Theodor: A Step Towards Smart Home Applications with Electronic Noses

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ABSTRACT

This paper presents preliminary results of the ongoing project TheOdor which explores the potential of electronic noses that make use of commodity gas sensors (MOS, MEMS) for applications in the smarthome, for example, to classify human activities based on the odors generated by activities. We describe the system and its components and report on classification results from first validation experiments.

CCS CONCEPTS

• **Hardware** → **Sensor applications and deployments**; *Digital signal processing*; • **Human-centered computing** → *Ambient intelligence*;

KEYWORDS

Electronic nose, Smart home, Odor, Scent, Sensor, Smell, MOS, MEMS, Classification, Machine Learning

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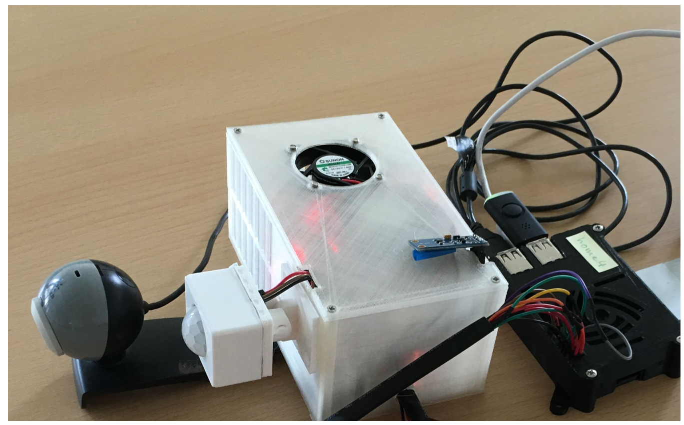

Figure 1: A complete measuring box of TheOdor prepared for long term recordings with a webcam and a motion sensor.

1 INTRODUCTION

Smart home technology has found its way into more and more households in recent years, turning ordinary homes into smart homes, and the technology is developing and spreading rapidly. The basic components of a smart home consist of actuators (e.g. power plug, light bulb, switching relay, door lock, ventilation, thermostat) and sensors (e.g. motion detector or light, contact, pressure, temperature, or humidity sensor) [6] which together form a causal relationship between cause (one or more sensors) and effect (one or more actuators) and thus implement a basic behavior [11]. For example, if a motion detector triggers and the light sensor indicates a low light condition, then the light is turned on.

Ideally, the behavior or functions of a smart home should support an inhabitant's daily routines or support the activities of an inhabitant. Necessary requirements to realize such behaviors are methods and approaches to recognize inhabitant's activities by means of the sensors of a smart home among other data sources (e.g. time of day). Therefore, human activity recognition (HAR) plays an important role in smart home research to recognize activities of daily living [24], for example, to assist in cooking tasks [23] or to help people with dementia with hand washing [14]. Most of the technologies used for HAR require inhabitants to wear a device with sensors, such as inertial sensors of a smartphone or smartwatch [19], or to have cameras mounted in the smart home [9]. A more unobtrusive way for HAR is to make use of sensors for the detection of odors that occur during activities, for example cooking, bath activities, or having a meal. Smart homes are particularly suitable environments for this approach as these are mostly closed spaces compared to working environments or open interactive environments. In closed spaces, the odors of activities remain there for a long time or until inhabitants ventilate them, making the use of HAR based on this approach more suitable than in open areas, where odors spread very quickly until they can no longer be measured. The research project and exploration platform TheOdor addresses exactly this area of application and investigates suitable machine learning approaches for HAR with prototypes (see Figure 1) that we built from scratch.

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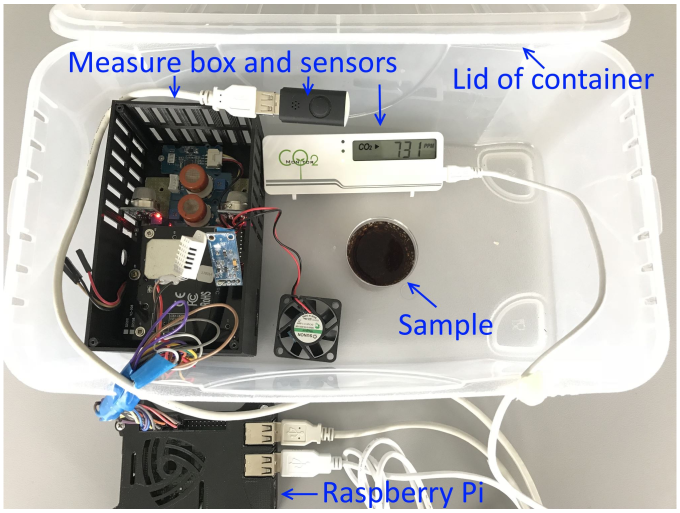

Figure 2: The experiment container with all sensors of TheOdor and a beverage in the center.

