RESEARCH REPORT

Institute of Transportation Studies | UNIVERSITY OF CALIFORNIA

Improved California Truck Traffic Census Reporting and Spatial Activity Measurement

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16. Abstract
The Federal Highway Administration (FHWA) vehicle classification scheme is designed to serve various transportation operational and planning needs. Many transportation agencies rely on Weigh-In-Motion and automatic vehicle classification sites to collect vehicle classification count data. However, these systems are not widely deployed due to high installation and operations costs. One cost-effective approach investigated by researchers has been the use of single inductive loop sensors as an alternative to obtain FHWA vehicle classification data. However, most models do not accurately classify under-represented classes, even though many of these minority classes pose disproportionally adverse impacts on pavement infrastructure and the environment. As a consequence, previous models have not been able to adequately classify under-represented classes, and the overall performance of the models are often masked by excellent classification accuracy of the majority classes, such as passenger vehicles and five-axle tractor trailers. This project developed a bootstrap aggregating (bagging) deep neural network (DNN) model on a truck-focused dataset obtained from Truck Activity Monitoring System (TAMS) sites, which leverage existing inductive loop sensor infrastructure coupled with deployed inductive loop signature technology, and already deployed statewide at over ninety locations across all Caltrans Districts. The proposed method significantly improved the model performance on truck-related classes, especially minority classes such as Classes 7 and 11 which were overlooked in previous research studies. Remarkably, the proposed model is also capable of distinguishing classes with overlapping axle configuration, which is generally a challenge for axle-based sensor systems.

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Executive Summary

Traffic counts using automatic detector systems that can distinguish different types of vehicles are a major source for traffic volume data, which is needed for highway project planning, development and financing, analyzing, monitoring and controlling traffic movement, traffic accident surveillance, highway repair and preventative maintenance, and many other purposes (Caltrans, 1996). Investments in detector infrastructure has been significant: there are approximately 3000 Traffic Census stations in California that are currently used to report traffic count and vehicle classification data for state and federal programs. Data concerning the truck fleet are especially important since trucks are responsible for much of the damage to the state's roadways, and different types of trucks cause different degrees of damage. The Truck Activity Monitoring System (TAMS), developed and hosted at the Institute of Transportation Studies at UC Irvine (ITS-Irvine), leverages existing in-pavement traffic sensors to provide truck activity data in California. This is accomplished by updating existing inductive loop detector sites with inductive signature technology and implementing advanced truck classification models to provide detailed truck count data for over 40 detailed truck body configurations. The initial system was originally developed by ITS-Irvine for the California Air Resources Board (CARB) for implementation at sixteen locations in the San Joaquin Valley and subsequently deployed statewide to over 90 detector locations in California with funding from the California Department of Transportation (Caltrans) to provide live coverage at state borders, regional cordons and significant metropolitan truck corridors.

This research project improved the capabilities of the TAMS through designing and developing the TAMS Traffic Census Reporting Dashboard — a centralized Federal Highway Administration (FHWA) vehicle classification data reporting module for the Caltrans Traffic Census Program. The module reports traffic count data to the national Highway Performance Measurement System (HPMS) to support the analysis of highway system condition, performance, and investment needs, and for apportioning Federal Highway Funds to individual states under the Transportation Equity Act for the 21st Century (TEA-21).

The main challenge for this project was that many truck classes with larger configurations (i.e., truck size, body types, number and placing of axles) are rarely observed in the roadway network, which increases the difficulty of developing a model to correctly classify these trucks from data gathered by the road sensors. In order to provide reliable and accurate FHWA vehicle classification data, this project developed a new neural network model specifically designed to improve the classification performance of under-represented truck configurations using the existing inductive loop sensor infrastructure. The data used to develop the model was collected at 16 different TAMS sites across California in 2012, 2013, and 2016. Four additional independent sites were selected to test the ability of the developed model to perform well at new locations. The overall accuracy of the final model was 0.92 (meaning the truck type was correctly identified 92 percent of the time) and the average F1 score[1] was 0.83 (out of 1), which outperforms the state-of-the-art signature-based

[1] The F1 score is a statistical measure that takes into the account of false positives and false negatives, which is particularly useful for evaluating models on datasets with an uneven class distribution.

classification model. The model performance on an independent dataset – obtained from locations outside the original dataset that was used for model development – achieved an accuracy of 0.87 and average F1 score of 0.72. These results demonstrate that the model is expected to perform well at new locations.

This project provides a cost-efficient solution for reporting FHWA vehicle classification counts through an enhancement to TAMS and can be used as a replacement of more expensive but less reliable axle sensors. The improved reliability also decreases the exposure of field personnel to safety hazards by reducing the need for maintenance operations. The upgraded TAMS Traffic Census Reporting Dashboard provides a streamlined process for generating reports for the traffic census programs by using data reported through TAMS, which is an improvement over the current reporting system.

Contents

Introduction

Commercial trucks vary in size, length, number of axles, how far apart the axles are spaced, and number of tires per axle. This is significant because different truck types cause different degrees and types of wear to pavement surfaces. The Federal Highway Administration's (FHWA's) Traffic Monitoring Guide outlines a standardized classification scheme that categorizes vehicles into thirteen classes (see Figure 1), based on tire and axle combination while partially taking into account general body configuration (*1*). This classification scheme has been widely used for pavement design to account for the dissimilar pavement impacts attributed to varying physical vehicle characteristics (*2*). In addition, aggregated FHWA vehicle classes have been used as inputs for on-road emission estimation models (*3*) as well as in freight forecast modeling (*4*, *5*).

