Federated Road Surface Anomaly Detection Using Smartphone Accelerometer Data

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Abstract: Road surface conditions significantly impact traffic flow, vehicle integrity, and driver safety. This importance is magnified in the context of service vehicles, where speed is often the only recourse for saving lives. Detecting road surface anomalies, such as potholes, cracks, and speed bumps, is crucial for ensuring smooth and safe driving experiences. Taking advantage of the widespread use of smartphones, this paper introduces a turn-by-turn navigation system that utilizes machine learning to detect road surface anomalies using accelerometer data and promptly alerts drivers. The detection model is personalized for individual drivers and continuously enhanced through federated learning, ensuring both local and global model improvements without compromising user privacy. Experimental results showcase the detection performance of our model, which continually improves with cumulative user contributions.

1 INTRODUCTION

Roads are fundamental to transportation networks, facilitating seamless connectivity and mobility. A robust road network enables efficient travel for individuals and the transportation of goods. However, various natural and human-induced factors can contribute to road surface damage, resulting in the formation of potholes, cracks, and other irregularities. While potholes and cracks typically arise from natural wear and tear, speed bumps represent a deliberate intervention by human actors to achieve specific traffic management objectives. Nonetheless, poorly designed or maintained speed bumps can also pose safety hazards, increasing the risk of accidents and injuries, particularly when drivers are unaware of their presence or fail to perceive them.

Road anomalies, including defects and speed bumps, pose significant risks to both human occupants and vehicular components. Indeed, encountering road surface anomalies at high speeds can lead to vehicle damage, malfunctioning of vehicle components, or even injury to occupants (Kosakowska, 2022). Proactive measures are essential for mitigating these risks. Drivers can take precautions by reducing their speed before traversing a speed bump or encountering surface irregularities. However, the challenge becomes more pronounced when drivers are unaware of upcoming anomalies on their route. In such scenarios, the need for an automatic solution becomes imperative. By leveraging technology, such as advanced sensors and real-time monitoring systems, drivers can be automatically notified of impending anomalies, enabling them to take necessary precautions and adapt their driving behavior accordingly. An automatic solution enhances driver awareness and safety and contributes to the overall efficiency and maintenance of road infrastructure.

Smartphones with GPS and navigation systems have transformed driving habits, allowing for efficient route navigation. Integrating automatic road anomaly notifications seamlessly complements these habits, providing timely alerts during journeys. Establishing a comprehensive database of road surface anomalies is essential, facilitated by crowd-sourcing from drivers via automated marking. Smartphones' accelerometer sensors capture signals reflecting the vehicle's acceleration, enabling precise identification and location of road surface anomalies when coupled with GPS data.

Classifying the footprint left in the acceleration signal by road anomalies necessitates a pre-trained classification model. Given potential variations in signals generated by different phones and vehicles, the model must be trained across various scenarios. While data from different users could be used to re-

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train the model, concerns about user privacy arise due to the revealing nature of acceleration data, which can disclose driving habits. Consequently, training the classification model locally on users' devices and aggregating these models into a single global model helps preserve user privacy.

This paper presents a proactive solution to enhance road safety by utilization of smartphone technology for real-time detection and notification of road surface anomalies. It introduces a turn-by-turn navigation system that exploits the widespread use of smartphones equipped with GPS, navigation systems, and accelerometer sensors. The system's primary objective is to detect road surface anomalies in real-time and provide prompt alerts to drivers to enhance road safety. Through machine learning techniques, the system automatically detects and classifies road surface anomalies based on the footprints observed in the accelerometer data. Upon detecting an anomaly, the system marks its location to alert approaching drivers. Furthermore, to enhance detection performance, the machine learning model undergoes additional training using user data. To address privacy concerns associated with user data, the system employs a federated learning approach. Local models are trained on users' devices, and the aggregated global model is utilized for anomaly detection while safeguarding user privacy.

