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Monitoring Street Infrastructures with Artificial Intelligence

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1 ABSTRACT

Sensor-based IoT data is enhancing information gathering methods for urban planning in many ways and, due to the growing data pool provided by these sensors, more and more cities and municipalities are consequently putting the use of artificial intelligence-based (AI) methods on their agenda. One area of urban planning that will benefit significantly from the new possibilities enabled by AI is that of infrastructure monitoring. As the topic of the investment backlog of German road infrastructures increasingly pushes into public discourse, many potential areas for application of such a system are opening up. Given the fact that a large part of the German road infrastructure was planned and built several decades ago, and considering that the traffic volume has increased tremendously since then, the urgency in the development of improved maintenance methods is evident: Today's solutions for infrastructure monitoring are either too labor-intensive, too resource-intensive or too inflexible for the scenario at hand. However, a promising avenue for further research opened up through the advent of mobile communication devices, such as smartphones, in combination with artificial intelligence approaches. This paper describes the methodology applied in the ongoing research project DatEnKoSt, in which these comparatively cheap and sensor-laden devices are used to realize low-cost acquisition methods: Mounting the smartphone in a vehicle, a multi-sensor datastream can be recorded, including, for instance, accelerometer data, GPS coordinates, image or even audio data. From the datastream, features correlated with the road condition can then be extracted, e.g., image processing methods may extract individual cracks from the image data, signal processing can aid analysis of the accelerometer data to determine strength of vibrations, etc.. Using supervised learning methods, these features may be mapped to standardized profiles of the current state of the infrastructure. Even more, predictive methods can, in addition to a mere monitoring of the current state of the infrastructure, enable new ways to provide more precise forecasts and eventually, leveraging optimization algorithms, automatically derive the right maintenance measures for each given situation. The municipal preservation of traffic routes becomes more efficient and sustainable. The methodology enables the potential for further use in the light of real-time as well as predictive road infrastructure monitoring such as winter road services.

Keywords: Sensor-Based, Predictive Maintenance, Street Conditions, Infrastructure Monitoring, Artificial Intelligence

2 THEORETICAL FRAMEWORK

In recent years, the discussion regarding the investment backlog in German road infrastructure has increasingly entered the public discourse, mainly because large parts of Germany's road infrastructure were planned and built several decades ago. Since then, general traffic volume increased steadily, with heavy goods traffic in particular causing disproportionate damage to the roads due to heavy vehicle weight (Bundesanstalt für Straßenwesen, 2017). This raises the question, how to detect and monitor these damages as well as predict potential issues in the context of small public budgets. For instance, if fine cracks in the asphalt aren't recognized as road deficiencies in the same way potholes are, they can cause just as much damage to vehicles. In general, two methods of collecting street-related data can be distinguished: A sensor-based approach –which our project is focussing on – and an approach based on user-generated-content (UGC), where people manually detect and report issues, as can be seen in various projects in recent years (FixMyStreet, 2015; Rock Solid, 2019). In order to understand the need for new approaches to monitoring and maintenance, it is worth taking a look at the recording practice currently in use. At the state level the condition of the classified road network is determined at regular intervals according to the precise guidelines for condition recording and assessment (Bundesanstalt für Straßenwesen, 2020) although very few local authorities can resort to such methods due to the high costs involved. Instead, the condition is usually determined in relation to the problem, but only retrospectively by specialist personnel, who record the problem areas on a sample basis and in a partially analogous manner (often still with pen and paper). Such measurements are subjective by nature, which leads to a suboptimal data basis for decisions on and prioritisation of investment measures.