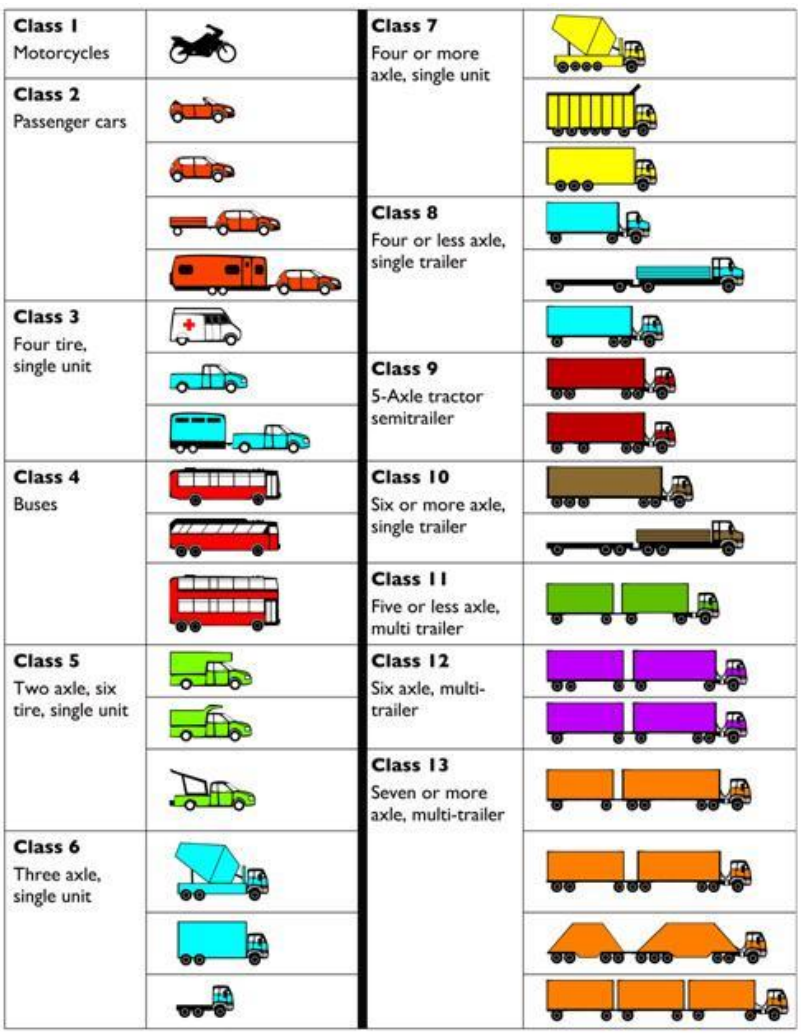

Figure 1. FHWA 13-category scheme for axle-configuration-based vehicle classifications.

Weigh-In-Motion (WIM) and Automatic Vehicle Classification (AVC) sites using axle sensor technologies can directly capture vehicle axle configuration information. Hence, these types of systems have been commonly used to report vehicle classification counts according to FHWA-based schemes. However, those sensors are not comprehensively deployed in the transportation highway network due to their high installation and maintenance costs. Conversely, inductive loop sensors are much more widely deployed in many jurisdictions as they have a much lower installation and maintenance cost. One problem with these sensors is that while they are quite accurate overall, they tend to do a better job of identifying non-trucks than trucks. Studies have investigated the use of inductive vehicle signatures to classify vehicles based on the FHWA classification scheme (*9*, *10*). However, the high accuracy in classifying passenger vehicles classes and Class 9 trucks (standard semi-trailers) conceals the deficiencies of the models in identifying other FHWA truck-related classes. Even though trucks generally account for approximately 5 to 20 percent of vehicles in traffic streams, the adverse impact of misclassifying trucks could be significant. For instance, implementation of previous models may underestimate the pavement damage caused by trucks, since pavement structures are disproportionately impacted by heavy trucks (*2*). From a planning perspective, unreliable truck counts may result in a flawed understanding of truck activities and misinformed policy decisions to manage future demand for truck movements and operations. Furthermore, the undercounts also occur within some truck-associated classes. Certain types of trucks in the FHWA classification scheme – such as Classes 7, 11, 12 and 13 – are not observed as frequently on the roadway network compared to other classes. On the other hand, Class 9 trucks are the most common multi-unit truck configuration observed along most corridors and show great variability in their body types. The main problem is that the models currently in use have trouble distinguishing between these less frequently seen, yet significant, truck types.

The basic assumption of canonical machine learning algorithms for classification problems is that the distribution of observation samples across categories are relatively similar or uniform (*13*). Consequently, datasets with an uneven class distribution pose a natural difficulty for many classification algorithms to correctly classify observations in under-represented categories, since their performance is naturally biased towards majority classes. Notwithstanding, many under-represented truck classes have significant influence in both pavement design (*2*) and freight forecast modeling (*4*, *5*).

To improve vehicle classification and reporting, this project developed an accurate FHWA vehicle classification model using a truck-focused dataset which was tested on data from independent test sites. The model represents a significant improvement over previous signature-based FHWA vehicle classification models (*9*, *10*) for all truck classes in terms of F1 scores (a statistical measure between 0 and 1 of the model's accuracy that accounts for errors in detecting harder to classify types), especially on minority classes such as Classes 7 and 11 which were overlooked by previous studies (*9*, *10*). The algorithm development in this project comprised three steps. First, a sample dataset was created that included a representative number of the harder to detect minority truck classes. Second, a deep neural network[2] (DNN) was developed. Finally, a bootstrap aggregating ensemble (bagging) methodology was developed and applied to the testing sample to address the problem of

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[2] A Deep Neural Networks (DNN) is a more complicated form of neural network that comprise many hidden layers, with the ability to obtain higher performance, efficiency, and accuracy.

accurately classifying more rarely observed truck types. The training and testing datasets were split using the stratified sampling method to retain the representativeness of the training instances for under-represented classes. The bagging DNN successfully improved on how well the model accurately identify the rarer truck types without misidentifying the more common types. The model was then tested using independent datasets drawn from different testing sites.

Literature Review

Axle Sensor Methods

FHWA axle-based vehicle classification data has been traditionally collected via axle-based sensors, such as road tube arrays (*5*), piezoelectric sensors (*14*), WIM systems (*15*) and wireless accelerometer sensors (*16*), all of which have the ability to detect the number of axle in the vehicle passing over the sensor and how far the axles are spaced apart. Transportation agencies across the United States rely on existing classification sites equipped with axle-based sensors for reporting FHWA vehicle classification counts. Efforts have been devoted to test the performance of classification sites and investigate methods to enhance the classification accuracy of these systems, which have problems distinguishing different vehicle classes that share the same axle configurations (*14*, *15*). For example, Classes 2 through 5 include two-axle vehicles (*15*), where the distance between the axles fall in overlapping ranges. In addition, axle-spacing between the first and second axle of Classes 3, 5 and 8 can be similar as well (*14*). This presents a natural challenge for classification systems based on axle sensors to distinguish the aforementioned categories. Kwigizile et al. improved the correct classification rate for overlapping classes by breaking down the 13 FHWA classes into 28 detailed subclasses and using an algorithm to assign the sensor reading to a particular subclass and truck type. (*15*). Kwigizile's model reduced the error rate of the calibrated WIM site from 9.5 percent to 6.2 percent. The author highlighted that the misclassification came from systematic errors due to overlapping axle configurations across FHWA classes. The inclusion of truck weight data reduced the error rate by a further 3.0m percent. However, truck weights vary by trip due to changes in payload. Hence, the use of weight data is not reliable and may affect the transferability of their model.