1.1 TheOdor Project

Our TheOdor project falls into the research of electronic noses for the recognition of human activities in smart homes. However, most research works on electronic noses are not concerned with the application in smart homes but rather for industrial use, for example for the determination of product quality [7, 15, 18] or bacterial cultures [12]. Recent research works, such as that at KIT [5], are taking a promising path by developing specialized sensors for the detection of odor molecules which may be the preference for HAR in future. Such developments are still in their infancy and not yet ripe for HAR research. If we focus on commodity gas sensors, Hirano et al. [8] presented the system uSmell which made use of more recent commodity gas sensors to explore the classification of odors for UbiComp applications. They demonstrated the use of such sensors for the detection of different beverages by their odors using a decision tree classifier and achieved 88 % accuracy. Due to their promising results, we used their findings and considered them in the design of our exploration platform TheOdor as the first step towards our goal.

The ultimate goal of the TheOdor project is not only to recognize and distinguish beverages but to determine whether and how reliably human activities can be derived from recognized odors. Hence, the sensor array of TheOdor includes the sensors that previous work employed in addition to more recent MEMS sensors. TheOdor is part of a larger smart home research installation in which TheOdor also serves to investigate the environmental conditions in a smart home. Therefore, TheOdor also includes sensors that measure brightness or fine dust particles (e.g. PM2.5).

In order to validate the gas sensor array of TheOdor for this step, we adapted the classification approach that [8] applied for validating their system. By this means, we made sure that the implementation (without our extensions) is valid in terms of previous findings. However, for HAR tasks, we believe that there are more suitable machine learning approaches (than statistical classification) to cope with the idiosyncrasies of gas sensors, such as sensor drift [10] or temperature/humidity dependencies [17, 20]. In future steps, we consider the sensor array of TheOdor as receptors of an electronic nose in which the electronic signals of the receptors generate multivariate time-series data. For such kind of data, a series of recent research works have shown the great potential of deep neural networks in comparison to other approaches [12, 16, 22], in particular, to compensate for sensor drift [10]. However, these works have not addressed human activity recognition in smart home environments.

In the following, we present the results of the first step, that is the design and implementation of the exploration platform TheOdor and the validation of the gas sensor array.

Table 1: Sensors used in the measuring boxes of TheOdor.

Model	Type	Main sensitivity (secondary)	Power (mW)
MQ2	MOS	Methane (Butane, LPG)	~800
MQ3	MOS	Alcohol	~750
MQ5	MOS	Propane (LPG)	~800
MQ9	MOS	Carbon monoxide	~350
MICS 6814	MEMS, MOS	Ammonia, Carbon monoxide, Nitrogen dioxide (Hydrogen, Hydrogen sulfide, Nitrogen monoxide, Isobutane, Ethanol, Propane)	~100
AS MLV P2	MEMS, MOS	Volatile organic components	~200
TFA	NDIR	Carbon dioxide	~300
DHT 22	Polymer capacitor	Temperature, humidity	~3

2 SYSTEM DESIGN OF THEODOR

In contrast to the system uSmell [8], we designed TheOdor as a compact and mobile stand-alone system that does not require a desktop PC. This allows TheOdor to be placed anywhere where odors occur without restrictions for experiments. TheOdor consists of two closed measuring boxes with sensors, each connected to and controlled by a Raspberry Pi 3 single-board computer as depicted in Figure 1 and Figure 2. Access to TheOdor is realized via WiFi so that TheOdor only requires a power socket to start its work.

