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Advancing Sustainable Mobility Infrastructure and Environment Through Automated Low Threshold Analyzation of Road and Cycling Path Surfaces

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This paper presents a novel application of digital ecosystems in the realm of sustainable mobility - the Automatic Bike Path Analysis (ABPA) system. ABPA utilizes machine learning techniques and smartphone-generated video data to automatically assess the condition of bike paths, aiming to enhance the safety and comfort of cyclists. By leveraging the concept of digital ecosystems, ABPA seamlessly integrates data collection, analysis, and visualization, offering a holistic approach towards real time infrastructure maintenance. This research highlights the potential of digital ecosystems to drive sustainable transformations and enhance the well-being of cyclists and sustainable mobility. The findings contribute to the growing body of knowledge in the intersection of digital technologies making a significant impact on fostering greener and more resilient mobility.

Keywords: AI, Machine Learning, Image recognition, CNN, Automatic detection, Conditions analysis, Bicycle paths, Surface condition

1. INTRODUCTION

The research project Automatic Bike Path Analysis (ABPA) is being carried out by Furtwangen University together with Outdooractive AG and Offenburg University. As part of the project, data of the condition of cycle paths is collected and analyzed using a crowdsourcing approach. This determined data is used to improve the level of detail of digital cycling maps. In addition, defects and problem areas are detected along the way and forwarded to the responsible authorities. This creates the opportunity to act quickly and increase safety for cyclists.

The aim of the project is to research how an image analysis method for classification of cycle paths can be developed and how this can be used to improve the cycle path infrastructure. Various methods and technologies are used that allow for automatic and efficient processing of large amounts of image data to obtain information about surface quality. The data recording is based on a low-threshold crowdsourcing approach in which smartphones serve as recording devices. The recorded data is analyzed using a three-stage AI analysis process. Through the use of data interfaces and seamless integration into digital map platforms, the ABPA system enables the visualization of cycle path conditions and improved options for maintenance measures.

Through the use of data interfaces and seamless integration into digital map platforms, the ABPA system facilitates the visualisation of bikeway conditions and maintenance needs on digital maps. Implementing efficient communication

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protocols, municipalities and public works authorities can also receive automatic, real-time notifications so that they can promptly address critical road anomalies and ensure the safety and comfort of cyclists.

2. DIGITAL CYCLING INFRASTRUCTURE

To date, there is no automated and continuous real-time analysis of cycle paths in Germany. The condition of the paths is currently determined by reports or targeted assessments. The German Cyclists' Club (ADFC), for example, offers a way for cyclists to report the condition of cycle paths. However, this is not done automatically. Cyclists submit reports via an online platform, such as a missing sign, a pothole or other ideas for improving the cycle paths [1].

Another method is the measurement and analysis by means of a special measuring vehicle, which drives along specific cycle paths [2]. With this approach, a continuous and efficient analysis of the condition and state of the cycle paths is not possible, as the measuring vehicle is not constantly in use and also incurs high costs.

Against the background of 426 cycling accident fatalities alone in Germany in 2020, not only scenic beauty and the simplest and most attractive routing possible are important for the planning and implementation of cycling tours in the field of active recreation and tourism, but above all aspects of road safety are highly relevant. In addition to structural measures that contribute to increasing the safety of cycle path infrastructures in cities and rural regions, the collection, provision and use of cycle path network data is also becoming increasingly important in the course of the digital transformation in order to increase safety in cycling and also to promote cycling as a sustainable means of transport for the mobility transition. [3]

3. STATE OF THE ART IN CYCLING CATH SURFACE DETECTION

The topic "surface condition of paths used by bicycles" is being pursued with very different approaches. An Austrian research team uses a bicycle specially made for data recording to record environmental and road surface data while cycling. Data from different sensor sources, such as lidar or position sensors, are recorded and then analysed using different algorithms. The research team also investigated data recording using smartphones. The acceleration sensor of a smartphone attached to the bicycle was queried. [4]