The automatic, sensor-based approach can be further distinguished. One option is a 'dedicated' approach, in which purpose-built vehicles are equipped with sensors (StreetScan, 2017; Ramboll, 2019; Vaisala, 2020) which are primarily configurated and maintained by service providers. In the second approach, which has an auxiliary character, ordinary vehicles are equipped with supplementary sensor technologies. Hence, no purpose-built vehicles are needed and the data-gathering is done by enhancing exisiting vehicles with easily attachable, consumer-market mobile sensor technologies (such as smartphone e.g.). DatEnKoSt, presented in this article, and other projects utilizing this second approach exemplify the flexibility and ease of implementation of such an approach (MIT Senseable City Lab, 2018; NewUrbanMechanics, 2019; RoadBotics, 2019; Vialytics, 2020). The reason lies in the fact, that we wanted to design a light-weight approach which can be adapted as easily as possible by the communities and tailored to the respective challenges at hand. In addition, due to limited resources, only prolonged investigation cycles are feasible for most communities, which makes an actually interesting real-time observation impossible. Those responsible therefore lack a tool, which, in contrast to classic, standardised procedures, proactively guarantees a more cost-effective and yet qualitatively adequate status assessment of road infrastructures. These new technological and methodological possibilities include mobile communication devices (IoT approach) for sensor data acquisition, which can continuously collect real-time data and use AI for evaluation.

3 METHODOLOGY

A suitable solution for monitoring and maintenance of streets for municipalities has to be affordable, simple and flexible to use. In this section, we first discuss why and how a combination of smartphones and AI algorithms can meet these requirements (Sec. 3.1) before giving a general overview of the approach (Sec. 3.2) and describing its major steps (Sec. 3.3-3.4).

3.1 Motivation

Public authorities need precise and as up-to-date as possible data in order to maintain their roads but they are struggling to find appropriate, cost-sensitive ways to gather these data. Existing, standardized forms of data acquisiton are offered by specialized companies but are too expensive for most municipalities: The average price per kilometer can reach up to €150. For an average German town that would mean hundreds of thousands of euros in order to obtain the data for their street network. In contrast, the methodology we put forward in this paper would allow for data gathering of comparable magnitude for a fraction of this sum. There are two main reasons why a standardized monitoring according to precise guidelines such as the German ZEB are so expensive. The first reason is that highly specialized measuring hardware is being used. Typically, measurement vehicles are equipped with multiple precise sensors: Multiple laserscanners, to measure the evenness of a road both in the driving and ortohogonal direction, several cameras to take images of potential cracks and potholes, a customized construct consisting of a slanted wheel and more sensors to determine the grip of the road. As an example, the measurement system S.T.I.E.R. by the German company Lehmann + Partner specialized in ZEB data acquisitions has an estimated value of roughly one million euros (Renninger, 2018). The second reason is the high manual effort for processing the acquired data. In particular, surface damages such as cracks have to be annotated for many thousands of photographs.

Interestingly, both reasons, the necessity of expensive sensors and the high manual effort for data labeling, can be adressed using AI, as examples from other domains than urban planning show. Regarding the necessity of expensive sensors to obtain measurements at a sufficient level of quality, the example of smartphone cameras demonstrates that intelligent processing methods can, to a large extent, compensate for the deficiencies of the comparatively cheap hardware used. Despite physical limitations due to the small size of their image sensor, such as noise, or of their lenses, such as color fringes, smartphone cameras can nowadays compete with medium-priced dedicated digital cameras. E.g., de-noising methods help to reduce visible noise, other image processing methods remove color fringes or distortion, and even image contrast and exposure can be optimized automatically using AI-based methods (Draa and Bouaziz, 2014). AI can also help when it comes to reducing manual data labeling effort. Supervised learning methods can learn how to label various types of data automatically based on a set of training data containing exemplars. One popular example is object detection, that is, recognizing relevant objects in images and assigning them to a defined class, such as “car”, “dog” or “building”. This task, which has applications in image search or surveillance scenarios, can be solved with accuracy levels of up to 90% using Deep Learning approaches (Zhao et al., 2019).

3.2 Overview

The insights outlined in the preceding paragraph motivate the idea to transfer the same approach to the domain of infrastructure monitoring, leveraging intelligent processing methods to allow for cheaper monitoring equipment and reduced manual effort.

