confidence level. We also characterised the time necessary to reach the saturation point of CO₂ produced by an individual, L_s . In each experiment, the sensors sample measurements every 5 min over a 210 min period. This includes an initial 30 min period for verifying the CO₂ levels are stable (i.e., correspond to L_i), a 120 min saturation period during with the CO₂ levels increase from L_i to L_s , and a 60 min grace period at the end to verify that the CO₂ decrease back to L_i .

Measurements. Samples were collected in three different experimental conditions. We first carry out an experiment where we collect measurements separately from the smart plant and the weather station for (i) a 1 day period with one occupant following a normal daily routine (e.g., working, eating, resting) at the apartment and (ii) a 6 hour period with no occupants at the apartment. The experiment allows estimating how well the sensors in the container capture air quality variations compared to using a separate device that is installed in the environment. Second, we collect measurements for a 3 hour period for each different testing place and one occupant (male, 38 years old) and evaluate the variation in the measurements due to distance. We repeat the experiment considering two occupants (a male and a female, 38 years old both) to evaluate the effect of having more than one person. Finally, we analyse the effect of face masks by having one or both participants wearing FFP2 face masks and collecting measurements for a 3 hour period at testing position 2 (dining table). Prior to starting the measurements, we always ensured that the mean CO₂ level matches the reference value L_i over a 30 minute period.

IV. RESULTS AND ANALYSIS

A. Characterising Measurements

Figure 2 contrasts the results when the sensor is integrated with the plant container and when it is used separately to measure CO₂ level variation. Figure 2(a) presents the result of Spearman's ρ_s between different factors. The correlation between the smart plant sensor and the dedicated sensor is consistently significant. This holds especially for variable pairs that are expected to be strongly correlated: CO₂-temperature ($\rho > 0.7$) and barometric pressure-relative humidity ($\rho < -0.9$). The decrease in correlation for some variables results from different weather conditions during sampling (i.e., a sunny day can increase the temperature in the sensing area compared to a cloudy day). These results indicate that placing

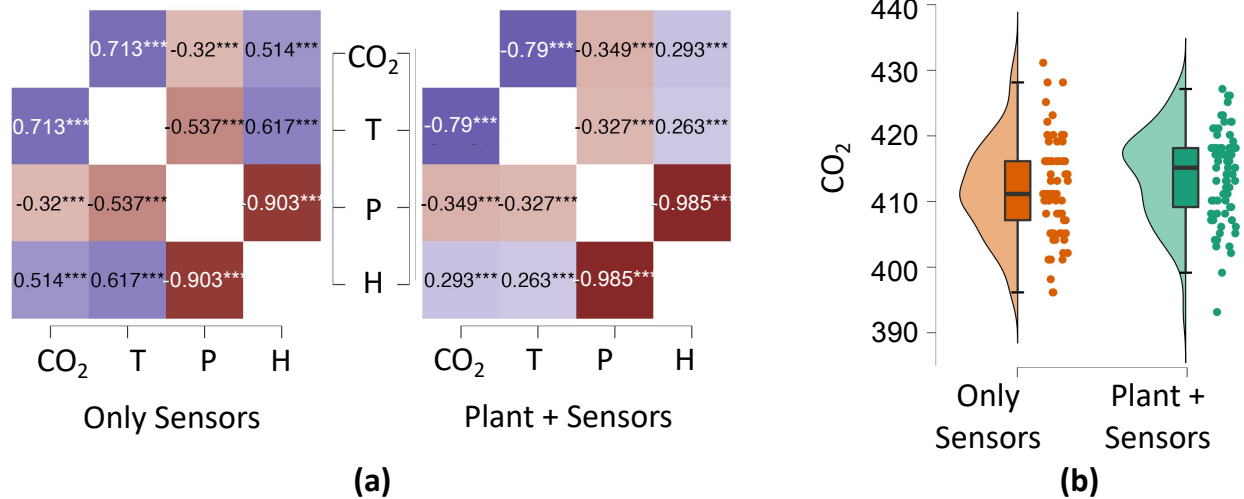


Fig. 2: Comparison between sensing methods. (a) Correlation of air factors, 24-hour sampling, one occupant. (b) CO₂ variation, 6-hour sampling, no occupants.