The BikeBox (BIBO) project of the Institute for Geoinformatics at the University of Münster is concerned with advancing urbanisation, urban mobility and eco-friendly mobility. For this purpose, students and young scientists developed a SenseBox, a microcomputer with sensors, for mobile use on bicycles. As a measuring instrument, BIBO is to collect data on the traffic routes used daily by countless cyclists. The data collected include temperature, light intensity and fine dust pollution. The results and findings will be used to find starting points that can help improve urban and environmentally friendly mobility by bicycle. [5]

Lee et. al. used an FCN-based model and a CNN-based model for an AI-based detection of potholes and cracks on roads. 9600 images were used as the training dataset. When the test dataset was input to the FCN-based crack detection model with 12 layers, an F1 value of 0.85 was obtained.

However, the crack images used in this study did not allow classification of crack types, and the FCN-based road surface crack detection model was limited to indicating the damaged area. The team is working on a more powerful model. [6]

4. ABPA SYSTEM

4.1 Method

The ABPA-System is composed of several components, including a smartphone app, a cloud-based control system and various microservices for data storage, analysis, and provisioning. To generate data, smartphones are attached to

the handlebars of test users' bikes and video data is recorded. These recordings are centrally stored and subsequently analyzed using AI.

4.1.1 Data Management

The project's data management covers the aspects of data model, generation, storage, access and safety. At Furtwangen University, the data generated by smartphones is stored on a central server. The data model is based on two entities: Records and LocationData. These two elements contain a mixture of structured meta and geodata that are associated with recorded, unstructured video data. This enables effective analysis and utilization of the collected data.

4.1.2 Data Access

RESTful web API server based on the Node.js framework Express is used. This server enables not only the storage, but also the distribution of data by means of communication via different requests. In doing so, it connects to an artificial intelligence (ABPA-AI) system and transfers the necessary data to it, such as geodata, video files and other information received by means of a special smartphone app. This data is finally inserted into a SQL table to provide a complete database for the ABPA-AI.

Security is the focus of the Express Server's work. To ensure that only authorized users have access to the data, authentication is required. For this, a JSON Web Token (JWT) is used, which is an open standard, and provides an easy way to authenticate and transfer information about a user.

The structured data resides on a central server within an SQL database, the architecture of which is depicted in the Entity- Relationship (ER) Diagram in Figure 1. This data is accessed and retrieved through SQL queries. The unstructured data - the video files - have been given a lot of attention. These are small in numbers, in comparison to the records and location data, but individual videos have high data volumes. Some videos quickly reach several gigabytes, many videos

Figure 1 Smartphone attached to handlebars with recording App

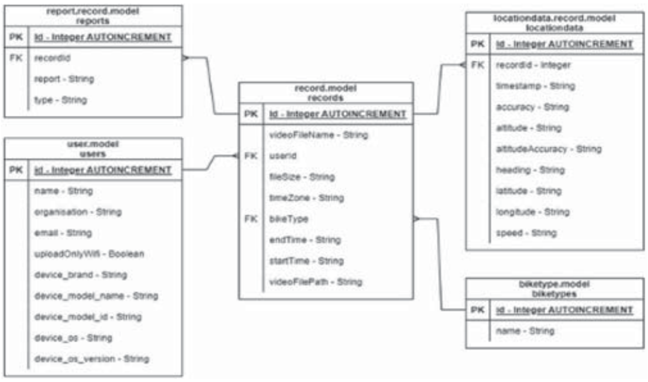

Figure 2 ER-Diagram of the SQL Database.

together already terabytes, which is why a highly scalable solution for the storage is necessary. Currently, the videos are stored on a dedicated dynamic server, which we will refer to as the NAS (Network Attached Storage).

In order to cope with the increasing amount of data from new videos in the future and at the same time to minimize the management effort and costs caused by the company's own server, the company is switching to an object store in the cloud. This data can be accessed via Internet communication technologies such as REST API.

In our journey towards system optimization, we are transitioning our Express server to NestJS and incorporating an additional image preprocessing service into our architecture. The server is going to send data to the image preprocessing microservice via a GraphQL API. The image preprocessing service turns the video files into images and crops out unwanted image elements among other processing steps. Once processed, the image information (file name and directory) is returned to the server. The server then initiates the ABPA-AI through another GraphQL API, which leads to the final classifications that are then stored in the SQL database.