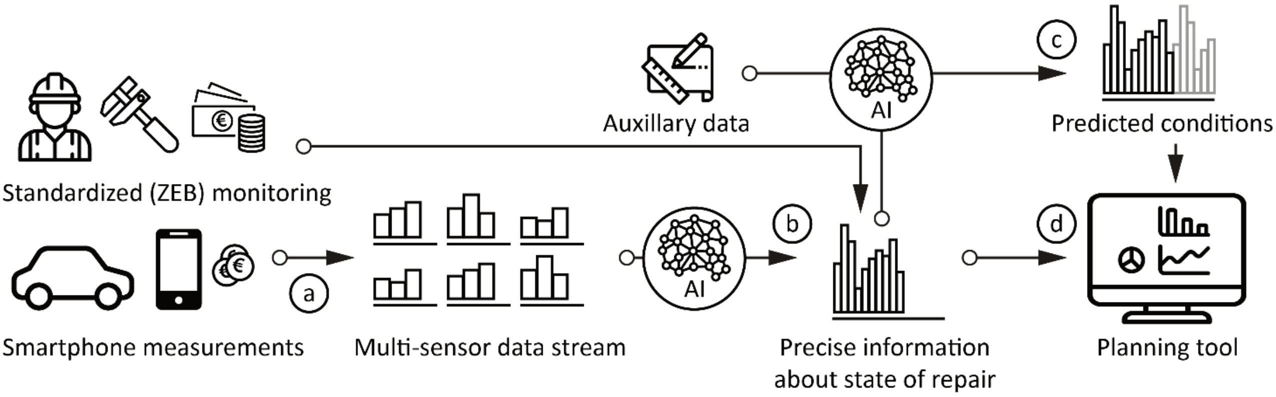

Fig. 1: Overview of the proposed methodology and the data flow.

The core of the proposed methodology (Fig. 1) is the use of smartphones as relatively cheap but still versatile measurement hardware. Modern smartphones are equipped with a wide range of different sensors: multiple image sensors, accelerometers, gyroscope sensors, microphones and GPS receivers, to just mention the most common ones. This means that, mounting such a device in a vehicle and driving along a road, a diverse stream of multi-sensor data can be recorded (Fig. 1, a). In doing so, the respective condition of a road is implicitly reflected in the recorded data: The accelerometer will record stronger vibrations for uneven or cracked roads than for freshly paved ones. When orienting the smartphone so that its camera is pointing towards the road, individual potholes and surface problems will become visible in the recorded photographs. To derive the actual road condition from the multi-sensor data stream, this mapping of road quality and recorded data has to be “inverted” for which supervised learning may be used to generalize from existing, standardized quality data for a set of roads (Fig. 1, b). This step will be detailed in the following section. Estimating the current state of the road network in this way already greatly lowers the monitoring costs. However, AI can additionally be used to assist in the decision for resulting maintenance tasks, based on the monitoring data. Combining sequence prediction and optimization approaches, the expected future condition can be estimated (Fig. 1, c) and automated suggestions for the next maintenance tasks to be undertaken can be generated (Sec. 3.4). Finally, the integration of the aforementioned AI components into a planning tool for municipal administrations (Fig. 1, d) is planned. The tool will allow the administrative staff to access recent monitoring results and predictive functions in an easy to use way.

3.3 Prediction of Road Condition from Sensor Data

The aim of this step is to map data recorded while driving along a particular street or road to a standardized quality profile as accurately as possible. On an abstract level, this corresponds to a supervised learning problem: Given smartphone sensor data and precise monitoring data – within the scope of this paper, we will focus on data obtained according to the ZEB standards – the goal is to train a machine learning method to predict the latter from the former. A model trained in this way takes the smartphone data recorded for a road segment as input and returns an estimate of important quantitites such as the evenness, the cracking and others.