the sensors in a plant container does not interfere with the measurements and results in similar values as using a dedicated sensor device – with the added benefit of not requiring a separate installation or deployment in the indoor space. Figure 2(b) compares the CO₂ variations when the space has no occupants. We used Welch test to assess the significance between the two conditions: sensors in the plant container (mean = 413.88, SD = 6.89) cf. dedicated sensors installed in the space (mean = 411.75, SD = 7.34) and found the differences not to be statistically significant ($t = 1.791$, $d = 0.298$, $p > 0.05$). Note that changes in weather conditions during the day can affect measurements, to overcome this issue the variation of CO₂ levels were measured from 01:00 a.m to 06:00 a.m. The results confirm that smart plants can be used to capture variations in accumulated CO₂ equally well as dedicated sensors installed into the space.

B. Robustness to different factors

Influence of Distance. Wilcoxon signed-rank test shows significant differences between CO₂ concentration at different testing places, and thus at different distances ($W = 1$, $p < 0.001$, $r_{bc} = -0.996$). As expected, CO₂ levels are higher when individuals are closer to the smart plant, see Figure 3. The variation in accuracy can be explained by the dissipation of CO₂ in the sensing area, which is lower when the individual is closer to the sensor. Thus, the accumulation characteristics in the CO₂ values can be used to provide coarse-grained estimates of the distance where the people are residing.

Number of Occupants. We next evaluate the response of smart plants to measure CO₂ accumulation when having more than one individual in the space. We compare the variation of CO₂ levels for one and two participants in the sensing area. Wilcoxon signed-rank test confirm the differences in CO₂ measurements are statistically significant ($W = 519$, $p < 0.001$, $r_{bc} = 0.966$). Figure 3 shows that saturation of CO₂ for two individuals doing home office tasks is about 200 ppm higher, showing that smart plants can be potentially used to obtain

information about the total number of occupants – or at least separate between single and multiple occupant situations.

Use of Face Masks. We next demonstrate the potential of smart plants to provide insights about compliance with face mask use requirements. Face masks have been shown to increase the level of exhaled CO₂ [20]. As the particle size of CO₂ exceeds the filtration rate of common face masks, the exhaled particles thus pass through the mask and result in faster CO₂ accumulation in the environment. First, we evaluate the difference in the increase of CO₂ levels (slope) over time considering distance and the use of face mask for one individual as experimental conditions. Friedman Test ($\chi^2 = 96$, $p < 0.001$, $W = 1$) indicates significant differences between CO₂ concentrations. Posthoc comparisons (Holm-Bonferroni) confirm that the differences are statistically significant for all cases, i.e., the speed of CO₂ accumulation can be used to identify mask use or non-use, regardless of distance. Second, we evaluate the difference in CO₂ slope for two participants at different testing places considering three conditions: (i) none wearing face mask, (ii) both wearing face mask and (iii) one wearing face mask while the other does not. Friedman Test shows significant differences between CO₂ levels ($\chi^2 = 64$, $p < 0.001$, $W = 1$). Posthoc comparisons (Holm-Bonferroni) prove that differences were statistically significant in all the cases. The results thus show that sensors integrated into smart plants can be used to provide insights about mask use of the people occupying the space.

Watering. Lastly, we evaluate the potential impact watering the plants has on the CO₂ measurements. Watering is crucial to transport nutrients through the plants and can potentially affect humidity due to water evaporation and plant transpiration. Humidity, in turn, often correlates with CO₂ concentrations [24] and thus watering can potentially mislead the sensor measurements. For this experiment, we water the plants in the early morning (06:00 a.m) providing 250 dl of water to each plant and collect measurements for three hours in an otherwise empty area. We compare the measurements with the

atmospheric CO₂ levels measured by the sensors in the plant container. Repeated Measures ANOVA shows no significant differences between CO₂ concentrations ($F= 519$, $p> 0.135$, $\eta^2 = 0.042$). Posthoc comparisons (Holm-Bonferroni) confirm that the differences were not statistically in all the conditions confirming that watering under the recommended conditions has no effect on the sensor measurements.