This enhanced architecture will be demonstrated in an accompanying Module view (see Fig. 2.). Please note that, as this project is ongoing, the actual implementation may slightly differ from the proposed architecture. However, this description serves as a comprehensive framework that is guiding our development trajectory.

4.1.3 Data Collection

To successfully train an AI model, a comprehensive data foundation is essential. The better the processing of the data, the better the results achieved by the AI. In addition to locating and collecting training data, additional preprocessing steps are required to create a meaningful information base. Initially, the AI model used in the ABPA project was trained using open-source datasets, as no proprietary video data was available at that time. The utilization of open-source datasets allowed for the initiation of the training process and the development of the AI model without relying on proprietary resources.

Although open-source datasets may have certain limitations, they were complemented by additional processing and integration of self-generated image material to expand the data foundation and enable more specific classification. Alongside the advantages, there were also challenges to overcome. The

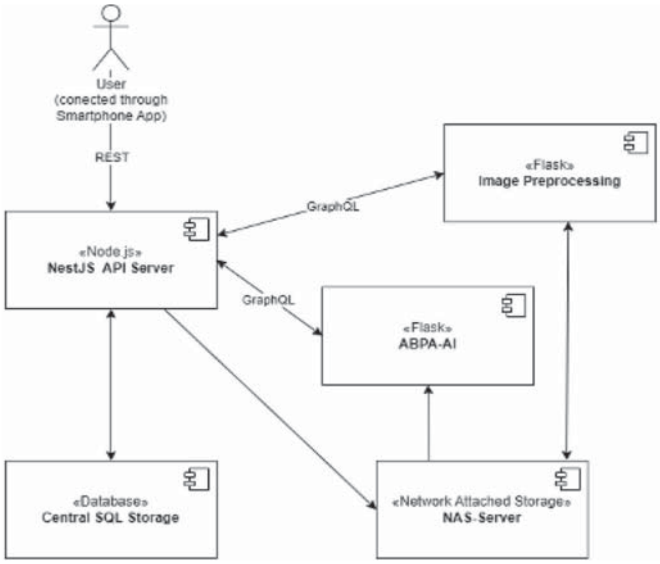

Figure 3 Model view of ABPA System.

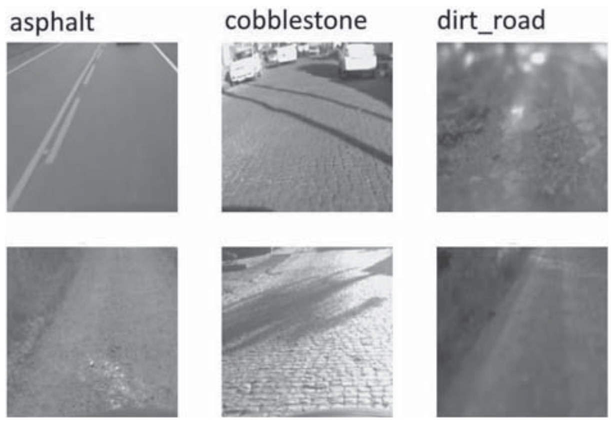

Figure 4 Training data example.

quality of the data could vary, necessitating careful verification and filtering to separate blurry or unreadable images and utilize only relevant and high-quality data for training.

The employed dataset includes the classification of three surface conditions: paved unpaved, or cobblestone surfaces. It should be noted that weather-related aspects, such as rain or dirty road surfaces, are not included in the dataset. Before the open-source datasets, which were available in the form of videos, could be read into the model, they had to be divided into individual frames. This allowed for the generation of approximately 90 thousand images for training. Subsequent processing steps include cropping, relevant image sections and filtering out blurry and unreadable images. Although these preprocessing measures reduced the training data by around 40 percent, this loss is compensated by the increasing quality of the data.