Achieving this requires three steps: First, a labeled dataset has to be constructed, consisting of both smartphone-recorded data (Fig. 2) and ground truth quality profiles for a set of street/road segments and ideally recorded at the same point in time or with small temporal delay. The second step involves the extraction of a set of descriptive features from the raw sensor data recorded for each segment. Different features can be extracted from different types of sensor data. The third step is then to train a supervised model to finally map the extracted features to the desired quality output based on the labeled dataset.

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Fig. 2: Smartphones are mounted on the windshields of vehicles and used as mobile sensor units. Image credit: Cyface GmbH.

3.3.1 Building a Dataset

Fig. 3: Exemplary road segments from a ZEB acquisition. Good segments are colored green, problematic ones range from yellow to red (black means no measurement was possible). The left image shows cracking while the right one depicts evenness. (Own Source)

The foundation for any machine learning application is a dataset. In our scenario, the dataset will consist of sensor data measured by using a smartphone on one hand and corresponding ground truth ZEB data for the same set of roads on the other hand. ZEB measurements are defined with respect to segments (cf. Fig. 3). These segments have a length of either 100 meters when measured for a road (outside of town) or 20 meters, respectively, when measured for a street (inside of a town). The location of each segment is uniquely defined by the two adjacent nodes (“Netzknoten”) of the road network that it is located in between of and an offset in meters that specifies the driving distance from one of the nodes. The smartphone sensor data is recorded over the course of multiple sessions, alongside a GPS track. Using a map matching algorithm (Karich and Schröder, 2014), data can be first assigned to the correct street or road it has been recorded on and then be split up according to the defined segments it covers. For the corresponding standardized data, we draw from two sources: Data for roads has to be acquired on the federal state level by law, usually in intervals of four years. In Germany, this data is publicly available upon request and can be used as is. As outlined in Section 2, the situation is different for most German communities which cannot afford the same measurements. Nevertheless, it is crucial to also include intracity streets in the dataset as their characteristics can vary from those of rural roads and a machine learning model only trained on country roads may not generalize well for communal roads, which our system is mainly intended for. Within the scope of our project we therefore commission a ZEB acquisition for a set of streets to obtain the necessary data.

3.3.2 Feature Extraction from Multi-Sensor Data

In the feature extraction step, a number of meaningful quantities is derived from the original raw sensor inputs. The idea behind this is to reduce the necessary complexity and amount of training data for the subsequent supervised model (Sec. 3.3.2) by providing it with data that has a more direct relation to the different quantities to be predicted than the unprocessed sensor data. While a prediction of actual ZEB results from multi-sensor data has not been done before, different researchers have proposed heuristical methods to derive rough estimates of "street quality" usually based on the data of only a single type of sensor at a time (Chugh, Bansal and Sofat, 2014). The processing steps proposed in these works can serve as building blocks to form a robust set of initial features. We will detail some frequently chosen types of features in the following, giving examples for accelerometer and image data.

Concerning accelerometer data, common simple features are the minimal or maximal sensor values recorded for a segment (Allouch et al., 2017), various statistical moments (mean, variance, …) of those values (Rajamohan, Gannu and Rajan, 2015) or features automatically extracted from the frequency spectrum, for example using correlation-based feature selection, of the sensor data which can be obtained using the fast fourier transform (Allouch et al., 2017).

Regarding image data, one type of approach that can be used for feature extraction in the context of our proposed system are crack detection methods. Given an input image, these methods highlight the parts of the image corresponding to potentially different types of cracks. Examples are the works of Mokhtari (2015), Quintana, Torres and Menéndez (2015) and Kim and Cho (2018). The output of these approaches can be easily translated back into numerical features for the final supervised learning step, e.g. using the percentage of (road surface) pixels in the image corresponding to cracks. This is not very different from the actual ZEB standards, where a similar estimate of the percentage of the surface suffering from cracks is determined, albeit in a manual way.