2 RELATED WORKS

Al-Sabaeei et al. (2024) present a comprehensive review of smartphone applications for road surface monitoring. These applications predominantly rely on two distinct approaches: vision-based data collection and the analysis of acceleration and vibration data. By exploiting these techniques, they aim to assess the condition of road pavements.

Camera-based methods have shown promise in detecting road surface defects and anomalies, with reported accuracy levels ranging from 80% to 98%. However, their effectiveness is influenced by factors like lighting conditions and image quality (Rahiman V et al., 2021; Lee et al., 2021; Kim and Kim, 2023). Despite their potential, vision-based methods have limitations. These methods require stable orientation of the smartphone camera towards the road surface, which conflicts with our system's objective of providing real-time notifications and navigation to users. As our system prioritizes positioning the smartphone camera facing the driver, this approach imposes constraints on phone placement, rendering it unsuitable for our application.

On the other hand, the use of vibrations data also depicts promising results. Chen et al. (2022) developed a convolutional neural network that based on smartphones' accelerometer data detects road surface transverse cracks with a 97% accuracy. Martinelli et al. (2022) exploited the same accelerometer data with with several machine learning techniques including decision trees, support vector machine to detect with an accuracy ranging from 84% to 97% in determining whether the road pavement is distressed or not. Several similar works showed that vibrations data are a reliable source for road surface anomalies detection (Dong and Li, 2021; Sholevar et al., 2022; Mazari Abdessameud et al., 2022; Tomiło, 2023; Yuan et al., 2023). Therefore, the fusion of vibration data and advanced machine learning techniques holds great promise for improving road safety.

Crowd-sourcing offers a valuable avenue for collecting precise road anomaly locations. In their study, Xin et al. (2023) propose a novel probabilistic-based crowdsourcing technique. By aggregating data from a large number of users, the accuracy of anomaly detection and localisation can be significantly improved. This approach effectively filters out potential false positives and false negatives by combining dynamic events detected from various smartphones onboard vehicles. Also, by harnessing this crowdsourced data, errors associated with GPS for anomaly localisation is mitigated, leading to more reliable results.

In their recent work, Jeong and Jo (2024) introduce a machine learning approach that leverages crowdsourced data to evaluate pavement conditions. Their methodology aims to develop classifiers by incorporating diverse data sources. However, a notable limitation arises: these classifiers are still constrained by the number of instances used during training since the classification model does not evolve. Interestingly, Jan et al. (2023) echo a similar concern in their research. They emphasize that challenges in pavement condition detection stem from differences in sensing platforms and vehicle parameters. These variations introduce complexities that impact the accuracy and adaptability of detection models.

To address the limitations of static training of classification models, the proposed solution involves employing federated learning techniques. Federated learning allows the model to adapt dynamically to different situations while preserving user data privacy. By combining this approach to detection base on accelerometer data and crowdsourcing for localisation, we can create more effective and adaptable systems for road safety.

3 METHODOLOGY

Driving over road surface anomalies without prior notice can jeopardize driver safety and vehicle integrity. Therefore, drivers should be aware of road anomalies along their routes. In this section, we elaborate on how our system utilizes drivers data to detect the presence of road surface anomalies. These detected anomalies are stored in a central database and utilized to alert subsequent drivers.

To streamline the use of our system, we engage with end users through smartphones. These devices offer users the ability to navigate their preferred routes while receiving alerts about upcoming road surface anomalies along the way. Also, the accelerometers embedded in these smartphones enable automatic detection of new road surface anomalies, enriching our database with real-time information.

To establish a robust and accurate database of road surface anomalies, the system relies on user-generated annotations. Users report encountered anomalies, such as potholes or cracks, detected by the integrated model. Each report includes details such as the anomaly type, precise location using GPS coordinates, and a confidence rate indicating the level of confidence in the model's detection, which can be enhanced through continuous training. The system consolidates confirmed anomalies by aggregating reports for the same location, considering the confidence scores associated with individual reports to determine the anomaly type.