In addition, the data foundation was supplemented with video material recorded using the ABPA app, which is centrally stored. The development of the app facilitates the process of recording bicycle routes and transmitting them to a central system. The app is user-friendly and does not require any specific technological knowledge or skills. Utilizing smartphones as recording devices, users can capture videos of bicycle routes in a fast and uncomplicated manner. The videos are then automatically transmitted to the system, where they are subsequently analyzed using an algorithmic procedure. A key advantage of utilizing smartphones lies in the ability to collect a large amount of data through multiple route recordings, enabling improved training of the AI. The results in higher accuracy and reliability of the algorithmic procedure.

Thus, the training material consists of both open-source data and self-generated image material captured using the ABPA app. Incoming videos are continuously processed and incorporated into the existing data to achieve the largest possible data foundation. This also includes a broader classification framework, as weather-specific aspects are gradually incorporated into the training of the AI model in this step, allowing for a more specified classification.

Overall, the combination of open-source datasets and self- generated image material from the ABPA app proved to be an effective strategy for constructing an extensive and diverse data foundation for training our AI model. Despite the challenges and limitations associated with open-source datasets, careful preprocessing and the integration of additional data established a solid basis for improving the accuracy and reliability of our algorithm.

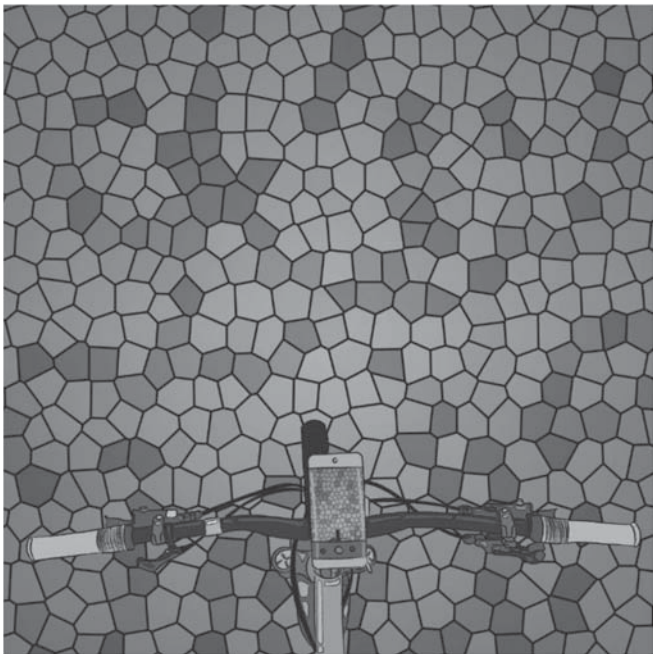

Figure 5 Surface type detection.

4.1.4 Multi-Stage Analysis

The ABPA projects features a pivotal component that involves an AI-based analysis procedure for capturing and evaluating information about bicycle routes, particularly pertaining the to their condition and surface quality. This information is analyzed and evaluated through a three-stage process, which encompasses the analysis of surface quality, condition, as well as additional features and characteristics, such as the analysis of road and path boundaries.

This process enables the collection of comprehensive and precise information about bicycle routes, which is of utmost significance for future decision-making and actions. Below, we describe each of the three stages in greater detail.

Stage 1: Surface type detection
In the first stage of the analysis procedure, recorded video data is used to detect and classify the surface of the bicycle route. Various visual features are examined to determine the surface characteristics, including texture, color, shading, and edges. Analyzing these features enables the classification of the surface into different categories. Ultimately, the different surfaces are categorized as either “paved”, “unpaved” or “cobblestone”. This allows for the determination of the underlying substrate of the bicycle routes. This stage utilizes AI-algorithms, such as convolutional neural networks (CNNs) and image processing techniques, to extract and analyze the visual features of the recorded video data.

Stage 2: Surface issue detection and condition reasoning
In this stage a comprehensive analysis of the condition of the roadway is conducted. The video data captured through the ABPA app is utilized to assess the current state of the bike path. The analysis focuses on potential problem areas that may compromise road safety, such as potholes, cracks, or other objects on the bike path. By identifying these issues, the ABPA project can contribute to improving road safety on bike paths by enabling responsible organizations and governmental agencies to quickly identify and address them. For the second stage, the SSD MobileNet V2 Object Detection Framework is employed. This framework provides high accuracy and efficiency in object detection. It is based on a Single-Shot Detector (SSD) approach, enabling rapid and precise object detection. By utilizing the framework, we can reliably identify potential problem areas on the bike paths, such as potholes or obstacles.