2.1 Measuring Boxes and Sensors

The measuring boxes were printed with a 3D printer and were designed to have a fan mounted on top of the box which blows air into the box on demand, see Figure 1. Furthermore, the boxes were printed with mounts in the box to optimally accommodate the sensors within the air flow in the boxes. Most of the sensors are based on the sensing principle of MOS (Metal Oxide Semiconductor) sensors [20] and some of them are built as MEMS (Micro-Electro-Mechanical System) which allows them a very small and compact package design.

Each of the measuring boxes accommodates a gas sensor array with four different MOS sensors (MQ2, MQ3, MQ5, MQ9) together with the temperature / relative humidity sensor DHT-22 [2], the

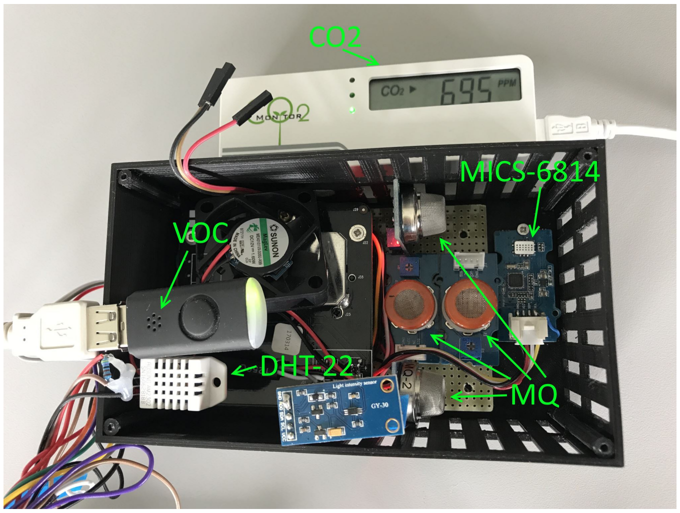

Figure 3: A measuring box of TheOdor with the sensor array.

VOC[1] sensor AMS AS-MLV-P2 [1], and the multi-channel gas sensor MICS-6814 [3]. The latter is a compact MEMS sensor having three fully independent MOS sensing elements in one small package. In particular, the MICS-6814 sensor is able to detect gas molecules that could not be detected by the sensor combination in previous work [8]. The signals of the MQ-MOS sensors have a voltage range of 0-5 V which are sampled through a 4-channel 16-bit analog-to-digital converter (ADS1115). In contrast to [8], TheOdor achieves a significantly higher accuracy with a granularity of 0.2 mV. However, the MICS-6814 sensor has already a 10-bit analog-to-digital converter integrated into the circuit, which provides a granularity of ~5 mV. The AMS VOC sensor is a completely self-contained sensor built into a USB-stick and delivers values between 450 ppm and 2000 ppm depending on the measured amount of volatile organic components.

In addition to these sensors, TheOdor includes an NDIR[2] CO_2 sensor (TFA AirControl Mini [4]) which could be freely placed outside the boxes. Other than the MOS sensors, the sensing principle of the NDIR sensor is based on spectroscopic mechanisms and enables to precisely measure the concentration of carbon dioxide independent of other gases. We also included temperature / relative humidity sensors since the response of MOS sensors depends on both temperature and humidity [17, 20]. While the sensors make use of internal heaters which mitigate the temperature dependency (from environmental temperature), the humidity dependency still exists. Hence, TheOdor also samples temperature and relative humidity in order to be able to compensate for the dependencies. Table 1 lists all sensors that are used in the measure boxes of TheOdor together with their power consumptions. Altogether, each of the boxes needs about 3.3 Watts and its connected Raspberry Pi requires about 1.5 Watts.

For future long-term data recordings in terms of activity recognition, we prepared TheOdor with a camera and a PIR[3]-based motion detector as depicted in Figure 1. The aim is to capture a series of pictures after motion has been detected in order to label the recorded odor data with labels representing actual activities that happened at that time.

[1] Volatile Organic Components
[2] Non-Dispersive Infrared
[3] Passive Infrared

2.2 Software

The TheOdor software runs on the Raspberry Pis and polls all sensors of the sensor arrays once a second for current sensor readings. The readings are then stored together with a timestamp in a local log file on the SD-card of the Raspberry Pis. In addition, the readings are pushed over the network to a server (if available, otherwise cached) which stores them in an SQL database. In order to have a synchronized timestamp of the recorded sensor data (across every component of TheOdor), the Raspberry Pis update and synchronize their system clock over NTP right after boot prior to polling the sensor array.