This methodology ensures that anomalies frequently reported with high confidence levels are classified as confirmed, thereby enhancing the system's accuracy and reliability in identifying critical road surface issues.

3.1 General Architecture

The proposed system comprises eight interconnected modules designed to collect, process, and analyze data from various sources, ultimately providing timely notifications to drivers regarding upcoming road anomalies. The general architecture of the proposed system is illustrated in figure 1. These modules are distributed over the client side and the server side. On the client side, we deploy five modules to manage:

- Navigation: The system retrieves essential information from a remote geographic database to calculate routes for the user, facilitating navigation along these routes with step-by-step directions. Furthermore, this module provides notifications regarding upcoming road surface anomalies to ensure user awareness and safety during the journey.
- Upcoming confirmed anomalies: Upon receiving the user-selected route, the navigation module interfaces with this module to obtain information regarding confirmed anomalies along the chosen route, including their locations. These anomalies are subsequently utilized to notify the user and evaluate the effectiveness of the automatic anomaly detection module.
- Anomaly detection: To detect whether the vehicle hit a road surface anomaly, the module receive accelerometer signals. These signals are then subjected to various operations, including reorientation from relative to absolute reference, and data filtering to eliminate artifacts and unwanted noise. The detection module retrieves one signal window at a time and performs an inference on the data (acceleration x, acceleration y, acceleration z and velocity) using the detection model management module. The result is a prediction vector indicating the class of the signal present in this window.
- Detection results verification: This involves the interface of this module with the Upcoming Confirmed Anomalies module, utilizing smartphone location data to compare the outcomes of the anomaly detection module with confirmed anomalies in the same location. Four scenarios may arise: i. When the same type of anomaly is detected, if the detection rate is low, accelerometer data is utilized to augment the training of the local model, thereby enhancing accuracy. ii. If the model fails to detect a confirmed anomaly or iii. identifies an anomaly with an incorrect type, accelerometer data is employed to refine the local model due to the model's likely inaccuracy. iv. In the event the model detects an anomaly not yet confirmed, a flag is dispatched to the distant server to report the anomaly's existence. In this case, accelerometer data awaits confirmation of the detected anomaly's type.
- Local detection model management: This module manages the local detection module. It conducts local model training using data collected from the device. Additionally, the module facilitates communication with the server to either contribute the local detection model to the global model or update the local model based on the received global model.

These client modules interact with a server that manages centralised actions and data. The server relies on three modules to deal with:

- Road Anomalies Flags Storage: This module maintains a record of the various flags received, as well as the confirmed road anomalies. Each re-