Stage 3: Surface characteristic detection
In the third and final stage, the captured data is examined for specific characteristics and properties of the subsurface. These properties may have an impact on the rideability and safety of the bike path. Examples of these properties include roadway width, the presence of physically separated bike lanes, barriers, or other structures. These properties are detected and labeled using AI applications. For this stage, we also employ the SSD MobileNet V2 Object Detection Framework. By utilizing this framework, we ensure reliable and fast detection of road characteristics such as bicycle lanes and barriers. This contributes to a comprehensive assessment of bicycle paths and enables targeted measures to enhance traffic safety and user-friendliness.

This work focuses on the development of the first stage of analysis in the project, which has already been completed. In this stage, the emphasis was on developing algorithms for the detection and classification of the road surface. Currently, the subsequent stages of the project are being addressed, including the examination of the road condition and the detection of surface characteristics. These two stages are still in the development phase, and as a result, final results are not yet available. Efforts are being made to develop algorithms and techniques using object detection to analyze the road condition and identify specific surface properties.

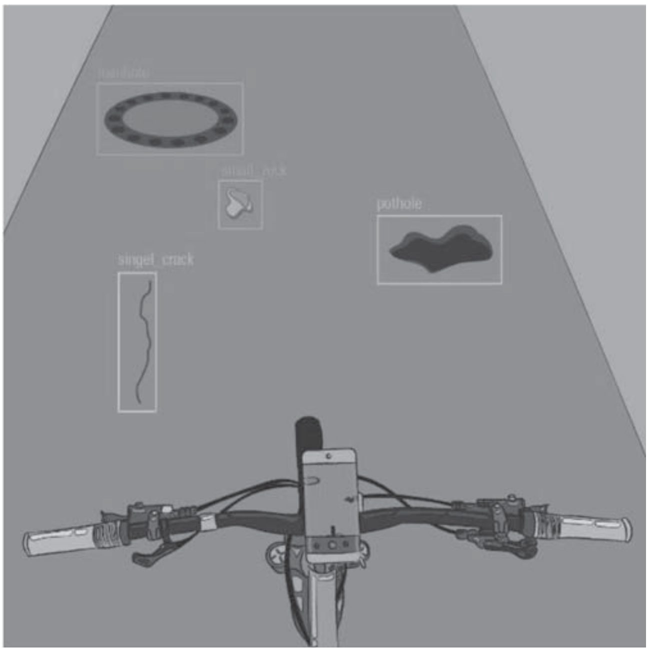

Figure 6 ABPA Object detection.

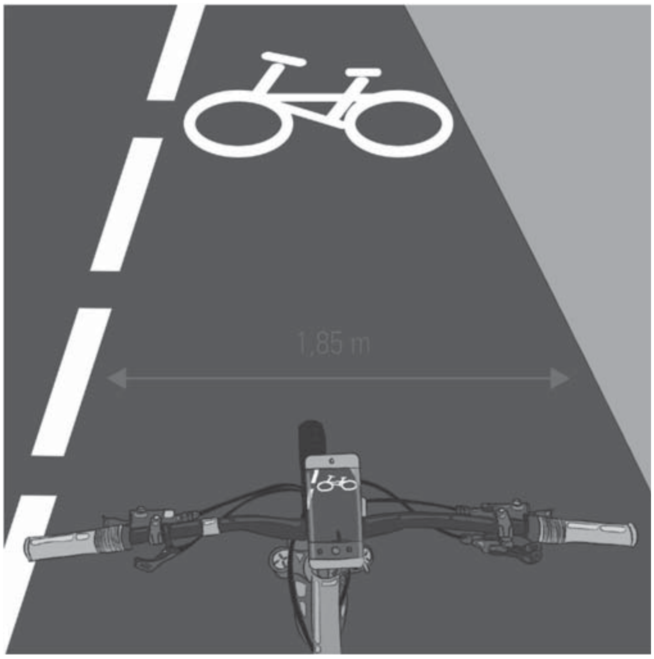

Figure 7 Surface characteristic detection.

