ESTIMATE ROAD ROUGHNESS USING SAMRTPHONE RESPONSE DATA - A SEMI-SUPERVISED LEARNING APPROACH

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Abstract

The smartphone-collected vehicle response data is being used to estimate the International Roughness Index (IRI). Among the existing smartphone-based methods, the data-driven approach, which involves training a machine learning model, is drawing more attention. However, surveying the IRI using conventional methods is expensive and there is limited labelled response data. In contrast, there exists a wealth of unlabelled response data from road users. This scenario presents opportunities for exploring semi-supervised learning (SSL) algorithms, which have been insufficiently researched in this domain. This study addresses this gap by applying an SSL framework to refine an IRI estimation model. Our results show that the SSL-trained model achieves a lower RMSE than the fully supervised trained model.

Introduction

Pavement deteriorates under the effects of traffic loading and environmental conditions, resulting in defects such as potholes and cracks. These failures affect ride quality and increase the likelihood of vehicle damage and safety risks. A road roughness index indicates the condition of the road, and the most prevalently used one is the International Roughness Index (IRI) (Yu et al., 2022). Conventional roughness index estimation (RIE) systems are labour-intensive, and require a complex set-up Qiqin Yu and Wix (2023). As a result, these systems are limited in surveying frequency and spatial coverage. Studies have proposed utilising a crowdsourcing-based approach to tackle these issues, since the proliferation of smartphones presents an opportunity to leverage data from road users (Staniek, 2021). The embedded sensors, such as the accelerometer and gyroscope, could be exploited to characterise road pavement based on the traversing vehicles' responses. Such a collaborative assessment approach could potentially supplement conventional instruments by locating distressed road segments more responsively and cost-effectively.

Existing studies have focused on increasing the accuracy of smartphone-based systems by applying statistical-based methods, vehicle mechanistic model-considered and machine learning methods (Yu et al., 2022). However, a dominant difference between the smartphone-based method and the conventional approaches is the amount of data generated. The data generated from the smartphone-based approach is thousands of folds to that of the conventional approaches. Many vehicles are driving on relatively fixed routes (e.g., from home to work), and the response data from these vehicles could effectively indicate the pavement roughness condition. In practice, collecting data in road segments labelled by ground-truth IRI is expensive and likely unavailable in remote regions. As a result, only a small amount of smartphone response data could be mapped with the ground-truth IRI. Meanwhile, there is a large amount of useful response data driving on road networks whose IRI is unknown and such data becomes unlabelled. It is believed that such response data should also be exploited to contribute to the IRI estimation model. Essentially, only a small percentage of samples are labelled while the majority remains unlabelled, and this scenario presents opportunities for exploring semi-supervised learning (SSL) algorithms and little research has touched this area. To fill the gap, this study proposes an SSL-based framework for estimating IRI by considering both labelled and unlabelled vehicle response data.

The rest of the paper is organised as follows. The Literature Review section summarises relevant studies in SSL and smartphone-based roughness index estimation (sRIE) methods. Next, the Methodology section elaborates on the proposed framework for IRI estimation using SSL. The Data Collection and Data Pre-processing sections provide information on obtaining and preparing data for training. The Experiment section details the training of the initial IRI-estimation model and the implementation of the SSL technique. Lastly, the Discussion section breaks down the contributions and limitations of this study and sheds light on directions of future research.

Literature review

Semi-supervised learning

As the quantity of available data grows and the hardware computational capabilities grow, deep learning (DL) has been making significant contributions in various applications (Pouyanfar et al., 2018). However, the prerequisite of these encouraging results usually relies on a large amount of labelled data, which is often expensive and difficult to obtain compared with unlabelled data (Ouali et al., 2020). Hence, semi-supervised learning (SSL) was proposed to leverage a volume of unlabelled data to improve the DL model performance based on a small number of labelled data. Specifically, with respect to loss function and model design, the SSL methods could be categorised into 5 groups, deep generative methods, consistency regularization methods, graph-based methods, pseudo-labeling methods, and hybrid methods (Yang et al., 2022). For example, given labelled data, the typical Generative Adversarial Networks (GAN), as described in

