User-Empowered Federated Learning in the Automotive Domain

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***Abstract*—The proliferation of data generated through everyday device usage has prompted privacy concerns among users. In the automotive sector, this issue is particularly acute, given the substantial volumes of data collected in accordance with manufacturers' privacy policies. Privacy-Enhancing Technologies (PETs), such as Federated Learning (FL), offer a solution by safeguarding the confidentiality of car data while enabling decentralised machine learning model training, thus preventing the need for centralised data aggregation.**

These FL-based models stand to benefit significantly from the diverse data distributions inherent in training across various features extracted from different cars. However, it remains imperative to ensure user awareness regarding their data processing, despite FL's privacy-preserving mechanisms.

To address this, we propose a User-Empowered FL approach, built upon the Flower Framework, empowering users to decide their participation in model training or merely inference without impacting the global model. We demonstrate this approach through an automotive case study utilising the *EngineFaultDB* dataset.

Finally, we outline future directions, particularly focusing on handling unlabelled data through self-supervised learning methodologies.

***Index Terms*—Federated Learning, Privacy, Automotive, Privacy-Enhancing Technologies**

1. Introduction

While data collection offers undeniable benefits for improving user experiences, it also fuels valid privacy concerns due to the vast amounts of data aggregated [1], [2]. Regulations such as the *General Data Protection Regulation (GDPR)* attempt to build a balance, but the complexity of privacy policies often undermines true informed consent. This issue persists across domains, including smart homes, web and mobile applications, and the automotive sector. For example, in cars, location data from GPS sensors and app usage habits can reveal sensitive information about a driver's lifestyle, whereabouts, or worse, where they reside [3].

Fortunately, *Privacy Enhancing Technologies (PETs)* [4], [5] come in aid, providing valuable tools to protect users' data in terms of both anonymity and confidentiality. Anonymity ensures that data cannot be linked to its respective owner, while confidentiality refers to the ability to obfuscate the information itself. In the automotive context, PETs can be employed to obfuscate sensitive data, apply anonymisation techniques to protect user identities or utilise *Federated Learning (FL)* to train predictive models without directly sharing raw data.

FL enables the training of a machine learning model distributed across multiple devices, without the need to aggregate data. This way, sensitive data remains on user devices, preserving their privacy. FL is particularly appealing in the automotive field, where vast amounts of data are generated by vehicle sensors [6]. However, the implementation of FL often raises questions about genuine user consent.

In many cases, FL occurs in the background, and users might not be explicitly aware of their participation in the training process. For example, while Google Assistant does allow users to opt in to contribute their audio recordings for traditional model improvement, the underlying FL process, which leverages on-device data for model updates, cannot be completely disabled [7], [8].

Our contribution focuses on this very aspect, proposing a baseline for obtaining explicit consent and raising awareness about local model training in the automotive domain. We believe that users should be actively empowered in deciding whether their data is used for FL and should be continuously informed and aware of the ongoing process.

As a case study, we demonstrate the feasibility of our approach using a neural network designed to work with the *EngineFaultDB* [9] dataset. This dataset contains 14 features relevant to predicting and classifying potential engine faults, which usually require manual intervention from a mechanic using diagnostic instrumentation. Our neural network assists both the driver and the mechanic in identifying the cause of the fault, thereby speeding up the repair process.

We trained the network in an FL setting using the *Flower framework* [10] and ported it to the Android Automotive platform. This allows us to showcase how our consent and awareness mechanisms can be integrated into a real-world automotive application, ensuring that users have control over their data while contributing to the improvement of the model.

The *EngineFaultDB* dataset provides a realistic scenario for testing the effectiveness of our approach. By using a neural network that operates on these data, we can assess the impact of FL on the model's performance while respecting user privacy. The Flower framework simplifies the implementation of FL on Android Automotive, making it easier to deploy and test our solution in a practical setting.

The paper is structured as follows: Section 2 provides a comprehensive introduction to FL, exploring existing approaches in the mobile and automotive sectors. Section 3 delves into the details of our proposed approach for user-empowered FL, emphasising explicit consent and awareness mechanisms. In Section 4, we evaluate our approach through a case study on engine fault prediction, demonstrating its practical application. Section 5 analyses the results obtained and explores potential improvements. Finally, Section 6 summarises our findings and outlines future research directions.

2. Background

Privacy concerns undermine the trust of end-users against technological innovations in the automotive sector, a fact supported by studies such as those highlighting cars as receptacles of personal data, often traded by manufacturers [11]. Consequently, PETs must be employed not only to protect drivers' personal data but also to ensure compliance with increasingly stringent regulations such as GDPR.