3.3.3 Supervised Learning

Supervised learning is a certain type of machine learning setting in which the task is to learn a mapping from input to output data where the mapping is not given explicitly but only implicitly in the form of a set of sample pairs of inputs and corresponding outputs, respectively (Russell and Norvig, 2016). In our case, the input data consists of the features extracted for the road segments in the dataset (Sec. 3.3.1) which in turn have been computed based on the original sensor measurements, the outputs are the corresponding standardized quantifications of the road's condition measured according to the ZEB guidelines. The wide range of possible supervised learning algorithms that may be used in this step include, among others, artificial-neural networks, decision trees or support vector machines.

3.4 AI-based Maintenance Support

Besides reducing the costs for a more objective and detailed data acquisition that captures the current state of repair of a community's streets as described in the preceding section, artificial intelligence methods can in a second step also facilitate maintenance planning. Sequence prediction methods can be trained using snapshots of the state at different points in time to generate forecasts of future degradation. Currently, maintenance planning on the federal state level is mainly based on heuristics that try to model these developments. A data-based approach using supervised learning can potentially offer more precise predictions than a heuristical model. In particular, additional knowledge such as the traffic volume over time, the type of pavement used or the speed limit can be taken into account in the machine learning process in a flexible way and enhance the forecast, even if their effects would be hard to capture using a hand-crafted model. On the technical side, several algorithms for sequence prediction have regained attention recently and will be evaluated within our project. Especially recurrent neural networks (Hochreiter and Schmidhuber, 1997) have proven to be valuable for difficult sequence prediction tasks like translation (Sutskever, Vinyals and Le, 2014) or image captioning (Vinyals et al., 2015). When combined with an optimization approach like a genetic algorithm (Goldberg and Holland, 1988), these predictive methods can, furthermore, be valuable for generating automated suggestions for maintenance planning to assist municipal planners.

4 FIRST RESULTS

In this section we present some of the findings from our still ongoing project.

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4.1 Image Analysis

Fig. 4: Automated ROI detection. We combine information from line detection using the Hough transform (left) and a semantic scene segmentation approach based on Deep Learning that is able to detect the parts of the image pertaining to the street or road (middle) to automatically determine a quadrilateral region of interest for each image. (Own source)

The image data recorded using the smartphone is one of the most valuable sources for the extraction of meaningful features that can then be relevant for the actual prediction of the condition. The first problem that has to be tackled working with the images is a suitable pre-processing. While the images used for standardized ZEB measurements are taken using multiple calibrated cameras mounted outside of the car so the camera viewing direction is orthogonal to the surface of a road and images show nothing but said surface, the situation is very different using a smartphone mounted in the windshield of a car for data acquisiton. Only a small portion of the image, the one showing the street or road surface of the current driving lane, is actually relevant for the feature extraction. To automatically detect this region of interest (ROI), we combine a line detection algorithm based on the Hough transform (Matas, Galambos and Kittler, 2000) (Fig. 4, left column) with a Deep Learning-based scene segmentation approach (Fig. 4, second column) (Zhou et al., 2018). While the line detection step enables us to identify the boundaries of the lane (lane markings or curbs, Fig. 4, middle column), and therefore the left and right delimitations of the ROI, the segmentation allows to choose the top and bottom ones such that we neither include portions of the dashboard nor of things located above the street's "horizon". This works quite well in most of the typical scenarios, both inside (Fig. 4, first row) and outside of a city (Fig. 4, second row). Current limitations become apparent in situations when there are no prominent lines that can be clearly attributed to lane markings or curbs (Fig. 4, last row), e.g. at crossroads or in turns. The computed ROIs for three sample scenarios are shown in the rightmost column of Fig. 4.

After the initial ROI detection, meaningful features for the supervised learning step have to be extracted. One approach to this is to use deep neural networks trained to detect the cracked regions within the cropped ROIs to determine the share of the road surface that is cracked. In our initial experiments we compared two existing methods: U-Net, a deep neural network which is able to produce dense segmentations of an object category of interest such as cracks (Ronneberger, Fischer and Brox, 2015) and a second approach which performs a patch-wise classification of cracked vs. non-cracked regions (Cha, Choi and Büyüköztürk, 2017). Exemplary results for a sample image are shown in Fig. 5. Both approaches can identify many of the present cracks and allow to estimate the relative area of the cracked surface.