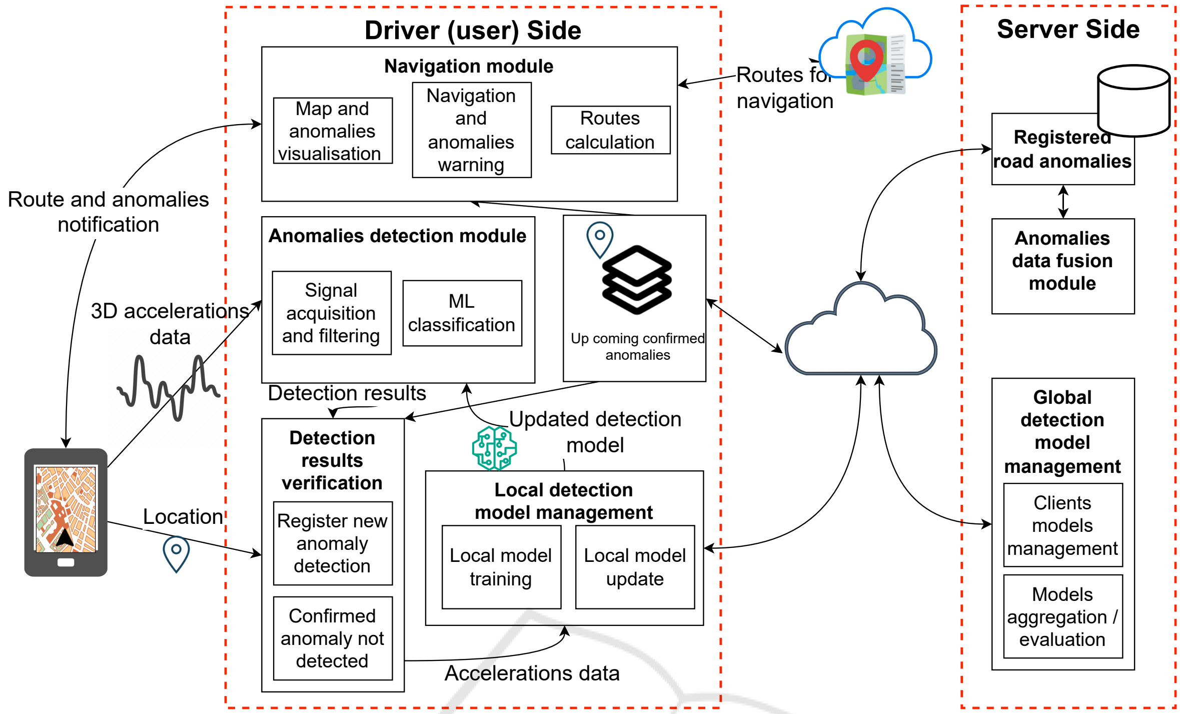

Figure 1: General architecture of the proposed system.

ceived flag includes details such as anomaly type, location, and flag reliability or confidence level. Confirmed road anomalies are those flags with high reliability or confidence levels.

- Anomalies data fusion: The aim of this module is to achieve a consistent state of the anomaly database. This data fusion process enables the flags received from users to be combined, providing a more complete and accurate information. Due to potential inaccuracies, flags from various sources might describe the same anomaly with different types and slightly varying locations. To address this, the Anomalies data fusion module employs a Weighted Majority Voting (WMV) technique (Tao et al., 2018) to consolidate flags for each anomaly and select the most reliable type. This process involves three key steps: data clustering, data fusion, and decision making. Subsection 3.3 describes the data fusion process flow. This process effectively combines flags from various contributors, resulting in a comprehensive and reliable record of anomalies.
- Global detection model management: This module ensures the update of the global detection model, and the update of the different user's local models. The update of the global detection model involves the aggregation of several local users models. This process involves retrieving weights from saved different users and combining them using a predefined algorithm (e.g., FedAvg). Finally, the resulting aggregated model undergoes evaluation to assess its performance.

3.2 Anomaly Detection

The proposed system provides an efficient automatic road anomaly detection service, leveraging smartphone capabilities to identify irregularities in road surfaces. It is a well-known phenomenon for vehicles to experience vibrations when encountering anomalies such as potholes. These vibrations are captured as a three-axis acceleration signal generated by the smartphone's integrated sensor. However, this signal is collected in the smartphone's local coordinate system, which depends on how the phone is mounted in the vehicle. To overcome this challenge, the proposed system employs an automatic correction service that utilizes Euler angles to reorient the acceleration data. This approach eliminates the dependence on the smartphone's physical orientation, ensuring consistent data interpretation regardless of how the user mounts the phone. The reoriented signal can still contain noise from non-informative vibrations, such as constant engine hum. To address this, we employ a high-pass filter. This filter removes low-frequency data, effectively resulting in a filtered vibration signal that's more suitable for further processing and anomaly detection. After preprocessing the vibration signal, it is divided into equal-length sliding windows to produce a series of consecutive samples.

Given the Long Short-Term Memory (LSTM) neural networks' demonstrated capability to automatically extract pertinent features from raw time series data and handle temporal dependencies, we advocate for a stacked LSTM architecture comprising two hidden LSTM layers, each containing multiple memory cells. This architecture is used to classify whether the window of the captured signal represents a smooth road or a road surface anomaly.