3 PRELIMINARY VALIDATION

Before starting long-term recordings to collect sufficient data for classification, we validated TheOdor with the validation approach of [8] for the classification of beverages. We prepared a container (l x b x h: 29 x 16 x 10.5 cm) which could be closed with a lid and into which a measuring box of TheOdor fits. The container also had sufficient space for a glass of beverage or sample of food as depicted in Figure 2. The Raspberry Pi was placed outside the container in order to avoid any interference (e.g. due to heat) with the measurements in the box. We also deactivated the fan and removed the lid of the measuring box since the odors released in the container were already caught in the container by the lid of the surrounding container. In addition, all openings of the container were covered with neutral foil and adhesive tape to seal the container. An additional neutral foil between the container openings and the tape was chosen to avoid contamination of the container volume with possible gas evaporation from the adhesives of the tape.

3.1 Methodology

Altogether, the odor data of 24 different foodstuff samples, as listed in Table 2, were selected for the experiment. The list consists all beverages used in [8] except moscato and grape juice. As a replacement for these two beverages, we included dornfelder red wine and grapefruit juice. In addition to beverages, the experiment was extended by including samples of different types of food in order to investigate whether the approach also works for food.

We proceeded with the collection of odor data as described in previous work. Each foodstuff sample was placed in the center of the container which was sealed with the lid afterward. Then, the measuring box of TheOdor in the container recorded sensor readings from the sensor array for ~180 seconds. For beverages, we took 50 ml and for the food we weighed 10 g. After each measurement of a sample, the container was opened and vented for 10 minutes by means of a fan to "reset" the gas concentrations, temperature, and humidity to the values of the room. The room was regularly aired by opening the window. After measuring a series with all samples, the same series was measured a second time so that the short-term repeatability of the measurements could be investigated since the