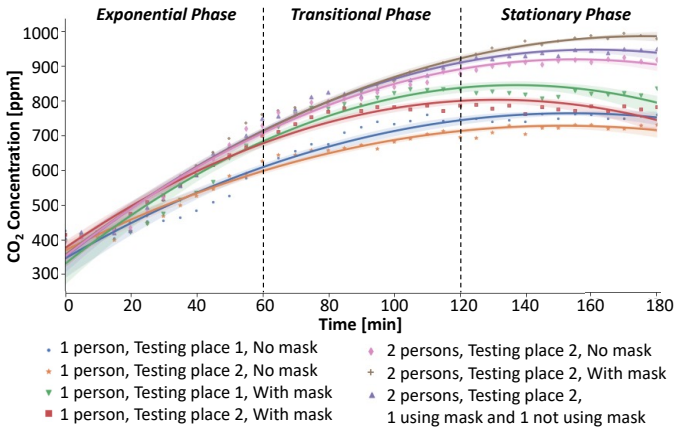


Fig. 3: CO₂ concentration curve for different experimental conditions.

C. Analysis of the Growth Curve

As shown in Figure 3, the growth in CO₂ concentration is non-linear and we can identify three distinct phases within the curve: (i) exponential initial growth phase, (ii) close to linear transitional period, and (iii) stationary phase where the concentration has saturated. We next analyse the different phases in detail to demonstrate how smart plants can offer more fine-grained insights into the current CO₂ growth stage.

Table I shows the average CO₂ level and slope for each phase. In line with the earlier results, we can observe a higher CO₂ concentration when face masks are being used, with the highest values resulting in the exponential phase from the case where all occupants wear a mask (653.6 ± 106.7 ppm, slope = 36.50 ppm). Another way to interpret the result thus is that face masks increase the growth rate in the exponential phase, but do not necessarily result in significantly higher concentrations in the saturated stage. Friedman Test considering distance, number of participants and use of face mask as experimental conditions shows statistically significant differences in the slope of CO₂ concentrations in all three phases: exponential ($\chi^2 = 46.757$, $p < 0.001$, $W = 0.995$), transitional ($\chi^2 = 59.229$, $p < 0.001$, $W = 0.807$) and saturation ($\chi^2 = 66$, $p < 0.001$, $W = 0.396$). Posthoc comparisons (Holm-Bonferroni) indicate that the differences were statistically significant in all the cases. The results thus confirm that, besides providing occupancy information, CO₂ concentration measurements provided by smart plants can give insights about the time that occupants have spent in an area.

When analysing the time that takes to return from CO₂ saturation level (about 825 ppm) to atmospheric levels (when the sensing area is empty, less than 425 ppm). We observe that about 150 minutes are necessary to reduce the amount

of CO₂ back to the initial reference value once the CO₂ level has saturated. This implies that the smart plant's sensors can provide information to support proper ventilation in areas where different people are meeting (e.g., meeting rooms, study rooms, working cabins, classrooms). Naturally increasing the ventilation rate can speed up the CO₂ decay and thus it is also possible to use smart plants to obtain insights into the ventilation rate used in the space. For example, increased ventilation rates have been suggested as a way to mitigate risks of COVID-19 spread [25], [26].

D. Modeling face mask use and occupation estimation

As the final step of our evaluation we demonstrate that smart plants can support coarse-grained classification of the use of face masks and occupancy estimation indoors.

Model. We consider a simple machine learning model that attempts to distinguish between people that use and those that do not use protective face masks. As shown earlier, the speed of change in the CO₂ levels depends on the number of people in the space and whether the people use masks or not. For demonstrating the general principle, we limit our analysis to scenarios involving one or two occupants. As before, this results in three categories for mask use (i) all persons wearing mask, (ii) no persons wearing a mask, and (iii) one person wearing a mask while the other is not using, and two categories for occupancy (i) one individual and (ii) two individuals. We evaluate two different input feature combinations that consider the slope of CO₂ concentration growth and the ambient temperature. We consider three simple classifiers, Random Forest, Gradient Boosting and AdaBoost, which can be run directly on the micro-controller of the smart plant container as these models have small memory requirements, low computational requirements, and low energy consumption.