Ian et al. (2020), consist of two neural networks, a generator, and a discriminator, and were supposed to generate new samples through adversarial training. As a consistency regularization method, Mean Teacher (Tarvainen and Valpola, 2017) leverages consistency regularization to train the model with both high accuracy and strong robustness by integrating Exponential Moving Average (EMA) during the training step. Meanwhile, the manifold assumption, a fundamental principle in semi-supervised learning (Learning, 2006), has been employed by GoodBadGNN to enhance the model's inference performance (Dai et al., 2017). Pseudo-label claimed a straightforward and effective approach for training a robust deep learning model by initially training it on labelled data and subsequently retraining the model with high-confidence predictions on unlabelled data (Lee et al., 2013). Moreover, since most semi-supervised learning methods rely on unique structure in the domain data, a hybrid method, the VIME (Value Imputation and Mask Estimation) was proposed for tabular data that does not have explicit structure as image data (Yoon et al., 2020). Overall, SSL methods are used to learn the underlying pattern from unlabelled datasets and hence to augment the labelled dataset. Specifically, Consistency regularization methods directly improve the performance and robustness of the DL model by contrasting learning. Pseudo-labeling enhances model performance by initially training on a limited labeled dataset, followed by generating predicted labels with high confidence from an unlabeled dataset, which are subsequently integrated into the training process to retrain the initial deep learning model.

In terms of using semi-supervised learning in data-driven pavement RIE, Liu et al. (2021) proposed a framework to estimate the IRI leveraging both labelled and unlabelled IRI data. Their study used the labelled IRI to back-estimate the mechanistic properties of the vehicle models, and then used the characterised vehicles to survey other unlabelled road segments. While their study claimed it was an SSL approach, it didn't apply any SSL algorithm to leverage the unlabelled response data to improve the performance of an IRI estimation model. To the author's knowledge, no other studies have applied SSL algorithms in estimating the IRI.

Crowdsourcing-based infrastructure health monitoring

Estimations made by a single smartphone may be inadequate in accuracy and consistency. Crowdsourcing smartphone measurements aim to aggregate measurements from a large number of participants. Big data enables analysis of the impact of practical factors, including speed, vehicle types, smartphone models, and mounting configuration/position, on the response-based IRI estimation method. Li and Goldberg (2018) proposed crowdsourcing systems to evaluate pavement roughness. Recently, Jeong and Jo (2023) implemented a validated IRI-estimation approach using response data collected from 29 vehicles, 8 smartphone models, and 5 mounting types. By considering various practical settings, their study was conducted in a controlled environment and the participants surveyed a single route of 18.2 km.

Methodology

This section provides an overview of the proposed framework for estimating the IRI by incorporating the profiler, sRIE systems and the crowdsourcing participants. The framework contains two modules. The first module features a multilayer perceptron (MLP) model for estimating the IRI, and the second module engages crowdsourcing data collection and leverages an SSL framework to improve the accuracy of the trained model. A schematic overview of the proposed framework is demonstrated in Figure 1.

In Module 1, model development, the selected state road network was surveyed using inertial profilers, the ground-truth IRI surveying instrument. Passenger vehicles were then deployed to survey the same road networks and their

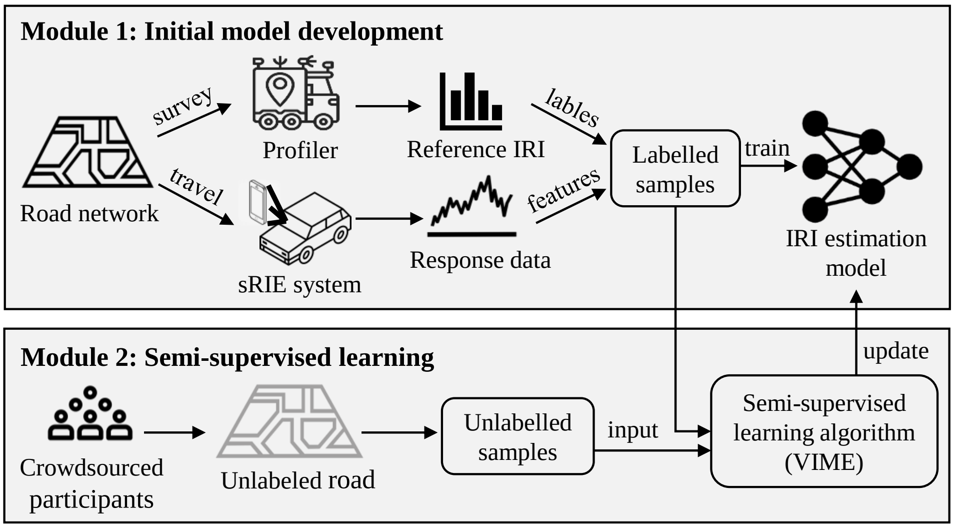


Figure 1: Semi-supervised learning-based IRI estimation schematic framework

dynamic response data was recorded using windscreen-mounted smartphones. A smartphone App was developed to collect the Inertial measurement unit (IMU) and GPS data. The obtained response data is essentially the time series of triaxial acceleration and is delineated into different road segments based on the GPS. Features from both statistical and frequency domains were then extracted to train an IRI estimation model using MLP.