Bitar et al. adopted a probabilistic approach to improve the accuracy of the classification site equipped with piezoelectric sensors (*14*). In their study, a comprehensive classification error analysis was conducted on the overlapping axle configuration across the FHWA scheme's categories. Their observation was that axle spacing distributions are different for classes that may share similar axle configurations. Although some truck classes have similar axle configurations, the average spacing between the axles may differ. Hence, the axle spacings associated with each class were fitted into Gaussian distributions. Subsequently, the optimal class boundary thresholds for the overlapping axle configuration were determined according to the estimated axle-spacing distributions. The error rate was significantly reduced from the original sensor outputs especially for Classes 3, 6, and 7 (*14*).

However, axle-based sensors do not provide any information about the truck's general body type to help identify it according to the FHWA classification scheme. For example, the error rate of their model on Class 4 (bus or bus with a trailer) was higher compared to the original sensor measurements. The average spacing between the axles of Classes 4 and 5 had a significant overlap and did not provide a clear means to distinguish these two very distinct truck body types — buses in Class 4 and single-unit trucks in Class 5.

In addition, a prototype wireless accelerometer system, which detects the pavement vibration when vehicles traverse the detection area, have also been explored for estimating axle-based classifications (16). The sensor identified the axle configuration through locating the vibration peaks. The accelerometer-based classification was evaluated using calibrated WIM classification results. This wireless sensor was able to achieve the same level of accuracy as the current WIM system in estimating FHWA classes. However, accelerometer sensors would experience the same limitations as other axle detectors in distinguishing classes with overlapping axle spacing ranges.

The detection sites equipped with WIM systems or piezoelectric sensors are sparsely deployed in the roadway network due to their high installation cost. Hence, researchers investigated existing inductive loop sensors as an alternative since they are widely deployed across the United States and their installation and operation cost are relatively inexpensive.

Single Inductive Signature Methods

Inductive loop detectors consist of wire loops embedded in the pavement. As a vehicle passes over the inductive loop detectors, the metal induces an electric pulse in the wire which is recorded by a sensor. Unlike conventional inductive loop detectors that simply provide vehicle counts, advanced loop detectors capture more detailed inductance changes when a vehicle traverses an inductive loop sensor. The resulting high-resolution waveform generated by the inductance change measurements is known as an "inductive vehicle signature" (*18*). However, the exact axle locations cannot be directly identified from inductive vehicle signatures (Figure 2), which is one challenge in classifying vehicles into the FHWA scheme.

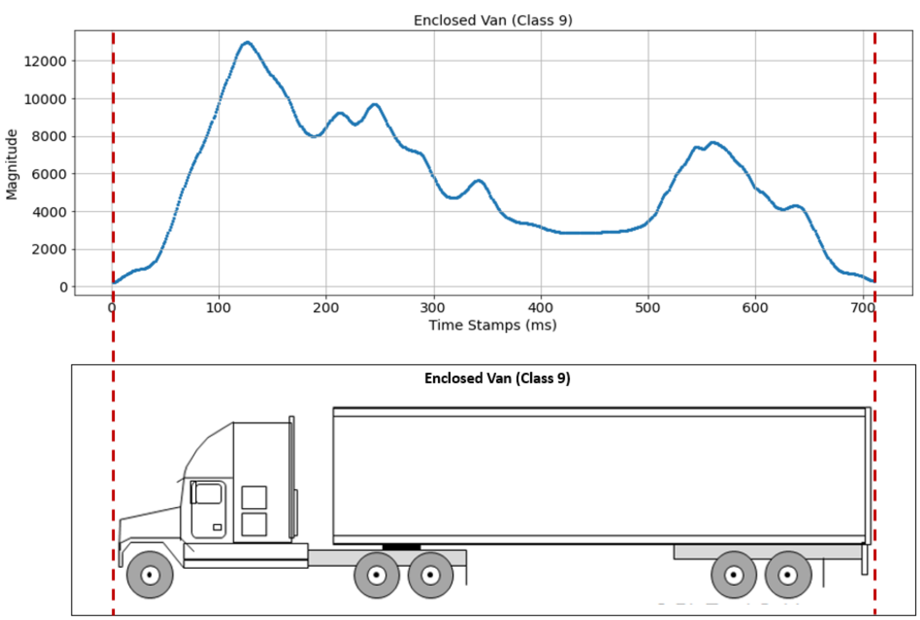


Figure 2. Class 9 enclosed van and its corresponding raw vehicle signature.

Jeng and Ritchie made the first attempt to classify vehicles on the basis of the FHWA scheme using single inductive loop signature data (*9*). The piecewise slope rates (PSR) of each interpolated signature were used as a reduced representation of each signature pattern. The PSRs of each signature were separated into five groups by visual observation of PSR plots of all vehicle classes (*19*). Unfortunately, due to data limitations, Class 10 to Class 13 trucks, which have disproportionately severe negative impacts on pavement structure, were not considered in their model development process. Later, Jeng et al. enriched their dataset with multi-unit trucks and proposed a new vehicle classification algorithm (*10*). The new algorithm was composed of two steps. First, vehicle signatures were transformed and reconstructed with wavelet transformation. Then, the transformed vehicle signatures were grouped into FHWA classes using K nearest neighbor. Even though the overall accuracy was 92 percent, due to the high performance on predicting the majority classes (Class 2 and Class 3), the method performed poorly on identifying several other truck classes (Class 6, 7, 8, 11, 12, 13). Hence, a focus of this project was to improve the performance of the model on these minority classes.

Data Description

Since truck size and weight laws vary by states and the mix of truck configurations vary across states (*6*), some state agencies modify the FHWA's 13 categories to meet their own transportation application needs (*1*). For example, Class 9 type 32 trucks in California are distinguished from other Class 9 trucks in the FHWA 13-category scheme and form a standalone class labeled as Class 14 (*7*). Since the data used in this study was collected in California at the statewide level, the model here classifies vehicles into the California-modified FHWA scheme (FHWA-CA). Table 1 provides a brief description for each class in the FHWA-CA classification scheme.

Table 1. FHWA-CA classification scheme definitions (8).