Use of face masks. Modelling the use of face masks based only on the growth in CO₂ concentration gives an average classification accuracy of 65% across the three algorithms. The performance increases when more information about the environment is included. Indeed, incorporating temperature as a factor increases average accuracy by more than 5% ($\approx 70\%$). When considering the length of the time window, the shortest five minute window results in the best performance through the performance with longer time windows is similar (lowest performance 64.53% for CO₂ growth and 69.03% for CO₂ growth and temperature). Thus, information about face mask use (or non-use) can be obtained using only few minute time windows. The main source of errors is the case where mask use is mixed between the occupants, resulting in 23.5% and 21.5% misclassification rates for the two feature combinations. In terms of classification algorithms, the three models have very similar performance.

Occupancy. The results for detecting occupancy are significantly higher, ranging from $\approx 85\%$ for CO₂ growth to 89% when both CO₂ growth and temperature are used as input features. Best results are obtained for 10 minute time windows, through similarly to the results for face mask use, the variation across time windows is small and the overall

TABLE I: Statistics of CO₂ concentration for different experimental conditions and growth curve phases.

Participants	Position	Wearing mask	Exponential Phase			Transitional Phase			Saturation Phase		
			Mean CO ₂	SD CO ₂	Slope	Mean CO ₂	SD CO ₂	Slope	Mean CO ₂	SD CO ₂	Slope
1	1	no	535.2	71.9	24.52	726.9	27.4	7.47	751.7	7.8	1.35
		yes	603.4	105.4	36.53	814.5	20.9	5.46	820.5	7.9	0.57
	2	no	557.6	67.6	23.35	680.8	18.9	5.27	722.4	8.5	1.52
		yes	624.7	74.9	26.03	776.5	9.8	2.26	777.4	7.3	0.28
2	2	no	646.7	94.7	32.47	838.0	33.3	10.34	912.6	7.1	1.69
		yes	653.6	106.7	36.50	850.7	55.6	17.12	973.2	13.6	3.55
	1 yes, 1 no		645.0	97.5	33.67	857.8	38.9	11.86	938.1	9.4	2.66

TABLE II: Classification accuracy considering the average level of CO₂ and temperature (T) given a time window, w . Classifiers: Random Forest (RF), Gradient Boosting (GB), AdaBoost (AB).

model → predicted	Classifier	Time window size [minutes]					
		5	10	15	20	25	30
CO ₂ → face mask use	RF	65.9	63.8	65.6	63.4	62.9	64.4
	GB	63.7	63.7	63.8	64.3	64.9	65.1
	AB	66.9	67.6	66.5	66.2	64.3	64.1
	Mean	65.5	65.0	65.3	64.6	64.0	64.5
CO ₂ → amount of people	RF	81	82.2	82.4	81.3	80.7	80.9
	GB	84.1	84.7	83.1	84.1	84.7	84.3
	AB	89.7	88.8	89.4	88.8	89.4	90.1
	Mean	84.9	85.2	85.0	84.7	84.9	85.1
(CO ₂ , T) → face mask use	RF	70.9	69.6	70.4	69.7	68.4	67.8
	GB	71.5	72.8	72.2	72.8	70.3	70.3
	AB	69	68.5	67.1	68.1	69.3	69
	Mean	70.5	70.3	69.9	70.2	69.3	69.0
(CO ₂ , T) → amount of people	RF	85.3	86.9	84.4	85.6	84.1	83.1
	GB	89.4	89.9	89.3	89	88.7	87.8
	AB	92.5	92.4	92.6	92.6	91.9	92.4
	Mean	89.1	89.7	88.8	89.1	88.2	87.8

model performance is highly similar across all time windows. As expected, the highest misclassification rates result for distinguishing between one or two occupants, and mask usage further complicates occupancy counting. AdaBoost has consistently the best performance for estimating the number of users in the space, though overall the three algorithms have very similar performance.

Summary. Overall the classification results demonstrate that smart plants can be used to model diverse indoor scenarios and provide insights about the indoor context. The best results are obtained for using a combination of sensors, with CH₂ growth rate and temperature resulting in reasonably high classification accuracy. Indeed, combining temperature information with CO₂ growth improves the performance by over 5% percentage points on average compared to only using CO₂ growth rate; see Table II. The performance depends on the complexity of the task, with face mask use being more challenging than occupancy detection. Naturally we expect the benefits to be highest in relatively stable environments, e.g., monitoring the area around a working space is likely to result in more stable estimates than monitoring an exercise room where physical activity affects the exhalation patterns of the occupants. Thus, the granularity and accuracy of the information that can be captured depends on the characteristics of the space that requires monitoring and alternative sensor modalities are likely to be superior in more dynamic environments. Nevertheless, smart plants can support a wide range of spaces and offer an affordable and easy-to-deploy solution for monitoring the space which simultaneously brings benefits through the positive effects of greenery.