In Module 2, since not the entire road networks were surveyed with the profiler, a large amount of unlabelled data is generated when the participants travel on a road whose ground-truth IRI is unknown. Therefore, routes are divided into two groups. Road segments that were surveyed by the profiler are called labelled roads since their ground-truth IRI is known and the vehicle's response data on these routes are labelled data. In contrast, other roads are called unlabelled roads and their vehicle response data is unlabelled. The SSL makes use of a small amount of labelled data with a large amount of unlabelled data (Liu et al., 2021), and increases the accuracy of the MLP model developed in Module 1. This study adopts the learning framework "VIME (Value Imputation and Mask Estimation)" that employs a data augmentation method, generating augmented samples for each feature set (Yoon et al., 2020). Specifically, unlabelled data are fed into VIME, which learns the underlying patterns within features. To achieve this, the original feature matrix X is shuffled to create a new feature matrix $\hat{X}$. A mask matrix M, with the same dimensions as the feature matrix X, is generated based on the Bernoulli distribution, and its counterpart $(1-M)$ is also computed. Finally, the corrupted feature matrix $\tilde{X}$ is acquired. In this case, VIME is trained to recover from the corrupted feature matrix $\tilde{X}$ to the original matrix X, enabling it to learn the underlying patterns within the features. As a result, VIME transforms the feature samples from labelled dataset into latent representations. These representations were then fed into the MLP model for IRI estimation. Figure 2 demonstrates the application of the VIME method in this application context.

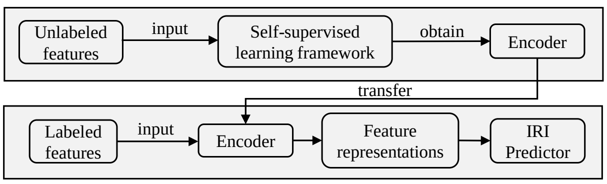


Figure 2: Semi-supervised learning method (VIME)

Data collection

This section details the experiment routes and set-up of the data collection instruments, including the profiler and the smartphone-based response data collection system.

Survey routes

As shown in Figure 3, six routes around the Clayton campus of Monash University, in Melbourne, Australia, were selected. The routes collectively span a total length of nearly 100km (including both directions). The major routes around the campus were selected as they were driven by university staff and students, who were the participants of the crowdsourcing study.

Figure 3: Experiment survey routes

Ground-truth IRI survey instrument

The ground-truth IRI was surveyed using an inertial profiler system from the National Transport Research Organisation (NTRO). This instrument was certified in accordance with the Austroads standards on profiler validation (Austroads, 2016). The inertial profiler consists of a laser profilometer and accelerometers. The laser profilometer measures the distance to the road surface while the self-movement of the vehicle body is integrated from the accelerometer measurements. Knowing the initial height of the laser profilometer, the roughness elevation profile can then be calculated. The IRI is then computed by running the Golden-Car simulation on the measured profile. Two repetitive runs were conducted on all routes to obtain robust ground-truth IRI measurements which were sampled at a 10m interval. The distribution of the ground-truth IRI values in five survey routes is illustrated in Figure 3.

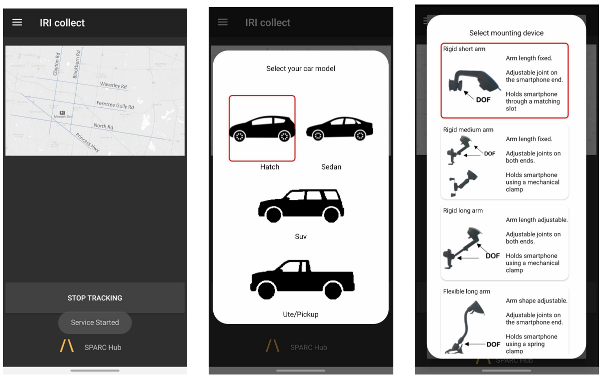
(a) Survey vehicle (b) Profiler (under front bumper)

Figure 4: Ground-truth IRI instrument

Table 1: Ground-truth IRI distribution

IRI Band	Quantity	Percentage
0-2	44,665	45.8%
2-4	44,213	45.4%
4-6	6,823	7%
6-8	1,445	1.5%
8-10	216	0.2%
>10	123	<0.1%

Figure 5: Smartphone IMU sensor axial orientations.