FHWA-CA Class	Vehicle Description	Class Includes	# of axles
1	Motorcycle	Motorcycles	2
2	Passenger Vehicles	All cars, Cars with one-axle trailers, Cars with two-axle trailers	2, 3 or 4
3	Other two-axle four-tire Single-unit Vehicle	Pickups and vans, Pickups and Vans with one- and two- axle trailers	2, 3 or 4
4	Bus	Two- and three-axle buses, Bus with trailer	2 or 3 (tractor)
5	Two-axle, Six-tire, single-unit trucks	Two-axle trucks, two-axle trucks with trailer	2 (tractor)
6	Three-axle single-unit trucks	Three-axle trucks, Three-axle tractors without trailers	3
7	Four or more axle single-unit trucks	Four-, five, six- and seven-axle single-unit trucks	4 or more
8	Four or fewer axle single-trailer trucks	Two-axle trucks pulling one- and two-axle trailers, Two-axle tractors pulling one- and two-axle trailers, Three-axle tractors pulling one-axle trailers	3 or 4
9	Five-axle single-trailer trucks	Two-axle tractors pulling three-axle trailers, Three-axle tractors pulling two-axle trailers, Three-axle trucks pulling two-axle trailers	5
10	Six or more axle single-trailer trucks	Three-axle tractors pulling three-axle trailers	6 or more
11	Five or fewer axle multi-trailer trucks	Multiple configurations (Multi-unit trucks)	4 or 5
12	Six-axle multi-trailer trucks	Multiple configurations (Multi-unit trucks)	6
13	Seven or more axle multi trailer trucks	Multiple configurations (Multi-unit trucks)	7 or more
14	Single and tandem axle on tractor, single and single axle on trailer	Single and tandem axle on tractor, single and single axle on trailer	5
15	Unclassified vehicles	Multiple configurations	2 or more

The vehicle signature data used in this project were collected at 20 different detection sites across California in 2012, 2013, and 2016 (16 for model training and testing, 4 for transferability test), with their geographical distribution shown in Figure 3.

Figure 3. Data collection sites for model training, hyperparameter tuning, and transferability testing.

The selected detector sites experienced high truck volumes and a wide variety of truck types. In addition, the data collection effort spanned various traffic conditions. A total of 44,438 vehicle signature records were processed primarily at the truck lanes in each facility, with a resulting vehicle class distribution as shown in Table 2.

Table 2. Vehicle class distribution of processed data.

FHWA-CA Scheme	Counts	Imbalance Rate	Number of Body Types
1	2	0.0001	1
2	2,946	0.1494	4
3	8,203	0.4159	2
4	772	0.0391	3
5	7,055	0.3577	32
6	1,535	0.0778	27
7	279	0.0142	9
8	1,463	0.0742	24
9	19,724	1.0000	40
10	138	0.0070	16
11	1,518	0.0770	21
12	268	0.0136	12
13	3	0.0002	1
14	764	0.0387	14

The imbalance rate presented in Table 2 quantifies the relationship between majority and minority classes. It is defined as the ratio of each minority class to the majority class (Class 9). One key challenge in the model development was to accommodate the imbalanced dataset. When training an imbalanced dataset, models are generally prone to enhance the prediction accuracy of majority class (*13*). This will lead to the majority classes and the overall model achieving relatively high prediction accuracy at the expense of minority classes (*13*).

Typically, the issue of imbalanced datasets in classification is addressed at either the data or algorithm level (*20*). At the data level, minority classes are typically oversampled, while majority classes are undersampled to balance the dataset. However, undersampling may compromise the generality of the model. For instance, Class 9 is a majority class comprising heterogeneous body types with distinct signature waveforms, as shown in Figure 4.

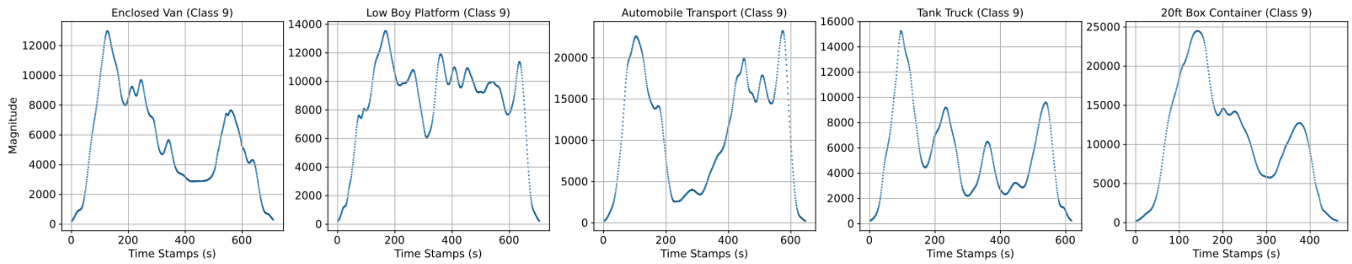


Figure 4. Vehicle signatures of different truck body types.

Undersampling may cause information to be lost by removing unique vehicle configurations that would have helped the model to better capture the characteristics of diverse vehicles found in this class. On the other hand, synthetic data methods which are generally used in oversampling could create overlapping instances between the minority class and the majority class, and further reduce the prediction accuracy for the majority class (*20*). Therefore, this study investigated algorithm-level enhancements to improve the performance of the signature-based FHWA classification model.

According to Table 2, both Classes 1 and 13 have training instances extremely small and less than thirty, which are empirically considered as insignificant sample sizes. Moreover, this project primarily focused on the FHWA-CA truck-related classes. Therefore, Classes 1 (motorcycle) and 15 (unclassified vehicle) were excluded in the modeling process. Since Class 13 share similar body types as well as axle configurations with Class 12 vehicles, they were combined in the model. Classes 1 and 15 (Unclassified vehicle) may be included and Classes 12 and 13 may be split in the future with further enrichment of the dataset.

Model Development

Prior to model development, stratified sampling was initially used to partition the model training and testing dataset with a 70-30 split, respectively, in order to ensure that a sufficient number of samples for each class could be observed in both the training and testing sets.

Feature Extraction

First, raw signatures were processed using cubic spline interpolation to eliminate noises and obtain a set of feature vectors with the same dimension and normalized on both the horizontal (time) and vertical (magnitude) axis (*19*). This yielded a vector of 31 magnitude features equally spaced along the normalized time domain with 30 degrees of freedom. Subsequently, 30 differences were derived from 31 magnitude values and then further normalized along the y-axis, which aligned magnitude and difference values to a common scale. Finally, the last value of the vector of 31 magnitudes was dropped to retain the independence of the feature vector. This resulted in 60 (30 magnitudes and 30 differences) independent features that were used as inputs for the vehicle classification model. The feature extraction process is presented in Figure 5.