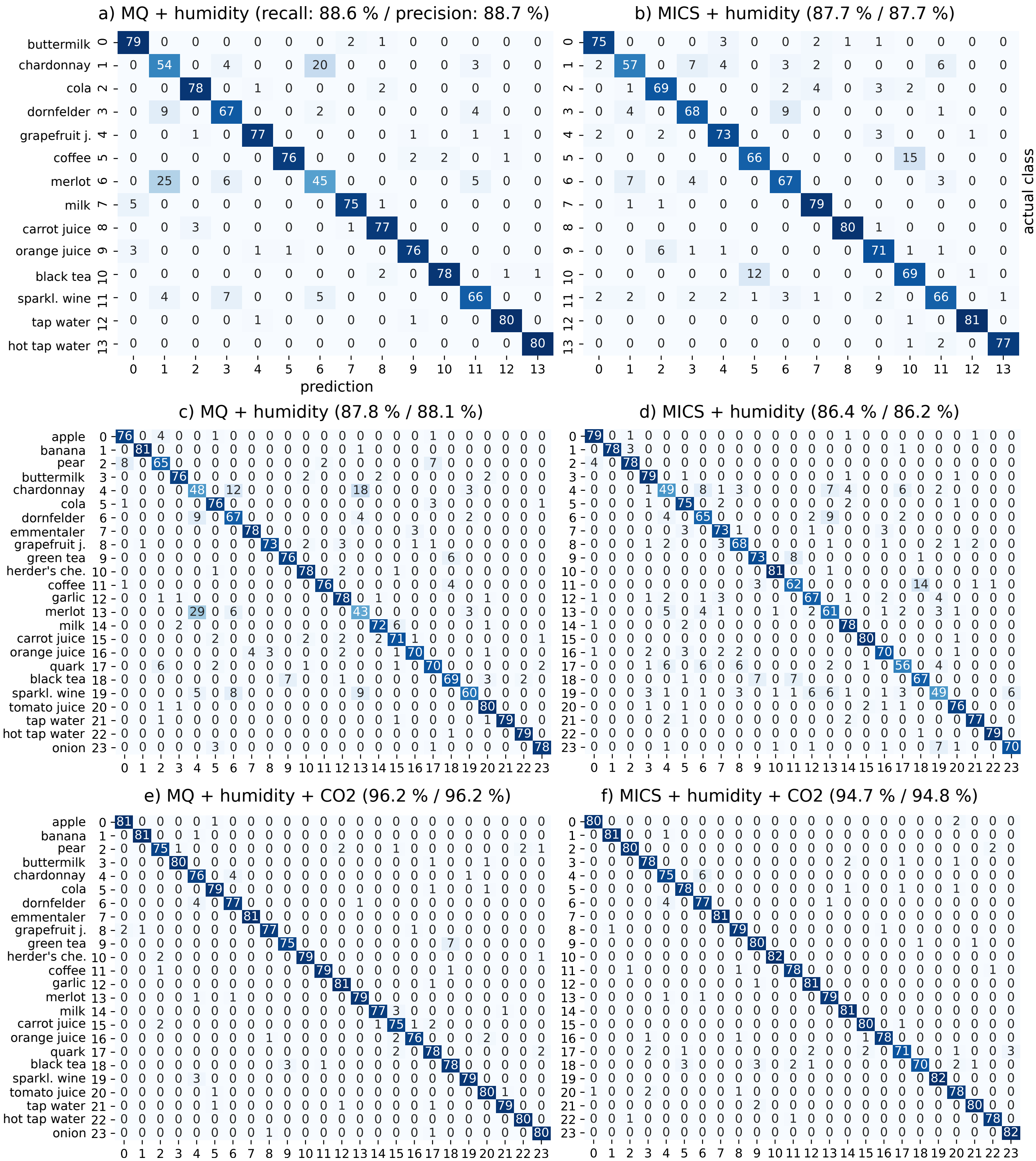

Figure 4: Classification results of different sensor data combinations and classes. For all classifications WEKA's C4.5 (J48) decision tree classifier with a 10-fold cross-validation was used. The data set consisted out of about 80 samples per class.

Table 2: Foodstuff used for gas concentration measurements. Beverage names, that are bold, are comparable with the beverages used in [8].

Foodstuff	**Type**
apple	fruit
banana	fruit
black tea	hot drink
buttermilk	dairy product
carrot juice	vegetable juice
chardonnay	white wine
coffee	hot drink
cola	soft drink with CO_2
dornfelder	red wine
emmenthaler	cheese
garlic	vegetable
grapefruit juice	fruit juice
green tea	hot drink
herder's cheese	cheese
hot tap water (no chlorine)	water
merlot	red wine
milk	dairy product
onion	vegetable
orange juice	fruit juice
pear	fruit
quark	dairy product
sparkling wine	white wine with CO_2
tap water (no chlorine)	water
tomato juice	vegetable juice

room conditions, odors of the foodstuff, and sensor behavior may have at least partly changed in the meantime.

3.2 Classification

The recordings of the experiment consisted of time-series data for two sessions (180 seconds each), for each of the sensors of the sensor array, and for each of the foodstuff samples at a samplerate of 1 Hz. The time-series data were then segmented into 5-second frames (each consisting of 5 samples) with no overlap. For each of the frames, the following features were calculated: average, linear regression, and variance. For classification, we combined the time-series data of both sessions which resulted in about 80 frames for each class (the type of foodstuff sample).

The classification was carried out with the C4.5 (J48) decision tree classifier implementation in the WEKA machine learning toolkit (version 3.9.2) [21] and a 10-fold cross-validation with stable random seed for all evaluations.

3.3 Results

The experiment included the MQ sensors used in previous work and additionally with more recent MEMS sensors as well as with additional odors of food. In the following, we use confusion matrices to discuss what effects the types of sensors and the number and type of odors have on the classification. To create the confusion matrices, the classifications were only performed with the time-series data of the selected sensors and odor types given in the discussion.

3.3.1 Comparison with uSmell. For the comparison with [8] and validation, only the data of the MQ sensors and the humidity sensor for the odors of the beverages were used. The results are shown in the confusion matrix in Figure 4a. Compared to the sensor combination of uSmell, our selection of MQ/MOS sensors contains three fewer sensors. Therefore, this comparison is not fully comparable. Nonetheless, the weighted averaged recall (88.6 %) and precision (88.7 %) are similar (marginally better) to the results of uSmell (88.1 % / 88.2 %).