(a) Home (b) Vehicle select (c) Mount select

Figure 6: Data collection App user interface.

Smartphone-based response data collection system

The vehicle response data is collected from common passenger car models of different body types. Four smartphones of the same model, each held using a different mount, were deployed to collect the vehicle response data, as demonstrated in Figure 5. The four mountings were different in their arm length and mechanism type and represented the range of commonly available models in the market. Meanwhile, an Android application was developed to collect the smartphone's IMU and GPS data. The collected data includes the timestamp, tri-axial accelerometer, tri-axial gyroscope, rotational sensor, GPS and speed. The App interfaces are shown in Figure 6. The user's vehicle body type and mounting type were also recorded in the App.

Data preprocessing

Data preprocessing contains two tasks, data mapping and data cleaning. Data mapping assigns the smartphone measurements with the ground-truth IRI. Each acceleration measurement now has its own latitude and longitude records. Meanwhile, the latitude and longitude of the start and end points of each 10m ground-truth IRI segment are known. By selecting the smartphone data points that are spatially closest to the reference start and end points of each segment and knowing their timestamp, the time window that corresponds to the reference segment could be determined. The mapping was completed by assigning the smartphone data points in this time window with their corresponding ground-truth IRI.

The next step is data cleaning. The raw smartphone sensor data contains invalid records that must be removed. Among the collected 1.82×10^7 sensor data, the number of "NaN" in the accelerometer, gyroscope and rotation sensors are 6.06×10^3, 1.02×10^3 and 1.38×10^6, respectively. These "NaN" records were imputed with the local mean, which was calculated from data points in the same segment where the "NaN" record sits. Moreover, it is worth noting that the profiler does not record an IRI when the travel speed is less than 20km/h. Hence, there was no ground-truth IRI (label) for some segments and as a result, the corresponding smartphone data was also removed. In addition, road roughness may not excite movement of the vehicle body when the travel speed is low. In this study, the minimum speed was set as 20km/h and response data recorded below this speed was also excluded.

Experiment

Multilayer perceptron training - Module 1

This section elaborates on the training of the MLP-based IRI-estimation model. Statistical and frequency features were extracted from the signals collected from the tri-axial accelerometer, the gyroscope, and the rotational sensor. Statistical features were chosen according to related empirical work (Souza et al., 2018), including mean, median, average magnitude value, standard deviation, zero-crossing rate, skewness, kurtosis, entropy, maximum-to-minimum difference, root mean square level, peak magnitude to RMS ratio, the mean number of peaks, crest factor and IQR (Interquartile Range). On the other hand, after applying Fast Fourier Transform (FFT) to the time-domain signal, 6 frequency features including spectral entropy, spectral irregularity, flux, bandpower, max peak and max peak location were computed. Additionally, categorical features such as car model and mounting device type were also included in the feature set. Consequently, when provided with a label (IRI value), the input to the DL model comprises a vector with a dimension of 258, encompassing 256 numerical features and 2 categorical features.

In the training process, the Adam optimiser was employed with a parameter learning rate of 1e-3. The networks underwent training with a batch size of 128, a seed value of 777 for reproducibility, and a total of 50 epochs. The framework used to construct the model in this study was TensorFlow (TF). In this study, 80% of the pre-processed data was allocated for training the model, while 10% was reserved for validation to fine-tune the model and optimise hyperparameters. The remaining 10% of the data was kept for testing. Different model structures were trialled and the fully connected layers with neurons of 128-256-512 performed the best. The model achieved an root-mean-square error (RMSE) of 0.57, as shown in Figure 7. The R-square of the linear regression between the estimated and ground-truth IRI was 0.79, as demonstrated in Figure 8. The calculation of RMSE is shown in the below formula.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$\boldsymbol{n}$: The number of samples,
$\boldsymbol{y_i}$: Ground-truch IRI ,
$\boldsymbol{\hat{y}_i}$: Predicted IRI.

Semi-supervised learning - Module 2

Besides the labelled data, unlabelled data is generated when vehicles drive on road networks whose ground-truth IRI is unknown. Based on these data, VIME was adopted as the semi-supervised learning methodology. The hyper-parameters (learning rate, p_m, and alpha) and output dimension were subsequently refined to align more suitably with the objectives of our work. After applying the SSL algorithm, the performance of the original DL model developed in Multilayer perceptron training - Module 1 improved, as evidenced by the lower RMSE, indicated in Figure 9.