An attempt to empower users regarding their data in the automotive domain consists of *PRICON* [12]. *PRICON* functions as a "privacy firewall", managing data flow between the car and online services. Through its interface, users can customise privacy settings, control data sharing between services, and select from predefined privacy profiles. It balances service functionality and the desired privacy level, necessitating user awareness of this trade-off.

2.1. Federated Learning

Federated Learning is a distributed machine learning paradigm that enables multiple clients (e.g., smartphones and vehicles) to collaboratively train a shared model without exchanging their raw data. Instead of sending data to a central server, each client trains a local model on its own data and then shares model updates (e.g., gradients) with the server. The server aggregates these updates to improve the global model, which is then sent back to the clients for further local training [13], [14].

FL can be categorised based on the distribution of data across clients [15]:

- *Horizontal Federated Learning (HFL)*: Also known as sample-based FL, HFL is applicable when clients have similar feature spaces but different data samples. For example, different hospitals collaborate to train a disease prediction model, where each hospital holds data for different patients but with the same set of medical features.
- *Vertical Federated Learning (VFL)*: Also known as feature-based FL, VFL is suitable when clients share data samples but have different feature spaces. For example, a bank and an e-commerce company collaborate to build a customer behaviour model, where they share the same customers but have different data about them (financial vs. purchase history).
- *Federated Transfer Learning (FTL)*: FTL combines transfer learning with FL. Clients start with a pre-trained global model and adapt it to their local data. This approach is useful when data is limited or when clients have similar tasks but different data distributions.

Federated Learning, while designed with privacy in mind, is not immune to attacks. Notably, it remains susceptible to inference attacks, where adversaries can glean information about the underlying training data from model updates [16]. Additionally, model poisoning poses a significant threat [17], as even a single malicious agent can manipulate the global model to misclassify specific inputs with high confidence. While various countermeasures exist to address these vulnerabilities, this work focuses exclusively on fundamental FL techniques and does not delve into attacks and their corresponding defences.

2.2. FL in Mobile Devices

Infotainment systems in modern vehicles are increasingly based on mobile devices, particularly those running the Android operating system [18]. These systems typically feature touch screens and offer functionalities similar to those found in smartphones. Users can make phone calls, navigate using GPS, listen to music, and more. By leveraging the familiar Android platform, these systems provide a seamless and intuitive user experience, integrating the convenience and versatility of mobile devices into the automotive environment.

Notable examples of FL in the mobile domain focus mainly on Image Processing [19], [20] which protects the confidentiality of users' pictures. Other applications of FL include next-word prediction [21] or emoji prediction [22] in a smartphone keyboard. Both the use cases allow the user not to share their conversation in a centralised dataset. Another example includes wake-word detection [23] such as the "Hey Google" [24] on Google Assistant, which preserves the confidentiality of the user's voice.

2.3. FL in Automotive

FL in automotive is predominantly used for autonomous driving purposes [25], [26], [27]. This enables the training of autonomous driving agents without using driving style data from users, as collection of these data can potentially breach their privacy [28].

Chellapandi *et al.* [29] explored a large number of applications for FL in the automotive environment, splitting it into eight categories including safety-related applications such as collision avoidance [30] or traffic sign recognition [31],

Lastly, FL has also been used to predict faults in electric vehicles in a study related to the one proposed in this paper [32]. The main differences between this work and ours are:

- The two works use different FL frameworks and different network structures;
- Our source code is publicly available online;
- Users of our solution can choose to not opt-in in the federated training process.

3. Our Approach: User-Empowered FL

The proposed approach contributes to user empowerment. In fact, the user is, first of all, informed about the use of their data for training the model. Additionally, the user is also empowered, because they can decide whether to train the model or not.

As a demonstration, we developed an Android Automotive application that manages both the training of the model in a federated manner and performing inferences without training, depending on the user's explicit consent. The app is based on the Tab Template and has been designed by following the Google UX Guidelines and design requirements for usability in cars [33].

At the core of our approach lies an explicit consent mechanism. Upon launching the application for the first time, users are presented with a clear and concise explanation of FL, its potential benefits, and the types of data involved in the training process.

They are then asked to provide explicit consent for their device to participate in FL. It is important to note that this consent is not assumed by default, hence, it must be actively granted by the user.

To ensure ongoing awareness, we employ a notification that becomes visible while the model is being trained locally on the user's device. This serves as a constant reminder that FL is in progress and provides a link to the application settings, where users can review and modify their consent preferences.

The Android app acts as the central control point for model management. When the app is started, it initiates the FL process to download the global model. During the usage, if the user has granted consent, the app trains the model locally on the user's data and uploads the model updates. Figure 1 represents a scenario involving three cars, where the drivers of the green cars granted consent to training, while the driver of the red car did not.