The confusion matrix reveals that the class chardonnay was most often confused with the class merlot and the other way round. This happens also with the other two alcoholic beverages dornfelder and sparkling wine, although not often. In uSmell, especially the class champagne was confused with the class chardonnay and the class merlot and in part also the other way round indicating that there were also some problems with alcoholic beverages.

3.3.2 MQ sensors vs. MICS sensor. The MICS sensor is a compact MEMS sensor which consumes only a fraction of the power that only one MQ sensor requires (see Table 1). The three independent sensors in the package cover most of the gas-molecule (primary and secondary) that the four MQ sensors are sensitive of. Therefore, it is advantageous to use the MICS sensor instead of the MQ sensors, which would lead to greatly reduced power consumption and less heat generation and thus increase the mobility of the electronic nose. To compare the classification performance with the MICS sensor, we conducted the same calculations as in Section 3.3.1 with the time-series data of the MICS sensor.

The results are given in the confusion matrix in Figure 4b. Recall and precision were nearly identical at 87.7 % which is about one percent less than with the MQ sensors. Compared to the MQ sensors, the classification of the time-series data of the MICS sensor shows fewer problems with false classification of alcoholic beverages but confuses the two hot beverages with caffeine with each other, that are coffee and black tea.

3.3.3 Classifying all foodstuff classes. Our extension of the original experiment for uSmell includes eight additional food samples and two more beverages (tomato juice and green tea) with the aim to test the approach also for food and other beverages. For this classification, we compared the time-series data of the MQ sensors against the MICS sensor. Both data sets also included the time-series data of the humidity sensor. The confusion matrices are given in Figure 4c and Figure 4d. For both matrices, recall and precision are slightly worse in comparison to using fewer classes (MQ + humditiy: recall: 87.8 % / precision: 88.1 %; MICS + humditiy: 86.4 % / 86.2 %). Figure 4c and Figure 4d show that alcoholic beverages (in part) still get confused with each other. The beverages involved are also the same as in Section 3.3.2 (MQ: chardonnay/merlot; MICS: coffee/black tea).

3.3.4 CO_2 NDIR sensor. Instead of the power-hungry MOS sensor MG-811 for CO_2, we included the more precise and energy-efficient NDIR CO_2 sensor from TFA. Adding the time-series data of the CO_2 sensor to the two sensor combinations (MQ + humidity / MICS + humidity) gives the confusion matrices shown in Figure 4e

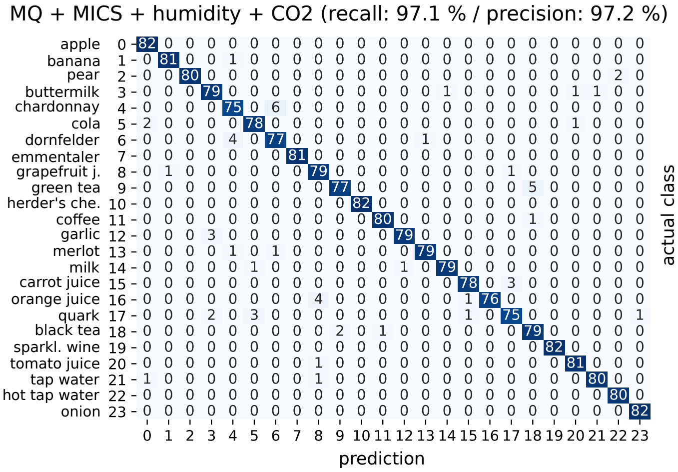

Figure 5: Classification result for the combination of MICS, MQ, humidity, and CO_2 sensor.

and Figure 4f. The MQ sensor combination receives a recall of 96.2 % and a precision of 96.2 % while the MICS combination receives a recall of 94.7 % and a precision of 94.8 %. Both combinations achieve about 8 % higher recalls/precisions after adding the CO_2 sensor and all classes show much higher recognition rates.

3.3.5 MICS, MQ, CO2 and humidity sensor. If we do not care about power-consumption and combine MQ and MICS sensors together with the humidity and CO_2 sensor, then we receive the confusion matrix given in Figure 5. The confusion matrix shows that the combination results in even better recognition than the other combinations with a recall of 97.1 % and a precision of 97.2 %.