3.3 Anomalies Fusion

As the system relies on user input to detect road surface anomalies, multiple flags may be received for the same anomaly, each varying in reliability and potentially indicating different anomaly types. Consequently, when multiple flags are accumulated for the same approximate location, a fusion process is initiated. As shown in figure 2, this fusion process incorporates three pieces of information: location, anomaly type, and confidence rating.

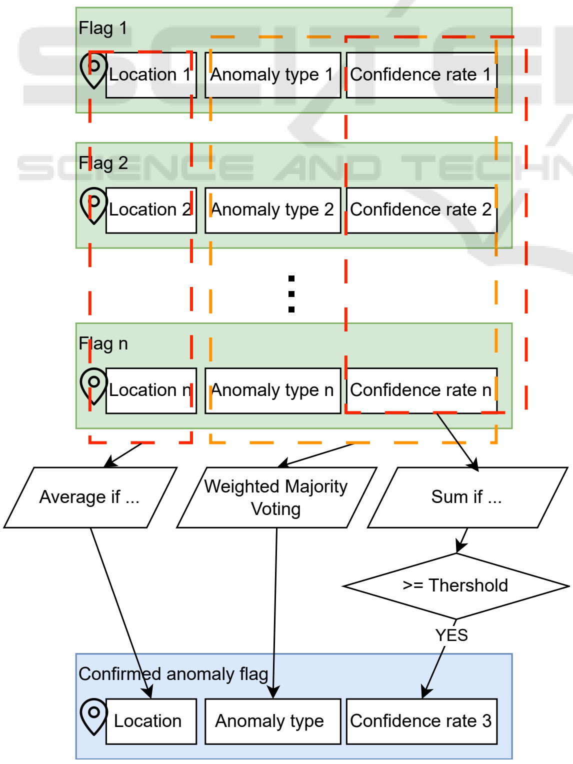

Figure 2: Schema of the fusion process of Road surface anomaly flags.

To determine the retained anomaly type, a WMV approach is employed, with the confidence rating of each flag used to weigh the different types. Once the elected type is identified, if the sum of confidences of the flags holding this type exceeds the defined threshold, a confirmed road surface anomaly is generated. However, if the threshold is not met, no conclusion is drawn. In terms of location, the final location is determined as the average of all locations associated with flags indicating the elected type.

3.4 Federated Detection Enhancement

The federated enhancement of the detection model relies on the local and global detection model management modules. These two modules interact with each other to exchange model parameters. The local detection model management module manages the local model training using captured signals that were wrongly classified. Global model management performs the aggregation of the different models received from users.

Local training is a crucial functionality designed to refine the local model by utilizing data stored in the local database. This feature is activated when the system accumulates a substantial number of misclassified signals. Upon retrieving the signal instances, the local training module proceeds to acquire label updates, as anomalies may have been removed or changed type during the data fusion process. Subsequently, the training process is initiated, adhering to pre-defined parameters such as the number of epochs. Upon completion, the new weights of the resulting model are applied locally for subsequent detection, along with essential metadata such as the user identifier, dataset size used in training, and loss function. This iterative approach ensures the local model is continuously updated and enhanced, leveraging recent data to improve accuracy and anomaly detection performance.

On the server side, a scheduled aggregation process is implemented. The aggregation process comprises several steps. Firstly, the weights of models trained locally by customers are retrieved. Next, an aggregation operation is performed to combine these weights using a FedAvg algorithm as described in algorithm 1. The aggregation algorithm begins by calculating the aggregate count of instances utilized in training all local models for the current aggregation cycle. Subsequently, each local model contributes to the new model in proportion to the number of instances employed for its individual training.

Once aggregation is complete, the resulting model is evaluated to measure its performance. This involves the use of a test and validation dataset to assess the accuracy and quality of the aggregated model. Depending on the results of the evaluation, a decision is made regarding the deployment of the model. If the aggregated model is deemed satisfactory, it is retained as the new global detection model and made available to users. This enables users to benefit from the improved detection performance offered by the aggregated model.