4.1.5 Analysis Methods

An AI model has been trained which is capable of partitioning incoming video data into individual frames and reliably analyzing and evaluating the ground conditions and characteristics. In this process, classification is carried out into either paved or unpaved surfaces. For the analysis, a dedicated AI system consisting of powerful components was developed by the research team, which works up to 30 times faster than conventional computers during AI analyses.

The machine learning framework used in this process is TensorFlow, an open-source framework developed by Google for executing machine learning algorithms. By connecting a powerful GPU, as is the case in this project, training image classification models is significantly accelerated. Another significant advantage of using TensorFlow is the use of the open-source deep learning library Keras, which explicitly builds on TensorFlow and provides additional capabilities that simplify programming of neural networks.

Convolutional Neural Networks (CNNs) were utilized for the development of the proposed method, as they are well-suited for processing image and video data and have proven their effectiveness in applications of image recognition, computer vision, and machine learning. In a CNN, the training data is filtered as input through multiple layers of neurons, with certain processes performed on the data in each

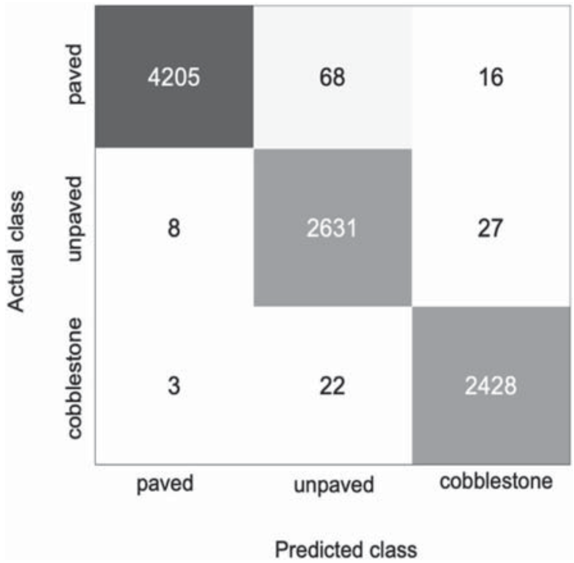

Figure 8 Results of the confusion matrix.

of the layers. The Convolutional Layers analyze the incoming images for features and extract them into a result matrix, which is then sorted based on its importance and relevance in the Pooling Layers. In the final layer, the input data is classified into the before mentioned categories.

As a result, the model can be quickly deployed, and the results of the initial analyses can be immediately utilized. To evaluate the performance of the model, 20 percent of the training data that did not influence the training process of the model was used for testing. The performance was assessed based on the F1-score, and a confusion matrix was created on a class level to measure the accuracy of individual classes (see Fig. 3). This approach allowed for the identification of the strengths and weaknesses of the model, enabling targeted improvement to be made to the model's weaknesses, and overall performance to be improved.

The initial analysis results, which included classification into categories of paved, unpaved, or cobblestone surfaces, showed promising results. The AI model was able to correctly classify surfaces in over 95 percent of cases. However, as the current dataset does not include some weather-related aspects, such as wet surfaces, it is regularly updated with self- captured images via the ABPA app, and the model is retrained based on new data. Additionally, all other categories resulting from the inclusion of ABPA video data in the dataset are incorporated into the AI model's training. Common classification errors are also analyzed to identify and optimize categories that may be more error-prone.

5. LOW THRESHOLD CROWDSOURCING

The smartphone app in the ABPA system enables low-threshold use and promotes crowdsourcing of data. The app is designed to be user-friendly and does not require any specific technical knowledge or skills, allowing a broad user base to actively participate in the data collection process. By simply recording cycling routes using smartphone video, users can contribute valuable data on road surfaces and conditions without much effort or cost. During the project period, the data will be recorded by a selected user group. A dissemination of the system to all cyclists can take place after the ABPA System is fully developed and researched.

