

# 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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## 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.

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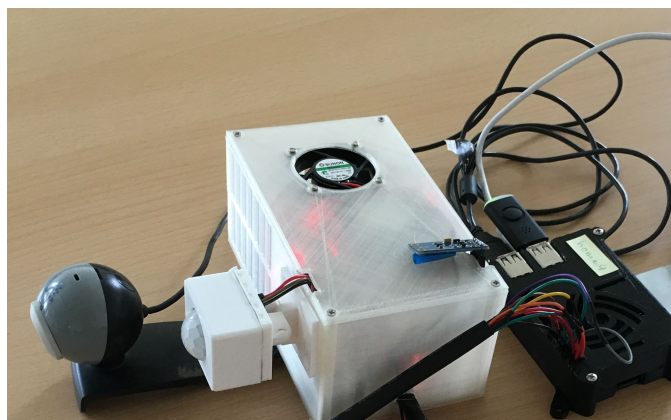
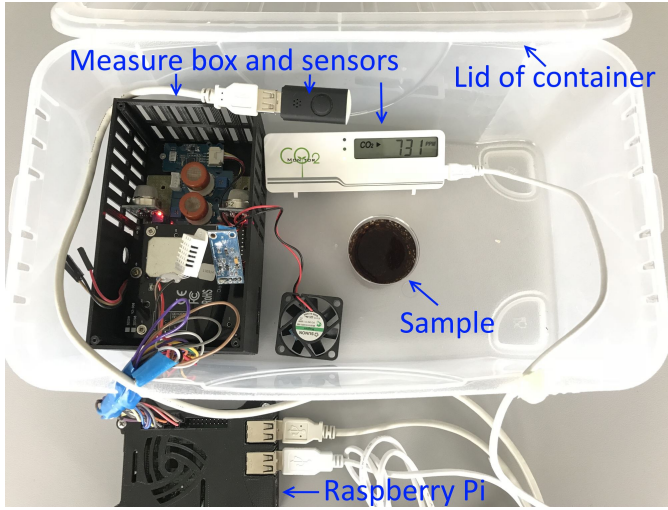


Figure 1: A complete measuring box of TheOdor prepared for long term recordings with a webcam and a motion sensor.

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 [25], for example, to assist in cooking tasks [24] 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.



**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

**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

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.

## 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

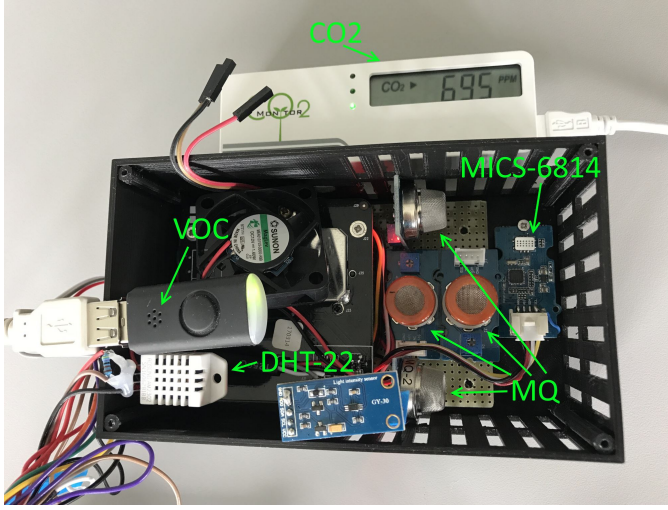


Figure 3: A measuring box of TheOdor with the sensor array.

VOC<sup>1</sup> 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<sup>2</sup> CO<sub>2</sub> 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<sup>3</sup>-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.

## 2.2 Software

The TheOdor software runs on the Raspberry Pi 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 Pi. 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 Pi 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.