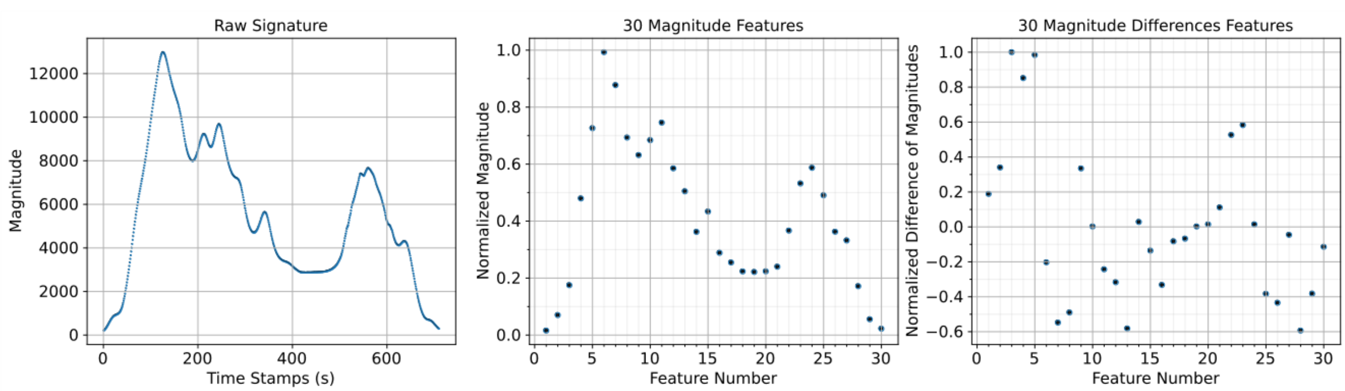
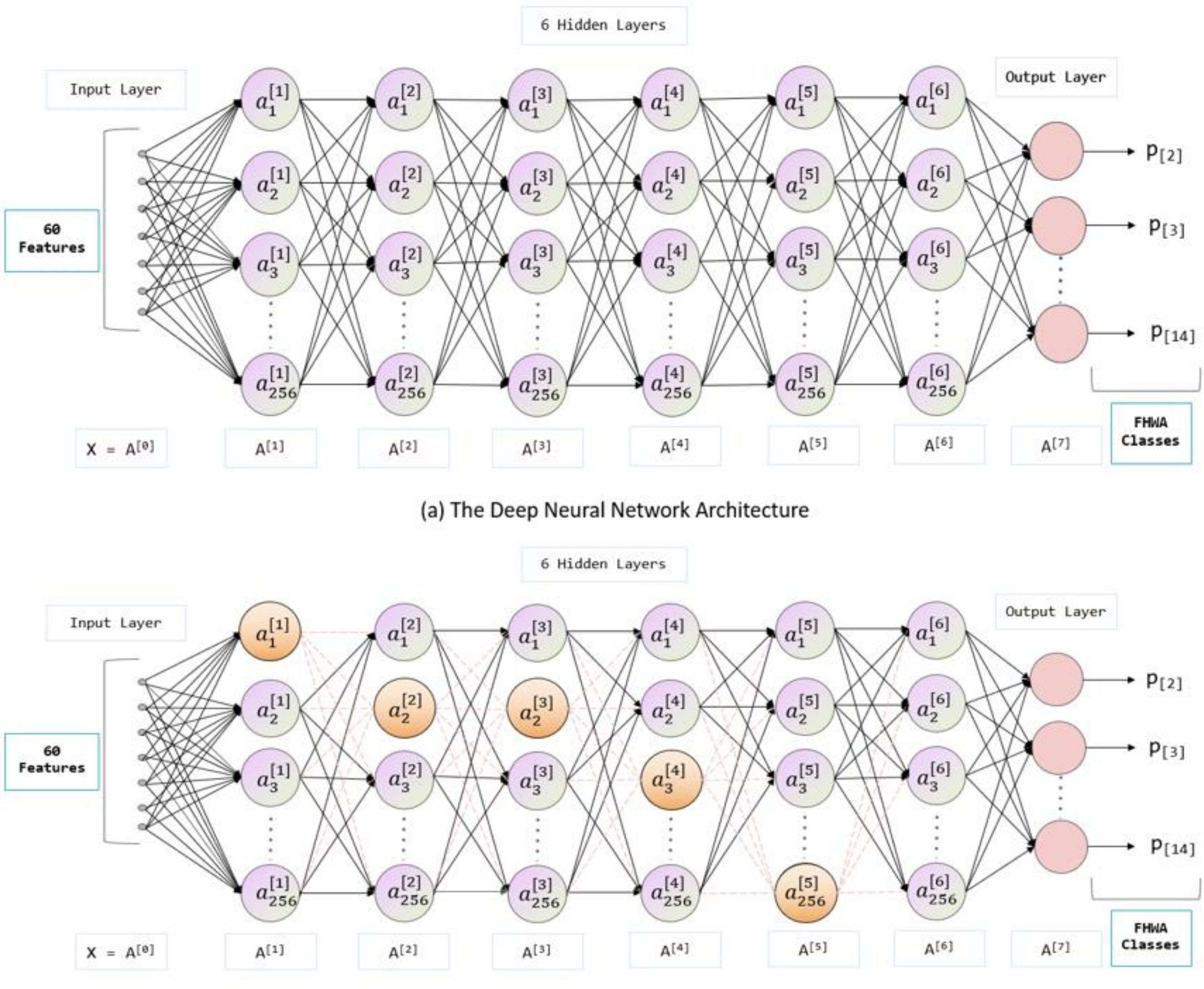


Figure 5. Preprocessing and feature extraction.

Deep Neural Network Architecture

A deep neural network model with dropout regularization was developed to classify vehicles based on the FHWA-CA scheme. The model was constructed with 6 hidden layers, 256 neurons on each hidden layer (shown in Figure 6). The Rectified Linear Unit (ReLU) (*21*) was used as the activation function on each hidden layer, while the Softmax activation function was applied on the output layer to represent the probability distribution over the 12 FHWA categories (where Classes 12 and 13 were combined). To avoid gradients vanishing and exploding, He (*22*) and Xavier (*23*) weight initialization methods were applied to the hidden layers with ReLU and Softmax activation functions, respectively. The deep neural network model was trained with a minibatch size of 100 and learning rate of 0.001. The Adam optimizer (*24*) was adopted to solve this highly non-linear optimization problem.



(a) The Deep Neural Network Architecture

(b) The Deep Neural Network with Dropout Layers

Figure 6. Model structure.