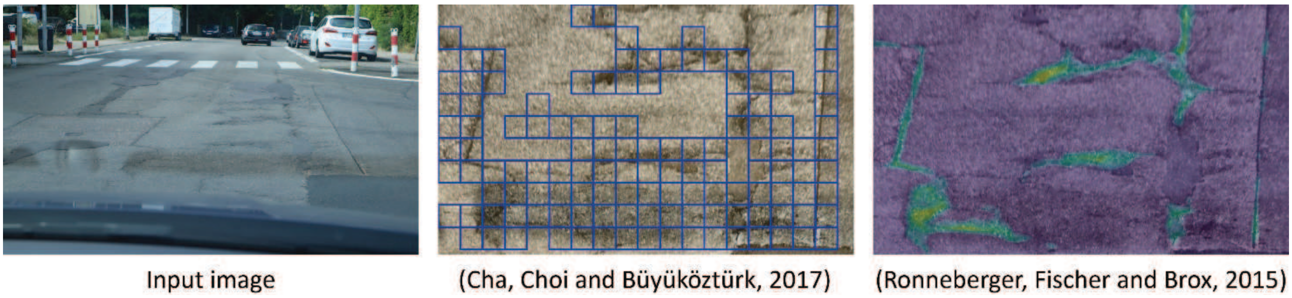

Fig. 5: Detection of cracks in the street surface. The left column shows the original input image from which the ROI is cropped using the described approach and then fed into two crack detection methods (second and third column). From these outputs, numerical features for the state of repair prediction can be derived. (Own source)

4.2 Accelerometer Data Analysis

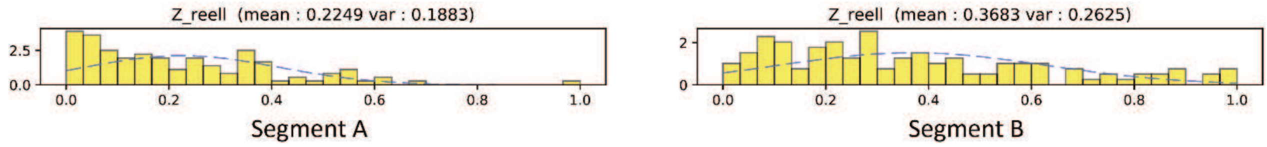

Fig. 5: Acceleration values measured for two 10m street segments together with fitted normal distributions. (Own source)

A second important type of sensor data is that recorded by the smartphone's accelerometer. Several researchers in the past have proposed to analyze accelerometer data to classify the quality of a street. Notable examples include the Roadsense (Allouch et al., 2017) and Maargha (Rajamohan, Gannu and Rajan, 2015) systems which both assign a coarse quality label to street segments. Another way to approach the monitoring problem is to try to detect individual anomalies such as potholes from the data (Silva et al., 2018). Our problem setting differs in that we follow a supervised learning approach that tries to estimate the values of different quality metrics as if they had been measured using a standardized approach. We thus resort to the features proposed in the aforementioned papers but rather use them as input to the final classification step rather than as immediate output of the monitoring system. One of those features is shown in Fig. 5, the variance of a normal distribution fitted to the acceleration values (measured in the direction orthogonal to the street's surface).

5 FURTHER FIELDS OF RESEARCH

The described approach offers a wide variety of potential use cases for communities and public authorities in general. Besides monitoring road conditions in various time intervalls as well as qualitive analysis regarding the asphalt conditions (detection of cracks, uplifts etc.) the project settings could also be applied to analyzing road markings and signages. This involves short term signages such as special road markings for constructions sites as well as permanent road limits and markings. Especially in the light of self-driving cars, the quality of these mentioned road markings will be crucial.