Data: Current global detection model, List of users detection models with their metadata
Result: Updated global detection model
Total_Data_Size ← $\sum$ *Train_Data_Size*
foreach *local_Model* ∈ ***local_Models*** **do**
  size ← Train_Dataset of local_Model
  Rate ← size / Total_Data_Size
  Names, Weights ← Get local_Model parameters names and weights
  foreach *name* ∈ ***Names*** **do**
    New_Global_Model[name] ← New_Global_Model[name] + (Rate × Weights[name])
  end
end
Save (New_Global_Model)

Algorithm 1: Local models aggregation algorithm.

4 EXPERIMENTAL SETUP AND PERFORMANCE EVALUATION

The performance evaluation of the proposed system comprises two main components. Firstly, the evaluation of the initial detection model that was trained using a public dataset. The second part consists of performance evaluation of the same model after a federated learning phase.

4.1 Training Dataset and Evaluation Metrics

We utilized the "Pothole lab" dataset (Lab, 2016), which comprises over 2500 instances of various road surface anomalies, including speed bumps, metal bumps, and potholes, alongside over 1500 instances of smooth roads. This dataset offers a diverse range of anomalies commonly encountered on roadways, enabling comprehensive evaluation of our detection system's performance. Each instance in the dataset provides acceleration data along three axes, facilitating a detailed analysis of vehicle motion and response to road surface conditions. To assess the effectiveness of our system, we employed standard evaluation metrics, including precision, recall, and F1-score. These metrics provide valuable insights into the system's ability to accurately detect and classify road surface anomalies while minimizing false positives and negatives.

4.2 Initial Classification Model Evaluation

To evaluate the effectiveness of the proposed classification model, we explored various combinations of training hyperparameters. These parameters encompassed the number of iterations on the training dataset, the window size representing an anomaly, the overlap between windows, and the number of memory cells in each LSTM layer. The evolution of accuracy and loss function during training for the combination yielding the best results is depicted in Figure 3.

Figure 3: Evolution of the accuracy and the loss function during training.

The evolution of accuracy and loss show that the model did not over or under learn. The obtained results for the evaluation parameters are shown in table 1.

Table 1: Achieved parameters values for the evaluation of the classification model based on Pothole Lab dataset.

Precision	Recall	F1-score
0.96	0.95	0.95

4.3 Federated Classification Model Evaluation

To evaluate the performance of the federated learning process, we conducted testing of the detection model in two distinct phases. In the first phase, we utilized the pre-trained model to assess the initial detection capabilities across multiple devices. This allowed us to gauge the baseline performance of the model before any federated training. Following this initial phase, we proceeded to the second phase, where the detection model underwent federated training. During this process, data from multiple devices were aggregated and used to refine the model's parameters, aiming to enhance its ability to generalize across diverse datasets while preserving user privacy. Subsequently, we conducted testing again to evaluate the performance of the model after federated training. By comparing the results of these two phases, we could assess the effectiveness of the federated learning approach in improving the detection model's accuracy and robustness across different devices and datasets. Figure 4 shows the followed process to achive the two phases evaluation.

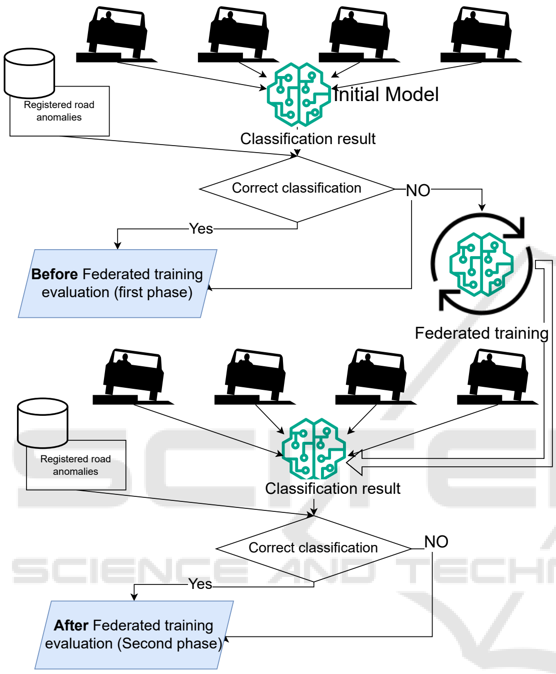

Figure 4: Schema of the fusion process of Road surface anomaly flags.