Balancing bias and variance of the deep neural network model was an essential task during the hyperparameter tuning process. Bias represents the expected deviation from the true value of the function while variance measures the deviation from the expected estimator which is caused by the unseen dataset. The deep neural network model is typically prone to overfit the training set as models increase in complexity, especially for the majority classes. This results in a trained model with low bias and high variance as shown in Figure 7a, where the training error tends to decrease (low bias) and the testing error tends to increase (high variance). Dropout regularization — a computationally inexpensive but powerful regularization method for deep neural network models — was implemented at each layer in the deep neural network to prevent overfitting (25). Thirty percent of the neurons within each hidden layer were randomly dropped out while the remaining 70 percent were retained (Figure 6b) during the training process. A comparison of early stopping without and with dropout regularization is shown in Figure 7c and Figure 7d, respectively. The training process needed to be terminated significantly earlier at 5 epochs without dropout regularization. This resulted in a poorer test data prediction accuracy of 0.87, compared with 0.91 for the latter.

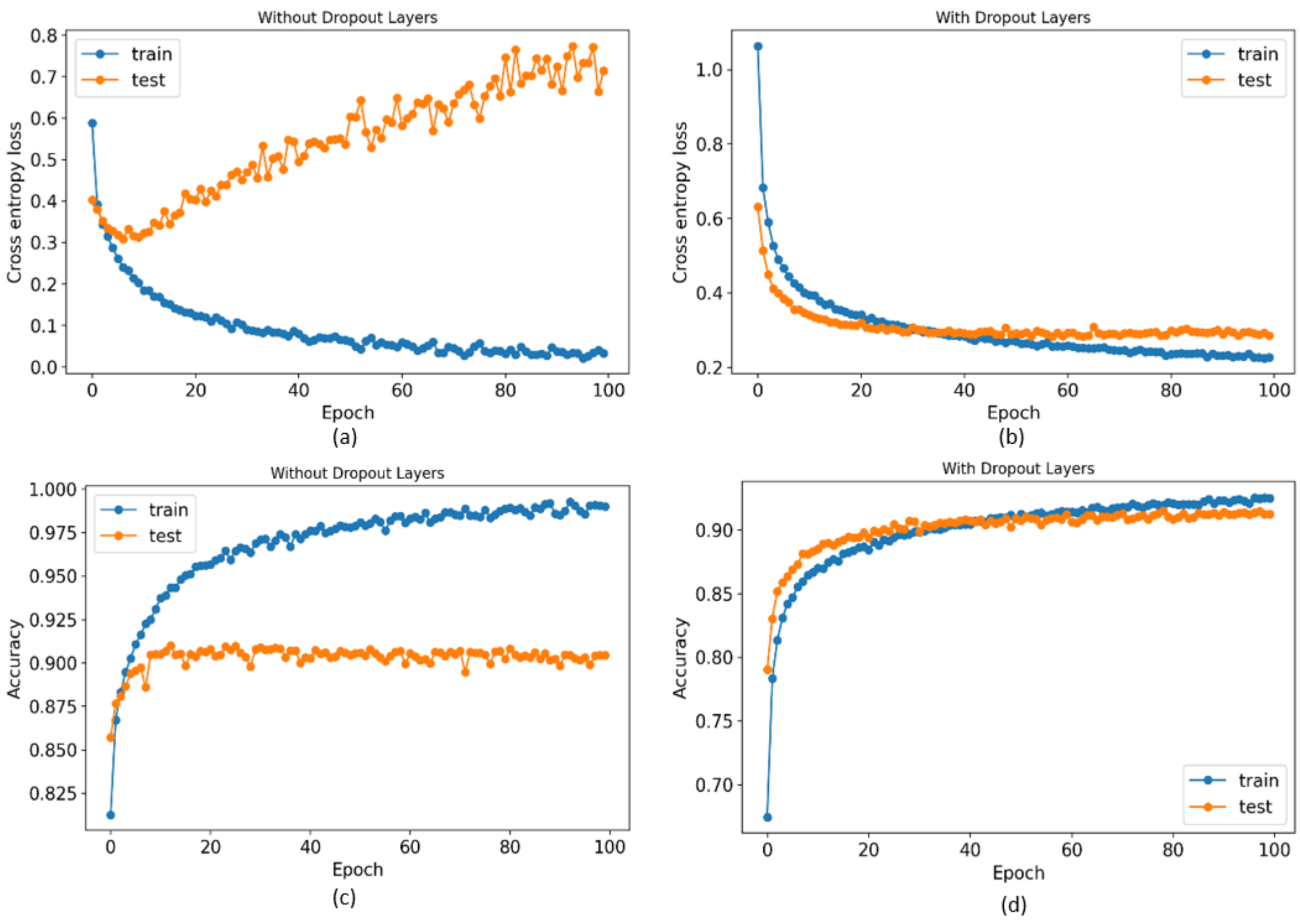


Figure 7. Learning curve.

Bootstrap Aggregating

As Table 2 shows, the labeled FHWA classes yielded an imbalanced class distribution. The number of instances belonging to a certain class, such as Class 9, was significantly higher than any other labeled classes in the dataset. The objective function of the designed neural network model is to minimize the global error rate. The entire cost function for a multi-class classification problem given m training instances labeled with n classes can be written as:

$$J = \frac{1}{m}\sum_{i=1}^{m} L(\hat{y}^{(i)}, y^{(i)})$$

$$= -\frac{1}{m}\sum_{i=1}^{m} \left(y^{(i)} log \hat{y}^{(i)} + \left(1 - y^{(i)}\right) log\ log\ \left(1 - \hat{y}^{(i)}\right)\right) \#(\ SEQ\ Equation \backslash *\ ARABIC\ 1)$$

Where, $y^{(i)}$ and $\hat{y}^{(i)}$ represents the true class and the predicted class of training instances i respectively.

As Equation 1 shows, the cost function does not handle the class distribution in the dataset. Without enough training instances to approximate the feature distributions of minority classes, the model is inclined to compromise the performance of minority classes to achieve a low global error rate resulting in poor performance on minority classes.

In order to have a better understand of feature distributions within each class, a bootstrap aggregating ensemble was adopted for the model development. Bootstrap aggregation (Bagging) is an ensemble strategy used to enhance the generalizability of the model by combining several models trained by multiple bootstrap samples (*26*). The basic idea of Bagging comes from the bootstrapping resampling technique, which is used to approximate the empirical distribution of observed data, especially for datasets with small class samples. Stratified bootstrapping was applied on the training set and ten sets of bootstrapped samples were formed by resampling the stratified training instances with replacement. The bootstrap samples were fed into the DNN model with the same model structure. Subsequently, the prediction scores from ten models were averaged and the class corresponding to the highest averaged prediction score was considered as the final decision. The bagging DNN model structure is shown in Figure 8.