The crowdsourcing model allows for continuous data collection across different locations and time periods. As a large number of people can use the app, this creates a rich and diverse data set that provides a broader basis for AI modelling and analysis. The integration of self-generated imagery uploaded by the app's users complements the open source datasets and allows for a more accurate and specific classification of road surfaces.

Crowdsourcing also allows regional differences to be captured, as users from different areas can record their cycling routes and contribute data. This allows specific challenges and characteristics in different regions to be taken into account and targeted actions to improve cycling infrastructure in different urban and rural areas.

6. USE OF THE ANALYSED DATA

The web interface of the ABPA system offers a clear and user-friendly presentation of the analyzed data. It allows users to view the recorded cycling routes, problematic locations such as potholes or cracks and the identified pavement on an interactive map or in a tabular view.

The map in the ABPA web interface shows the cycling routes of the users by means of colour-coded lines. Each colour represents a different surface, for example asphalt, unpaved or cobblestone. The colour differentiation facilitates the visual capture and interpretation of the data. Zoom and navigation functions allow the user to zoom in and out of the map to focus on specific regions or road sections. Additionally, there are single pictures captured from the videos to show details of the surface.

Figure 9 Webinterface with the analyzed cyclingroutes and problematic locations.

In addition to the map view, there is a tabular representation of the collected data. This table lists the cycling routes that users have recorded with the smartphone app. Next to each route, the associated information such as the starting point and destination, the length of the route, the recorded ground surface and any problematic spots are listed. This tabular view allows to quickly browse the data and search for specific information.

For problematic places such as potholes or cracks, there are special markings or symbols in the map view that point out these places. These problematic places are analyzed automatically by the ABPA-AI. Users also can encounter obstacles during a cycle route recording and mark them. This information is stored in the database and helps to optimize the ABPA-AI.

The web interface also offers filter and search functions that allow users to sort and filter the data according to various criteria. For example, specific pavements can be searched or only cycling routes with problematic locations can be viewed. These functions facilitate the targeted search for relevant information and enable a detailed analysis of the data.

The ABPA system's web interface has a powerful geofencing feature that allows specific areas to be delineated on the map and assigned to individual municipalities or authorities. This feature is used to facilitate the management and prioritisation of problematic locations, such as potholes or other critical road sections, and to optimise the flow of information.

Through geofencing, specific geographical areas can be marked and specific properties or responsibilities to these areas can be assigned. For example, certain road sections or bicycle routes can be assigned to a specific municipal area or competent authority. This allocation allows municipalities or authorities to take responsibility for the maintenance and repair of the road sections.

The automated notification assistant uses this geofencing function to transmit time-critical information about potholes or other problematic locations to the relevant authorities. When a user encounters and marks such a spot during their cycling route recording, geofencing is activated. The ABPA System automatically identifies which municipality or authority is responsible for managing this area, based on the previously defined assignments.

As soon as a problematic location is detected within the demarcated area, a notification is automatically sent to the responsible municipality or authority by email or web API. This notification contains important information about the exact location of the spot, the condition of the road section and other relevant details. In this way, the responsible authorities are promptly informed about potential hazards and can take immediate measures to ensure the safety of cyclists and other road users.

The analyzed date data, when harnessed through a digital service tailored for bike couriers, opens up a world of possibilities. Services could provide real-time insights into the condition of bike paths, identifying potential hazards like potholes or cracks, ultimately ensuring the safety of couriers and timely deliveries. By utilizing the analyzed data, bike couriers can optimize their routes, reduce delivery times, and enhance operational efficiency, leading to cost savings and improved customer satisfaction. Moreover, the service can offer predictive maintenance insights, allowing courier companies to keep their bike fleets in top condition. Overall, the analyzed data, when integrated into a digital service, empowers bike couriers to operate more safely, efficiently, and competitively in the urban delivery landscape.

7. CONCLUSION

The ABPA system, consisting of a smartphone app, a cloud-based controller and various microservices for data storage, data analysis and data provision, can have various impacts on cycling safety and sustainability in the mobility sector.