If the user does not provide consent, the service simply uses the global model for inference without performing any local training.

4. Case Study: Engine Fault Prediction

As a proof-of-concept of our approach, we defined a scenario based on a dataset provided by Vergara *et al.* [9], *EngineFaultDB*. *EngineFaultDB* contains over 50.000 entries consisting of 14 features. Each entry is labelled in one of the 4 categories, each one referring to a specific engine fault, except the first one that represents normal engine conditions as shown in table 1. This dataset has been used to train a feed-forward neural network, provided by Vergara *et al.*, which is based on [34], depicted in Figure 2.

In particular, we split up the dataset equally between three clients all running in an Android Automotive app. We assumed that two users expressed consent in their respective apps, while the third client did not express their consent to train the model as shown in Figure 3. Then, we trained the model the model for 10 epochs with batches of size 16. After training with the first two users, we verified that the

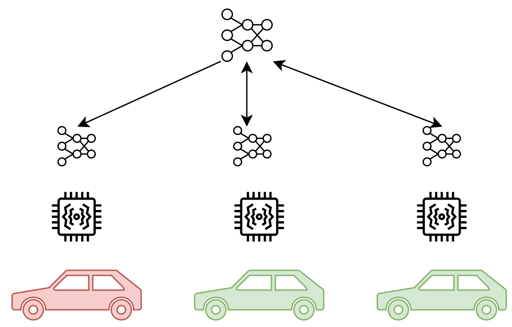

Figure 1. Representation of Federated Learning

TABLE 1. FAULT TYPES

ID	Type	Description
0	No-Fault	Normal engine operation
1	Rich Mixture	Excess fuel in the air-fuel mixture
2	Lean Mixture	Insufficient fuel in the air-fuel mixture
3	Low Voltage	Insufficient voltage in the electrical system

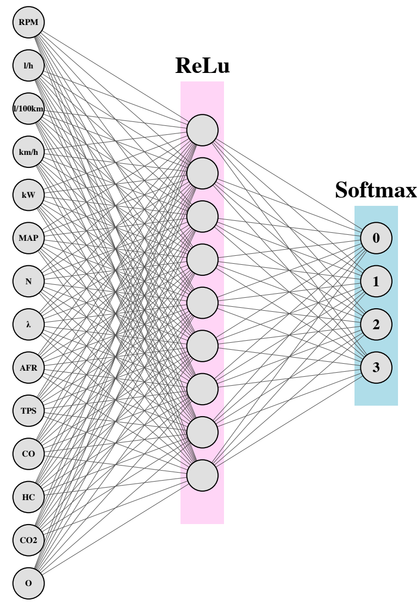

Figure 2. The Neural Network trained

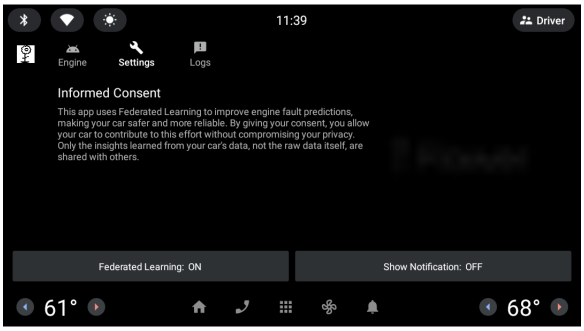

Figure 3. Settings Screen

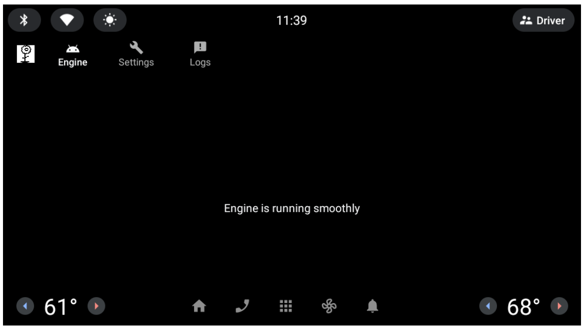

Figure 4. Engine Status Screen

third user could still use the global model without participating in the training as shown in Figure 4. Further optimization of functions and parameters, such as exploring different numbers of epochs or batch sizes, may yield improved results and is identified as a potential avenue for future research.