The VOC sensor of AMS was not included for the previous comparisons, as it was not present in uSmell either. For the combination of all sensors in this section, we also tried to include the VOC sensor in the classification. However, this resulted in only very little improvement of the classification results (recall: 97.2 %, precision: 97.3 %).

4 LIMITATIONS OF THE STUDY

There are several factors that limit the application of commodity gas sensors for the classification in real-world scenarios where non-ideal conditions usually exist. The authors of [8] already described several limitations of their studies which also applies to our study. Most of them are related to the physical (reaction and distribution) behavior of gases and the reactive materials used in the sensors.

Different sensors of the same type (i.e. two MQ3 sensors) are not interchangeable as they usually have different baselines and even the baselines drift over time as shown by Hu et al. [10] or Ma et al. [13]. However, they also demonstrated that this behavior can be successfully handled for classification.

Depending on the architecture and volume of a room in which the gases distribute, the gas concentrations might be too low to be detected by a sensor. In addition, in rooms, air masses usually move (e.g. by ventilation, heating, thermal differences) and gases may be lighter or heavier than air, so some gas molecules reach a gas sensor much faster or slower which makes the classification based on a combination of molecules more difficult.

Another limitation of the study is that individual odors are classified independently of each other. Hence, the results cannot be used to consider a combination of odors.

5 CONCLUSION

Based on our exploration platform TheOdor, we performed several comparisons with different combinations of sensor types and food types. In general, recognition rates can be increased by including more recent MEMS sensors and more precise (NDIR) sensors. Our extension to the experiment in [8] has demonstrated that the application of the approach also works for food samples. The comparison of MQ sensors and the MEMS sensor revealed only few differences in classification performance. If power-consumption is an issue, then the use of MEMS sensors instead of the MQ sensors help drastically reduce power-consumption at marginally lower classification performance.

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REFERENCES

[1] 2018. Datasheet AS-MLV-P22, micromachined, low-power VOC sensor, ams AG. https://ams.com/documents/20143/36005/AS-MLV-P2_FS000137_2-00.pdf/88d6f92f-69b0-3a3b-8d51-134576697ef5

[2] 2018. Datasheet DHT 22 / AM2302, Digita relative humidity / temperature sensor, Aosong Electronics Co., Ltd. https://www.sparkfun.com/datasheets/Sensors/Temperature/DHT22.pdf

[3] 2018. Datasheet MiCS 6814, MEMS three channel gas sensor, SGX Sensortech. https://raw.githubusercontent.com/SeeedDocument/Grove-Multichannel_Gas_Sensor/master/res/MiCS-6814_Datasheet.pdf

[4] 2018. Datasheet TFA Mini-CO2, Air Control Mini, DOSTMANN electronic. https://www.dostmann-electronic.de/download/528-5020-0104.pdf

[5] 2018. What's That Smell? - Electronic Nose Recognizes a Variety of Scents. KIT Press Release. https://www.kit.edu/kit/english/pi_2018_050_what-s-that-smell-electronic-nose-recognizes-a-variety-of-scents.php

[6] A.J. Brush, Jaeyeon Jung, Ratul Mahajan, and James Scott. 2012. HomeLab: Shared Infrastructure for Home Technology Field Studies.

[7] A Galdikas, A Mironas, D Senulien, V Strazdien, A Šetkus, and D Zelenin. 2000. Response time based output of metal oxide gas sensors applied to evaluation of meat freshness with neural signal analysis. *Sensors and Actuators B: Chemical* 69, 3 (2000), 258 – 265. https://doi.org/10.1016/S0925-4005(00)00505-0 Proceedings of the International Symposium on Electronic Noses.

[8] Sen H. Hirano, Gillian R. Hayes, and Khai N. Truong. 2015. uSmell: Exploring the Potential for Gas Sensors to Classify Odors in Ubicomp Applications Relative to Airflow and Distance. *Personal Ubiquitous Comput.* 19, 1 (Jan. 2015), 189–202. https://doi.org/10.1007/s00779-014-0770-7

[9] Weiming Hu, D. Xie, Tieniu Tan, and S. Maybank. 2004. Learning activity patterns using fuzzy self-organizing neural network. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* 34, 3 (June 2004), 1618–1626. https://doi.org/10.1109/TSMCB.2004.826829

[10] Xiaonan Hu, Qihe Liu, Hongbin Cai, and Fan Li. 2014. Gas Recognition Under Sensor Drift by Using Deep Learning. In *Practical Applications of Intelligent Systems*, Zhenkun Wen and Tianrui Li (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 23–33.