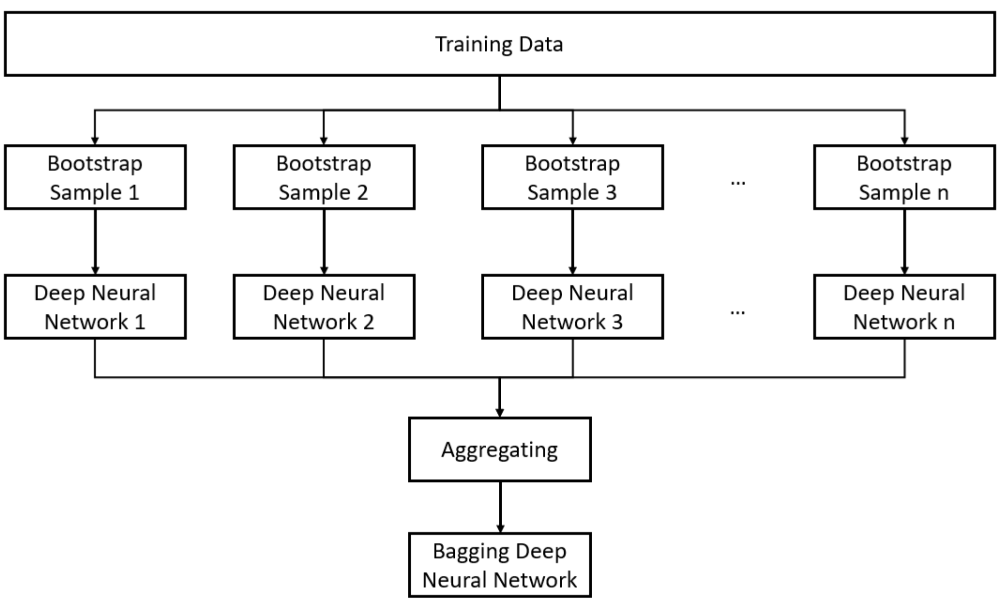


Figure 8. Illustration of Bagging DNN.

Model Results

Evaluation Metrics

Determining appropriate performance measures is an essential task for evaluating the model built upon an imbalanced dataset. The accuracy measure (Equation 2) — which is derived from a confusion matrix (Table 3) — presents the percentage of total instances being correctly classified.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \#(\ SEQ\ Equation \setminus *\ \ ARABIC\ 2)$$

Table 3. Generic confusion matrix.

		Predicted Class	
		Positives	**Negatives**
Actual Class	**Positives***	True Positives (*TP*)	False Negatives (*FN*)
	Negatives*	False Positives (*FP*)	True Negatives (*TN*)

Note: For the illustration purpose, the positive cases were assumed to be the minority class and negative cases were the majority class.

The accuracy measure is determined by both *TP* and *TN* (Table 3) on the numerator of the fraction. If the *TN*, which represents the correctly classified instance from the majority class, is disproportionally larger than *TP,* the accuracy value will still be large, even though the performance on the minority class remains poor. Therefore, this accuracy measurement is sensitive to class skews, and is not a reasonable metric for selecting models developed on an imbalanced dataset (*27*).

This section discusses three metrics that have generally been used to evaluate the performance of classification models built with imbalanced datasets. Precision (Equation 3) and recall (Equation 4) are two basic metrics, which are directly calculated from the confusion matrix (Table 3). Both precision and recall do not involve the true negative value, which represents the number of majority instances being correctly classified. Hence, these two metrics evaluate the model performance of majority and minority classes independently. The F1 score in Equation 5 is the harmonic mean of precision and recall. This metric accounts for precision and recall simultaneously while evaluating the models. In order to evaluate the models developed using imbalanced datasets, the F1 score was primarily used in this study for the model comparison.

$$Precision = \frac{TP}{TP + FP} \#(3)$$

$$Recall = \frac{TP}{TP + FN} \#(4)$$

$$F1\ score = \frac{2 \times Recall \times Precision}{Recall + Precision} \#(5)$$

Results Analysis

Figure 9 shows the recall distribution — which is also referred to as "Correct Classification Rate" (CCR) in previous research (*28*, *29*) — for the DNN models built with 10 sets of bootstrapped samples. Minority classes such as Classes 4, 7, 10, and 12 & 13 resulted in relatively high prediction variances since limited training instances were used to learn from the features for each single model. Therefore, the bagging ensemble model was needed.