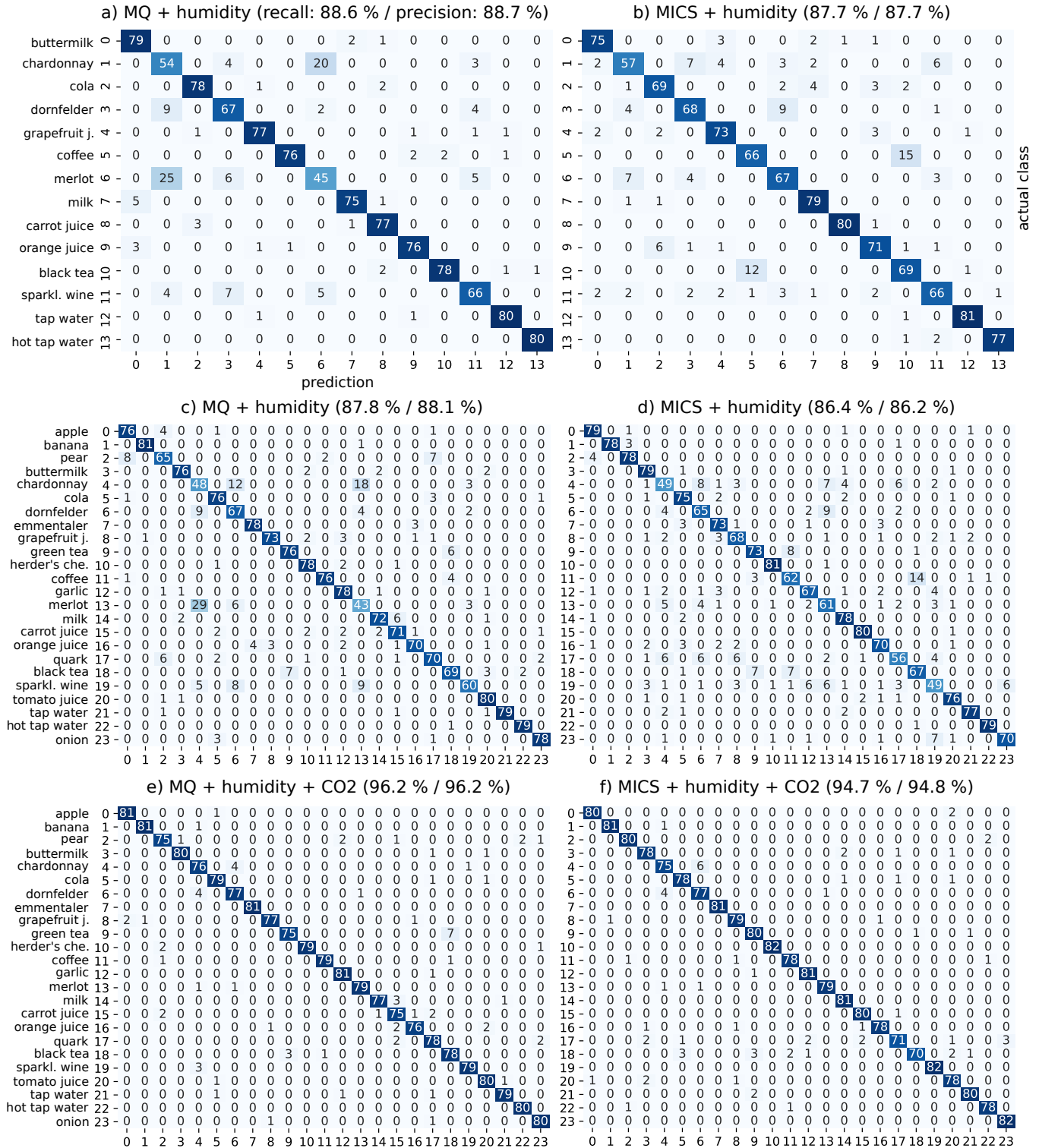
We proceeded with the collection of odor data as described in previous work. Each foodstuff sample was placed in the center of the container which was sealed with the lid afterward. Then, the measuring box of TheOdor in the container recorded sensor readings from the sensor array for ~180 seconds. For 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

<sup>1</sup>Volatile Organic Components

<sup>2</sup>Non-Dispersive Infrared

<sup>3</sup>Passive Infrared





**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
<b>black tea</b>	hot drink
<b>buttermilk</b>	dairy product
<b>carrot juice</b>	vegetable juice
<b>chardonnay</b>	white wine
<b>coffee</b>	hot drink
<b>cola</b>	soft drink with $CO_2$
dornfelder	red wine
emmenthaler	cheese
garlic	vegetable
grapefruit juice	fruit juice
green tea	hot drink
herder's cheese	cheese
<b>hot tap water</b> (no chlorine)	water
<b>merlot</b>	red wine
<b>milk</b>	dairy product
onion	vegetable
<b>orange juice</b>	fruit juice
pear	fruit
quark	dairy product
<b>sparkling wine</b>	white wine with $CO_2$
<b>tap water</b> (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 + humidity: recall: 87.8 % / precision: 88.1 %; MICS + humidity: 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



- [14] Alex Mihailidis, Jennifer N. Boger, Tammy Craig, and Jesse Hoey. 2008. The COACH prompting system to assist older adults with dementia through hand-washing: 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. *Analisis* 28, 3 (2000), 207–215. <https://doi.org/10.1051/analisis: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] Peng Xu, Kai Song, Xiaodong Xia, Yinsheng Chen, Qi Wang, and Guo Wei. 2017. Temperature and Humidity Compensation for MOS Gas Sensor Based on Random Forests. In *Intelligent Computing, Networked Control, and Their Engineering Applications*. Springer, 135–145.
- [24] 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>
- [25] 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>