Table 2 details the feature space, providing Unit of Measure (UoM) and brief descriptions. Although this information was partially available in the *EngineFaultDB* paper [9], we were able to verify that:

- Features listed with the green checkmark (✓) can be obtained through the Android Automotive APIs. We obtained this information by analysing the related documentation [35];
- Features listed with the orange checkmark (✓) can be retrieved via the OBD-II interface. We obtained this information by analysing different user manuals available for OBD-II car scanners. Another possibility is to implement the gathering of said features as custom properties on Android Automotive. However, the possibility of gathering these data ultimately depends on the car (i.e., the car must be equipped with appropriate sensors).
- Features listed with the red cross (×) require additional instrumentation for collection.

Given the above, this test case focusing on user privacy and awareness in the automotive domain, demonstrates the feasibility of this approach in a simulated environment, even when not all users consent to use their data for the training.

5. Discussion and Future Directions

By combining explicit consent with persistent awareness, our approach empowers users to make informed decisions about their participation in FL. Users have full control over whether their data is used for training and are continuously reminded of the ongoing FL process. This transparency fosters trust and ensures that FL is conducted in a privacy-respecting manner.

Our proposed approach is designed to be flexible and adaptable to different FL scenarios. The consent mechanism and notification content can be easily customised to match the specific application and model involved. The Android Automotive architecture can also be extended to incorporate additional features, such as providing users with insights into the model's performance or allowing them to control the frequency of FL updates.

5.1. Limitations

The proof-of-concept of our approach has a few limitations, which we hereby list:

1) This specific experiment with Federate Learning cannot be replicated exactly in real-world conditions. This is because certain features in the *EngineFaultDB* dataset are derived from specialised equipment not found in standard vehicles.
2) In many real-world scenarios, obtaining accurate labels for data is often hard or impossible. Labelling of data similar to the ones found in *EngineFaultDB* is challenging because when a fault occurs, a generic engine light illuminates on the car dashboard. Diagnostic data provides a brand-specific error code not directly linked to the fault, necessitating manual intervention. Consequently, cars cannot automatically label new data, a problem known as *unlabelled data* [36], [37]. This remains an important area for future exploration in Federated Learning.
3) Finally, the current dataset is built on data gathered from a single engine, while in real-world scenarios there are many different types of engines. This is a limitation that our proof-of-concept inherits from the *EngineFaultDB*, and datasets developed in the future might solve this problem.

5.2. Future Directions

Given our proof-of-concept approach and its limitations, which were described in the previous subsection, we hereby list some possible directions for future research endeavours.

1) Future work will investigate the feasibility of designing a network capable of inferring fault types using only sensors found in standard vehicles.

TABLE 2. FEATURES

Feature	UoM	Description	How to get
Engine Speed	RPM	Rotations per minute of the engine	✓
Consumption per hour	l/h	Fuel consumption rate per hour	✓
Consumption per 100km	l/100km	Fuel consumption rate on 100km	✓
Speed	km/h	Travel speed of the car	✓
Power	kW	Power produced by the engine	✓
Manifold Absolute Pressure	kPA	Pressure within the intake manifold	✓
Force	N	Torque of the engine	✓
Lambda	ER	The air-fuel equivalence ratio.	✓
Air-Fuel Ratio	AFR	Ratio of air to fuel in the combustion chambers	✓
Throttle Position Sensor	%	Provides information about the angle of the throttle	✓
Carbon monoxide	%	CO concentration in the exhaust	×
Hydrocarbons	ppm	Concentration of unburnt hydrocarbons in the exhaust	×
Carbon dioxide	%	CO2 concentration in the exhaust	×
Oxygen	%	Oxygen amount in the exhaust	×

2) Future work will investigate incorporating techniques such as self-supervised learning to address this challenge.
3) Future work could extend the feature space to include more variables, such as engine specifications or type of fuel, to develop a more general model. Such a model could be trained in a decentralised manner using FL.

6. Conclusion

In this paper, we presented a novel approach to FL in the automotive domain, emphasising user privacy and awareness. By integrating explicit user consent and notifications, our approach empowers individuals to actively participate in the FL process while maintaining control over their data.

The flexible design, based on the Flower framework, of our ongoing approach allows for customisation to various FL scenarios. Upon its open-source release,[1] the approach can be further developed and improved with additional features, such as training another model.

While our current work focuses on privacy and user control, the challenge of unlabelled data in FL remains an important area for future investigation. Future research will explore the integration of self-supervised learning and other techniques to leverage unlabelled data effectively within the FL framework.

The contributions of this work lay a foundation for more transparent and user-centric FL systems in the automotive industry, with potential applications extending to other domains where privacy and data ownership are paramount. By fostering trust and collaboration between users and machine learning models, we pave the way for developing more accurate, robust, and ethically sound AI solutions.

1. https://github.com/marcellomaugeri/User-Empowered-Federated-Learning-in-Automotive

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