With the low-threshold use of the smartphone app and the crowdsourcing model helps to build a broad and engaged user community that actively contributes to improving the cycling infrastructure and the data basis for the ABPA system. The participatory nature of crowdsourcing promotes a collective responsibility for improving mobility and thus contributes to a more sustainable transport design.

The system collects data from cycling routes, especially about the condition of road surfaces. By identifying potential problem areas such as potholes and obstacles on cycle paths, the ABPA system enables the optimization of road infrastructure. By automatically assigning problematic locations to the appropriate responsibilities and quickly notifying the authorities, potential danger spots are quickly identified and eliminated, contributing to improved road safety.

In this way, safer and more pleasant cycling routes can be created, which encourages the use of environmentally friendly modes of transport such as cycling and thus contributes to sustainable mobility.

In addition, the continuous collection and analysis of data in conjunction with AI algorithms enables the long-term improvement of AI models. This can lead to more accurate predictions and more efficient systems that can provide better long-term solutions to sustainability problems.

The analyzed data from the ABPA system offers a versatile resource for numerous follow-up projects. Firstly, it greatly benefits urban planning by providing essential insights into the condition of cycling infrastructure. The data supports traffic management strategies. Real-time information on road conditions helps optimize traffic flow, reduce congestion, and minimize accidents. This can contribute to the development of intelligent traffic management systems, ensuring that the road network is used efficiently and promoting sustainable modes of transport like cycling.

The data can be used for environmental impact studies. Understanding how cycling contributes to emissions reduction and improved air quality in urban areas is crucial for sustainable city planning. The ABPA data can also assist researchers and environmentalists in assessing the environmental benefits of cycling, supporting eco-friendly policies.

Moreover, this dataset can be a resource for health and wellness initiatives within a scientific context. An in-depth analysis of cycling routes, frequency, and the associated environmental conditions can offer a solid foundation for promoting active and healthier lifestyles. Scientific research can leverage this information to design evidence-based interventions aimed at encouraging physical activity through cycling, thus contributing to enhanced public well-being.

Additionally, the data can support safety interventions and educational campaigns. By identifying high-risk areas, authorities and advocacy groups can develop campaigns that promote safety and cycling awareness, reducing accidents and improving road sharing.

In summary, the analyzed data from the ABPA system is an incredibly versatile asset with a multitude of applications. It not only enhances road safety and cycling infrastructure but also serves as a foundation for sustainability, urban development, safety, health, and innovation in future mobility.

REFERENCES

1. J. Funke, “wa.de,” 2020. [Online]. Available: https://www.wa.de/hamm/adfc-hamm-macht-bestandsaufnahme-radwege-schwachstellen-radwegenetz-13902668.html. [last accessed 06.10.2020].
2. “Verkehrsministerium Baden-Württemberg,” [Online]. Available: https://www.fahrradland-bw.de/news/news-detail/zustand-derradwege-1/vom/18/9/2019/. [last accessed 06 10 2020].
3. “Bundesministerium für Verkehr und digitale Infrastruktur,” [Online]. Available: https://www.bmvi.de/SharedDocs/DE/Artikel/StV/Verkehrssicherheit/verkehrssicherheit-auf-zwei-raedern.html [last accessed 31 01 2023].
4. S. &. L. S. Kranzinger, “Eine Bestimmung der Oberflächenqualität von Fahrradinfrastruktur durch Smartphone-Beschleunigungsdaten mithilfe des k-means++-Algorithmus/Determination of the Surface Quality of the Bicycle Infrastructure by Smartphone Acceleration Data Using the k-means+,” *AGIT Journal 7*, pp. 104–116, 2021.
5. I. f. Geoinformatik, “Institut für Geoinformatik,” Universität Münster, 2022. [Online]. Available: https://www.uni-muenster.de/Geoinformatics/gi-at-school/projekte/bibo.html. [last accessed 31 01 2023].
6. T. Y. Y. C. C. &. R. S. Lee, “CNN-based road-surface crack detection model that responds to brightness changes,” *Electronics 10*, 2021.