A systematic validation procedure was undertaken to evaluate the efficacy of VIME. A predetermined label rate, ranging from 30% to 90%, was set to extract a labelled subset of the initial entire labelled dataset. The selected labelled subset was then employed to train the supervised model elaborated upon in Section Multilayer perceptron training - Module 1. Simultaneously, the remaining data was regarded as unlabelled data, and the encoder in the VIME algorithm was trained using this unlabelled data to learn the underlying feature patterns and generate a novel representation for each sample. Then, the labelled subset data along with the representations of the original unlabelled subset were both used to retrain the model. This semi-supervised trained model was then compared with the model trained exclusively using the labelled data subset. This study trialled different label rates ranging from 30% to 90% with a step of 10%, and the RMSE values of the two streams of models are plotted in Figure 9. It is shown that both lines go downwards as the label rate increases, indicating that the performance of both models improves with more labelled data. However, it should be noted the SSL-trained model consistently sits marginally below the fully supervised-trained model, suggesting that the SSL-trained model achieves a lower RMSE, and therefore shows a better performance across the entire label rate range. It should be noted that the improved performance is not solely attributed to using more data, and the implication is that leveraging both labelled and unlabelled data to capture underlying patterns more effectively improves the model's generalisation and performance on unseen data.

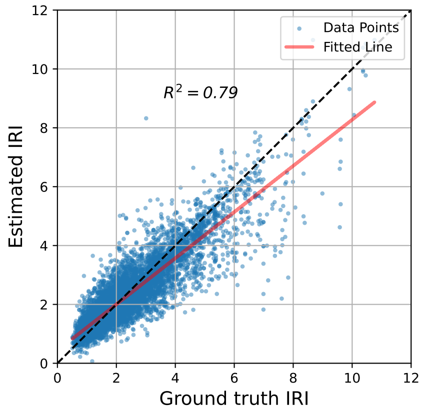


Figure 8: Estimated IRI vs Ground truth IRI datapoints and regression line.

Discussion

This section summarises the contributions of the proposed SSL framework, discusses the limitations of the methods developed, and suggests the areas of future research that promote the application of data-driven sRIE systems.

Contributions

Our study advances the field of data-driven road roughness evaluation, by introducing an SSL framework that leverages real-world data. Key contributions include:

Considering the real-world practical set-up challenges.

This is the first study to simultaneously utilise real-world data while accounting for variations in car models and

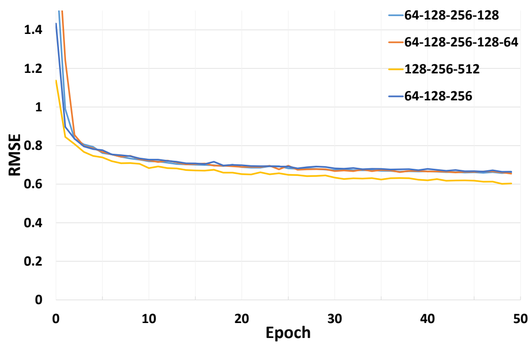


Figure 7: The MSE vs Epoch plot between different MLP model structures using validation dataset.

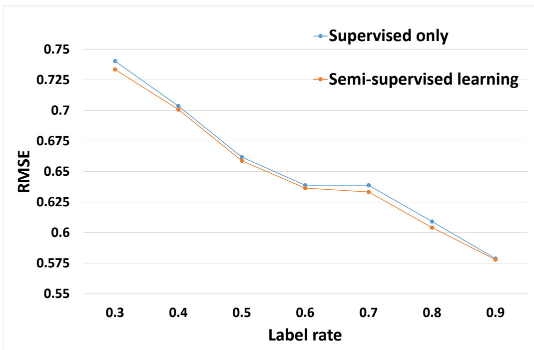


Figure 9: RMSE of the fully-supervised and semi-supervised models in different label rates.

mounting devices, unlike previous studies that worked on simulated vehicle responses or involved single vehicle and mounting configuration.

Adopting SSL to leverage unlabelled data.

Extending the application of SSL in data-driven infrastructure health monitoring, our study validates the idea of using limited labelled data while leveraging the crowdsourced unlabelled data to improve the model's performance, as demonstrated by the lower RMSE values. It's important to note that this improvement partially results from the inclusion of additional unlabelled data, which results in a more comprehensive dataset than what is available to fully-supervised models. Our findings underscore SSL's potential for scalable and cost-effective infrastructure monitoring, especially in contexts where labelled data is limited.