[11] Justin Huang and Maya Cakmak. 2015. Supporting Mental Model Accuracy in Trigger-action Programming. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15)*. ACM, New York, NY, USA, 215–225. https://doi.org/10.1145/2750858.2805830

[12] Martin Längkvist and Amy Loutfi. 2011. Unsupervised feature learning for electronic nose data applied to Bacteria Identification in Blood. In *NIPS workshop on Deep Learning and Unsupervised Feature Learning*.

[13] Zhiyuan Ma, Guangchun Luo, Ke Qin, Nan Wang, and Weina Niu. 2018. Online Sensor Drift Compensation for E-Nose Systems Using Domain Adaptation and Extreme Learning Machine. *Sensors* 18, 3 (2018).

[14] Alex Mihailidis, Jennifer N. Boger, Tammy Craig, and Jesse Hoey. 2008. The COACH prompting system to assist older adults with dementia through handwashing: An efficacy study. *BMC Geriatrics* 8, 1 (07 Nov 2008), 28. https://doi.org/10.1186/1471-2318-8-28

[15] Lakshmi P. Pathange, Parameswarakumar Mallikarjunan, Richard P. Marini, Sean O'Keefe, and David Vaughan. 2006. Non-destructive evaluation of apple maturity using an electronic nose system. *Journal of Food Engineering* 77, 4 (2006), 1018 – 1023. https://doi.org/10.1016/j.jfoodeng.2005.08.034

[16] Pai Peng, Xiaojin Zhao, Xiaofang Pan, and Wenbin Ye. 2018. Gas Classification Using Deep Convolutional Neural Networks. *Sensors* 18, 1.

[17] Philip J. D. Peterson, Amrita Aujla, Kirsty H. Grant, Alex G. Brundle, Martin R. Thompson, Josh Vande Hey, and Roland J. Leigh. 2017. Practical Use of Metal Oxide Semiconductor Gas Sensors for Measuring Nitrogen Dioxide and Ozone in Urban Environments. *Sensors* 17, 7.

[18] Olivier Ramalho. 2000. Correspondences between olfactometry, analytical and electronic nose data for 10 indoor paints. *Analusis* 28, 3 (2000), 207–215. https://doi.org/10.1051/analusis:2000280207

[19] Muhammad Shoaib, Stephan Bosch, Ozlem Durmaz Incel, Hans Scholten, and Paul J. M. Havinga. 2016. Complex Human Activity Recognition Using Smartphone and Wrist-Worn Motion Sensors. *Sensors* 16, 4 (2016). http://www.mdpi.com/1424-8220/16/4/426

[20] Chengxiang Wang, Longwei Yin, Luyuan Zhang, Dong Xiang, and Rui Gao. 2010. Metal Oxide Gas Sensors: Sensitivity and Influencing Factors. *Sensors* 10, 3 (2010), 2088–2106. https://doi.org/10.3390/s100302088

[21] Ian H Witten, Eibe Frank, Mark A Hall, and Christopher J Pal. 2016. *Data Mining: Practical machine learning tools and techniques.* Morgan Kaufmann.

[22] Liyuan Xu, Jie He, Shihong Duan, Xibin Wu, and Qin Wang. 2016. Comparison of machine learning algorithms for concentration detection and prediction of formaldehyde based on electronic nose. *Sensor Review* 36, 2 (2016), 207–216. https://doi.org/10.1108/SR-07-2015-0104 arXiv:https://doi.org/10.1108/SR-07-2015-0104

[23] K. Yordanova, S. Whitehouse, A. Paiement, M. Mirmehdi, T. Kirste, and I. Craddock. 2017. What's cooking and why? Behaviour recognition during unscripted cooking tasks for health monitoring. In *2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops).* 18–21. https://doi.org/10.1109/PERCOMW.2017.7917511

[24] Mi Zhang and Alexander A. Sawchuk. 2012. USC-HAD: A Daily Activity Dataset for Ubiquitous Activity Recognition Using Wearable Sensors. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*. ACM, New York, NY, USA, 1036–1043. https://doi.org/10.1145/2370216.2370438