We deployed the detection model across four different devices to evaluate its performance in a real-world setting. Each device was equipped with the trained model and tasked with detecting road surface anomalies during typical driving scenarios. The anomaly database of the system was populated with existing anomalies known to occur on the test road. As the vehicles traversed various road conditions, including smooth surfaces and areas with known anomalies such as potholes and speed bumps, the accelerometer sensors in the smartphones captured data reflecting the vehicle's acceleration along three axes. This data was then processed by the detection model to identify and classify road surface anomalies. During detection, the system compared the detected anomalies with those stored in the database. Any discrepancies or inaccuracies in classification were noted, and anomalies that were wrongly classified were earmarked for further training of the model. Following the test, the results were analyzed to assess the precision and recall of the detection model under real-world conditions. The obtained results for the two phases are detailed in table 2

Table 2: Achieved parameters values for the evaluation the classification model before and after the federated training (FT) process.

Phase	Precision	Recall	F1-score
Before FT	0.77	0.73	0.73
After FT	0.84	0.79	0.79

5 DISCUSSION

The evaluation of our system comprised two distinct phases. Initially, we conducted an assessment of the classification model's performance before implementing federated learning. This evaluation, conducted solely on the trained dataset, yielded promising results, with a precision of 96% and recall of 95%. These high scores indicate the reliability and effectiveness of the model in accurately detecting and classifying road surface anomalies.

Subsequently, we proceeded with the evaluation of the federated learning component. Upon deployment of the model across four different devices, an initial test revealed a slight decline in performance, resulting in a precision of 77% and recall of 73%. This drop in performance can be attributed to variations in the data used for training and testing, highlighting the challenge of ensuring consistency across diverse datasets.

To address this issue, we initiated a federated training process, aggregating results from multiple devices and relaunching the test. The subsequent evaluation demonstrated a notable improvement in performance, with a precision of 85% and recall of 79%. These enhanced results underscore the effectiveness of the federated learning approach in refining and optimizing the detection model.

Overall, the findings indicate that while the initial performance of the model was commendable, the incorporation of federated learning significantly enhanced its performance, underscoring the importance of collaborative and distributed learning methods in improving the accuracy and robustness of detection systems.

6 CONCLUSION AND PERSPECTIVES

This paper presents a proactive solution leveraging smartphone technology for real-time detection and notification of road surface anomalies. Through the integration of machine learning techniques and accelerometer data, our turn-by-turn navigation system effectively identifies and alerts drivers to potential road surface anomalies, thereby enhancing overall road safety. The evaluation of our system demonstrated promising results, with the classification model exhibiting high precision and recall rates in detecting anomalies. Furthermore, the implementation of federated learning proved instrumental in refining the detection model's performance across diverse situations, highlighting the efficacy of collaborative learning approaches in improving detection accuracy while preserving user privacy. Overall, our system offers a practical and effective approach to addressing road safety concerns, with the potential to significantly reduce the incidence of accidents and improve the overall driving experience. As future work, further optimization and refinement of the detection model could be explored, along with the integration of additional sensors or data sources to enhance anomaly detection capabilities in various road conditions. The most promising additional sensor is the camera technology that can augment anomaly detection capabilities. Cameras can capture visual information about road surface conditions, allowing for the detection of anomalies before vehicles encounter them.

DISCLOSURE OF AI TOOLS USAGE

The preparation of this manuscript involved the use of Copilote and ChatGPT to correct and improve the language through the manuscript. Subsequently, the authors reviewed and edited the content as necessary, and take full responsibility for the paper's content.

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