Setting a benchmark for SSL-based pavement roughness evaluation.

By integrating semi-supervised learning with real-world data collection, our proposed framework utilises both specialised survey instruments and public vehicles, and the SSL method yielded a lower RMSE than the model trained with full supervision. This study sets a benchmark for future studies exploring this field and contributes to the knowledge of a scalable and cost-effective approach for real-time pavement roughness monitoring.

Limitations

Limitations of this study are acknowledged:

Ground-truth data imbalance.

As an inherent property of the experiment route's roughness, the ground-truth IRI data is imbalanced, as illustrated in Table 1. Specifically, the ground-truth data sit mostly in the range of 0-4 mm/m and lacks in high IRI ranges (above 6 mm/m) and such imbalance limits the SSL algorithm's performance. Since the SSL algorithms involve learning the patterns of the unlabelled features, and due to a lack of response data for high-IRI road segments, there is not enough data for the algorithm to learn the patterns from. As a result, the SSL can exhaustively learn the complete patterns of features in the low-IRI range, and improves the model's estimation accuracy in this range better than that on the high-IRI range.

Limited semi-supervised learning method.

This study only explored one SSL method, namely VIME. While VIME has shown promising results in our context, our study struggled to find other open-sourced SSL methods that work on tabular data features, instead of the image data, which is predominantly studied in SSL. The improvement in the model's accuracy achieved in this study using VIME does not represent the benefits that generic SSL methods could provide in this application context.

Resource intensity of Semi-supervised learning.

Under the context of crowdsourcing-based road roughness monitoring, crowdsourced smartphone sensor data could become resource-intensive, in terms of computational power and data storage. Moreover, SSL techniques involve iterative mutation of the raw data, posing challenges for scalability and real-time data processing, which could be crucial for data-driven monitoring approaches.

Future works

Implementation using crowdsourced data

Our research has validated the effectiveness of using SSL techniques to leverage unlabelled data in training the IRI estimation model. In the next stage, the team plans to engage crowdsourcing participants to collect unlabelled data in real-world scenarios. It is expected that more variations exist in the public participants' practical set-ups and the response data collected under such conditions contains underlying patterns that could be learned by self-supervised and semi-supervised learning algorithms. Consequently, by accounting for these variations, a more robust and adaptable estimation model could be developed.

Dependency on participant compliance

Crowdsourcing relies on the active and correct usage of our data collection app by participants and the robustness of collected data depends on the participant's compliance with collection rules. Such an issue, which exists in crowdsourcing-based research studies, becomes more critical when the scale of the data collection grows. Hence, strategies to enhance participant compliance and retention become necessary. These strategies could may more engaging App user interfaces, regular reminders, incentives aligned with long-term participation, etc., and can be explored in future research.

Incorporating connected vehicles in RIE

While this study adopted smartphones as the roughness data collector, the prevalence of connected vehicles has drawn research focus. These vehicles are equipped with GPS and motion sensors and the data is uploaded to the manufacturer's servers, providing a rich data source. However, the integration of data from connected vehicles in the proposed SSL framework poses many challenges. One of the primary concerns is addressing inaccuracies that may arise from differences in vehicle types. Identifying and rectifying these inaccuracies is crucial to ensure the validity of roughness monitoring using this approach.

Applying other SSL methods

A comparative analysis of other SSL techniques could be explored in future research. Such exploration would also enable a more comprehensive understanding of the strengths and limitations of various semi-supervised learning strategies in this application context.

Conclusion

This study proposed an SSL-based framework for IRI estimation and validated its effectiveness using real-world data. Smartphone-collected vehicle response data was collected from different mounting configurations and vehicle models. An MLP-based IRI estimation model was first trained and an SSL algorithm (VIME) was adopted to learn patterns from the unlabelled data and to generate new representations of the data features used to predict the IRI. The results suggest that the SSL-trained model achieves a lower RMSE than the fully supervised trained model, when the same amount of labelled data was provided. Our study adds to the body of knowledge in smartphone-based road roughness monitoring by 1) developing an IRI-estimation model trained using real-world vehicle responses, considering the vehicle and mounting variations, 2) proposing an SSL framework that leverages both labelled and unlabelled response data, 3) improving the accuracy of an existing model by using SSL techniques, and 4) validating the benefits of incorporating SSL in crowdsourced pavement roughness monitoring.

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