V. DISCUSSION

Augmenting Computations. Our work demonstrates that smart plants can work as effective sensing infrastructure in indoor environments, but they could potentially be used to support also limited form of computations. For example, plants could be used as an additional computing infrastructure for real-time object recognition [27] or other tasks where the velocity of the data is fast. Indeed, scarcity of available deployments is a key challenge for edge computing and smart plant deployments could support improving the density of edge computing support.

Indoor Health Indicator. Indoor air pollution is estimated to be responsible for the deaths of an estimated 3.8 million people each year [28]. Smart plants can provide insights of air quality, and thus they can be used to offer indicators for healthier living environments. Changes in sensor values can also be used to detect activity that affects the indoor air quality, e.g., cooking can cause increase in the level of indoor pollutants. The magnitude of changes in sensor values can then be used to determine whether there is adequate ventilation and inform the occupant when this is not the case.

Further Optimisations. Naturally further optimisations are needed to improve the accuracy of the plant sensors. For example, as our experiments demonstrated, the values are sensitive to the monitoring context and common sensor modalities available on plants are better at capturing relative rather than absolute changes. Further improving the accuracy would require insights into the monitoring context and applying calibration on the sensors. Potential way to support this is to take advantage of the fact that most sensor-enabled devices interact with a smartphone or another device that is used to control the space, and these devices could be used as a source of information to support the calibration. A simple example is to use proximity sensing, similarly to what is used by contact tracing apps, to estimate changes in the number of people in the space and to use this information to adapt the model that is used on the plant. Another potential improvement is to rely on more advanced classification models, such as deep learning. These can potentially improve the classification performance but would also require external computing support, optimally in the form of dedicated edge nodes, whereas the models we considered can be run directly on the plant containers.

Comparison to Other Modalities. Sensors for monitoring the indoor environments generally cost from around \$30 to several thousands of dollars, depending on the technology and the software that is available. At the cheapest end are low resolution thermal array sensors which are aimed at detecting

occupancy status and changes in it [5] whereas the high-end includes sensor units integrating high precision 3D cameras, air quality monitors, and other sensor modalities. The price point of smart plants is close to the cheaper end, with an advanced sensor-enabled container costing less than \$100. Note that these costs include only the cost of the sensor technology, and the main benefit of smart plants come from driving down the costs of installing, operating, or maintaining the sensors. Indeed, the same container can be re-used multiple times and even upgrading the sensors only requires changing the container, not detaching or uninstalling older sensors and reinstalling new ones.

Future Scenarios. Plants not only serve as decorative elements that can affect the mental state of people around them, but they can also be used to change properties of the space. A simple example is the use of plants to improve the air quality of indoor spaces, and another example is the use of plants to reduce noise in the environment [29]. Future offices could deploy plants on robots (e.g., roomba or similar ground vehicles) and have them move around the space to enrich the space and support the workers – while simultaneously transporting the sensors that can monitor the quality of the indoor space. While futuristic, this kind of scenario is well possible in the near future, offering a potential way to simultaneously improve the quality of the indoor environment and support its occupants.

VI. SUMMARY AND CONCLUSION

We demonstrated how sensors in smart plants can be harnessed for monitoring indoor environments and serve as a proxy for human behaviour. Plants are typically placed close to areas that humans occupy, and they increasingly are equipped with sensors that monitor growth conditions but that also can be used to make inferences about human presence. The price of the sensors is also inexpensive, making it easier to monitor an indoor space using sensor-equipped plants than to install separate sensor infrastructure – let alone needing to wire or install separate power for the sensors. Through experiments we demonstrated that smart plants are able to detect human occupancy, the number of individuals that are close by, and even able to provide insights into whether the people are wearing protective face masks. While there is significant potential in the use of smart plants for indoor sensing. Our work demonstrates that smart plants have significant potential to support the monitoring of indoor spaces, offering an affordable and easy-to-deploy solution that supplements existing approaches.

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