A more institutionalised use of mobile sensors in the future is desirable, as general quality and availability of data, especially real-time data, would be greatly improved. Modern cars itself contain a huge amount of sensors (an average AUDI contains 4000 various sensors for instance), and they can collect internal and external data. The potential to make use of this data for planning purposes is tremendous and very promising for research (Massaro et al., 2017). Although in addition to the discussed approach, the given example of DatEnKost will use artifial intelligence for predictive purposes as well. From this perspective, it is not about the current status of roads, instead the aim will be to predict cracks in the road (or other traffic influencing issues) in the future based on current data. Besides this, the spatio-temporal perspective of the measurements is crucial in general. While data provided by current methods is highly dependent on measurement cycles, this approach would also allow a consistent, real-time map-based view of road conditions. The implementation of such a system could either be done by equipping community-owned vehicles or by employing volunteers. A combined solution of urban fleet vehicles, which regularly run test intervals during their regular operation, in combination with a crowdsourcing approach, i.e. data acquisition by private individuals, represents the most promising configuration. A broader database for instance allows for insights, not only into structural, but also temporary changes in road condition e.g. due to weather. This incorporates weather damage, winter services, wet leaves, etc.. The potential of this approach is shown in a study by MIT,

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which found in a comparable setting that even a small number of vehicles can be sufficient to cover a large part of the urban network (O'Keeffe et al., 2019). The approach used to detect road damage can also be easily transferred to thematically similar problem areas, for example to report temporary danger spots. This applies, for example, to temporary road surface impairments, such as damp foliage in autumn, or the inspection of tram markings. In this context, it would also be possible to equip the municipal winter road clearance services accordingly in order to detect potential danger spots and ensure that the use of road salt is demand-driven. Depending on the application requirements, this technical solution can be integrated into private vehicles or into vehicles of public authorities and thus represent a multitude of potential thematic fields of application in the context of 'predictive maintenance'. The multi-functionality of the "sensor smartphone" allows the further integration of other sensor funcitonalities in order to gather additional relevant data such as environmental data, driving times, parking situation, etc.

Though, this flexible and adaptive approach also comes with potential risks. From a technological point of view, the respective field is still novel and innovative and thus needs further pratical elaboration in order to create reliable and profound data. Besides the need for field studies regarding the data gathering methods, processing extremely large amounts of data has to be institutionalized. In addition, respective to the given use case, the quality of the data is to be guaranteed, which will be especially relevant in crucial aspects such as bad weather and lighting conditions. There are also legal questions to be answered, for example in regards to image recordings and related to that, the social acceptance is also to be considererd, as, especially in Germany, the population is highly sceptical in regards to data protection and image rights. And if data gathering will be done with a UGC-approach, the mentioned obstacles have to be taken in consideration in order to convince citizens to particiapte.

6 CONCLUSION

Due to the fact, that the thereotical promises will have to be verified in further project work, the general practicability and reliability of the project approach have yet to be proven. These demands will be caused by difficult to foresee environmental influences as well as technical constraints. Will the smartphone-based approach be adapted only on designated cars for instance, the range of potential influencing factors could be reduced and controlled. In this approach, specialized road analysis won't be replaced, because their demand especially in the light of high quality of data and reliability in accordance with LIDAR-measurements will persist in the future for detailed quantitative analysis. Though, for an adhoc qualitative analysis, the described methdod will enable multiple options for communities. A further benefit is the potential integration of UGC. Though, this use comes with the given general uncertainity regarding the "quality" of sensor installation in the car which has to taken into consideration. The findings of the project will demonstrate that the innovative combination of light-weight sensor technology and corresponding AI components for cities and municipalities is a universally applicable toolkit, the possible use of which makes a positive contribution to the fields of work of the municipal authorities. As shown in the paper, the approach provides the chance for public authorities to install a lightweight system based on a sensor-application which is easily installable. By developing adjacent services based on this toolkit, communities can offer other cost-effective services and and save personnel and organizational costs in the long run. With the interoperable design, the integration of other sensor connected via smartphone, the flexibility also for other potential use cases is given. Thus, the objective of a demand-oriented road maintenance system for communities with frequent update possibilities becomes achievable.

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