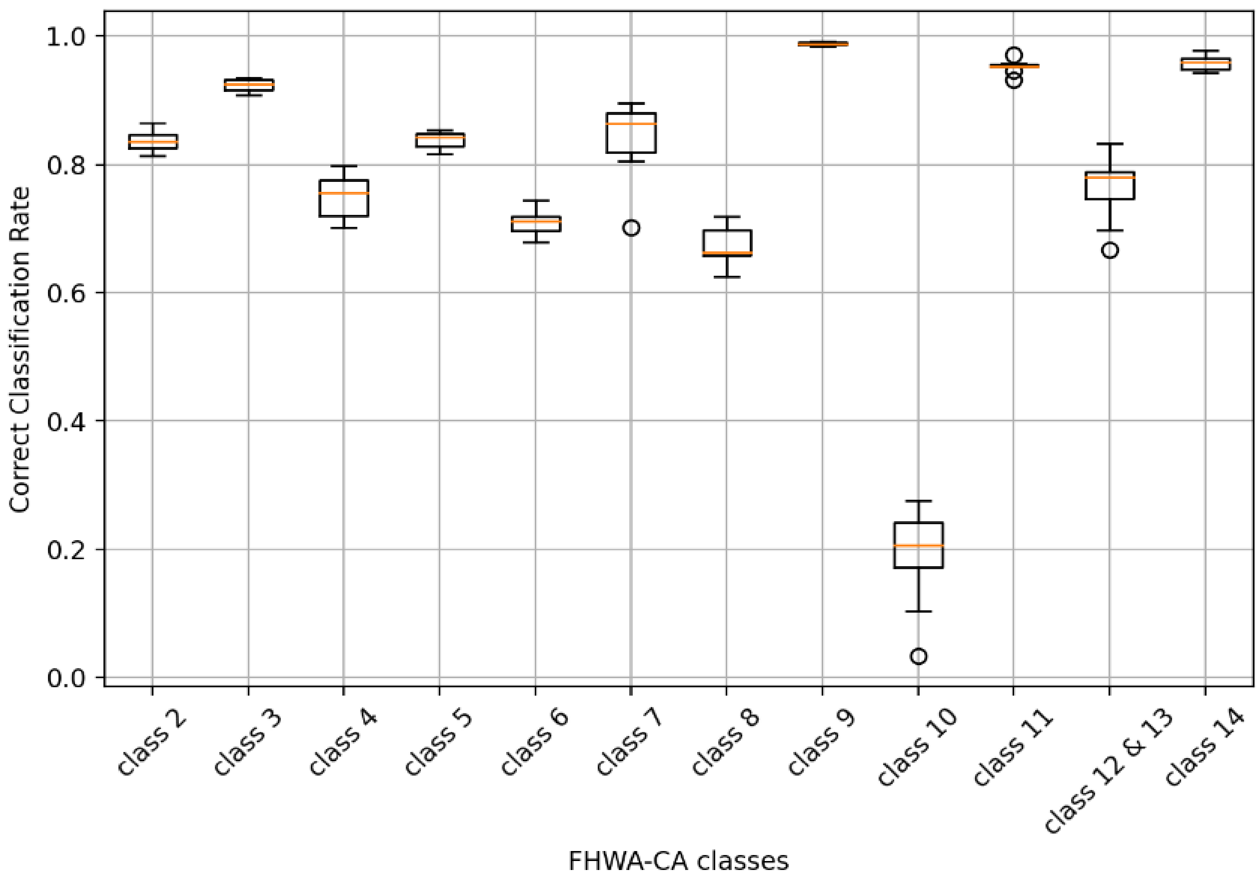


Figure 9. Correct classification rate across all classes.

Table 4 shows the F1 score for each class of three model structures. The dropout technique enhanced the generality of the DNN model and improved the F1 score for the testing set for all classes. With the bagging ensemble, the model performance improved across most of the minority classes without compromising the model performance on the majority classes. The overall accuracy of the final model was 0.92 and the average

F1 score was 0.83. This bagging DNN was applied on a spatially and temporally independent detection site and was still able to achieve an accuracy of 0.87 and average F1 score of 0.72.

Table 4. Test result comparison.

	F1 Score of Single DNN Without Dropout	F1 Score of Single DNN With Dropout	F1 Score of Bagging DNN	Test Samples
Class 2	0.85	0.85	0.87	847
Class 3	0.87	0.88	0.89	2,057
Class 4	0.71	0.81	0.83	268
Class 5	0.82	0.85	0.87	1,579
Class 6	0.72	0.80	0.80	362
Class 7	0.77	0.86	0.84	77
Class 8	0.69	0.73	0.78	427
Class 9	0.98	0.98	0.99	4,318
Class 10	0.22	0.35	0.36	29
Class 11	0.96	0.94	0.96	276
Class 12 & 13	0.78	0.79	0.81	66
Class 14	0.96	0.97	0.97	175
Accuracy	**0.89**	**0.91**	**0.92**	**10,481**
Average F1 score	**0.78**	**0.82**	**0.83**	**10,481**

The performance of the bagging DNN approach was also compared with a state-of-the-art Wavelet-KNN-based classification algorithm developed by Jeng et al.(*10*). Jeng et al. evaluated their model performance on each class using CCR. For the overall model performance, the accuracy value was selected as the evaluation metric in their study. However, such accuracy is biased towards the majority class, which was class 2 in their dataset. Therefore, the F1 scores of their model were recalculated for a fair comparison. As Table 5 shows, the bagging DNN model achieves the same level of accuracy in terms of the accuracy metric. Considering the F1 score, the bagging DNN outperform the previous model (*10*). Except for Class 2, the F1 scores for all classes are significantly higher than the previous approach (*10*). This indicates that the imbalanced dataset issue was well-managed by the bagging DNN model.

Since trucks have disproportionately negative impact on pavement structures (*30*), having accurate information on road usage by different truck-related classes (from class 5 to class 14) is essential to effective pavement design. Therefore, these two models were also evaluated using a weighted average, where truck-related classes were assumed to be at least two times more important than passenger vehicles. As Table 5 shows, the bagging DNN model was superior to the state-of-the-art signature-based FHWA vehicle classification algorithm on identifying truck-related classes. The bagging ensemble model achieved a weighted average F1 score of 0.82, where the Wavelet-KNN model only had a value of 0.47.

Table 5. Model comparison.

	Bagging Deep Neural Network			Wavelet-KNN (10)		
	Recall (CCR)	F1 Score	Testing Samples	Recall (CCR)	F1 Score	Testing Samples
Class 1	N/A	N/A	N/A	0.83	0.81	74
Class 2	0.85	0.87	847	0.97	0.97	11,177
Class 3	0.93	0.89	2,057	0.78	0.79	1,568
Class 4	0.78	0.83	268	0.59	0.10	17
Class 5	0.86	0.87	1,579	0.67	0.72	543
Class 6	0.75	0.80	362	0.48	0.39	65
Class 7	0.87	0.84	77	0.67	0.13	3
Class 8	0.71	0.78	427	0.46	0.33	48
Class 9[1]	0.99	0.99	4,318	0.86	0.91	754
Class 10	0.17	0.36	29	0.67	0.11	3
Class 11	0.97	0.96	276	0.58	0.26	14
Class 12 & 13[2]	0.76	0.81	66	0.75	0.50	4
Class 14	0.97	0.97	175	N/A	N/A	N/A
Accuracy	**0.92**		**10,481**	**0.92**		**14,270**
F1 score	**0.83**		**10,481**	**0.50**		**14,270**
Weighted Average F1 Score (1:2)	**0.82**		**10,481**	**0.47**		**14,270**

Note: [1] Class 9 in the Wavelet-KNN model was combined with Class 14.[2] Classes 12 and 13 were split in the Wavelet-KNN model with CCR of 1.00 and 0.50 respectively, and with F1 scores of 0.45 and 0.50 respectively.

Error Analysis

As shown in Table 6, the model presented in this study achieved an F1 score greater than 0.80 for most classes, except for Classes 8 and 10. According to the confusion matrix in Table 6, 8.7 percent of Class 8 vehicles are misclassified as Class 3 and 4.7 percent of Class 8 vehicles are misclassified as Class 5. This is mainly caused by the overlapping body types across Classes 3, 5 and 8.

Table 6. Confusion matrix for test set.

	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12&13	Class 14	Testing Samples	F1 Score
Class 2	716	122	0	8	0	0	1	0	0	0	0	0	847	0.87
Class 3	75	1921	1	44	0	0	13	3	0	0	0	0	2057	0.89
Class 4	1	6	208	39	7	1	4	2	0	0	0	0	268	0.83
Class 5	6	165	12	1359	23	1	10	3	0	0	0	0	1579	0.87
Class 6	1	0	8	72	271	9	1	0	0	0	0	0	362	0.80
Class 7	0	0	0	3	7	67	0	0	0	0	0	0	77	0.84
Class 8	0	37	4	20	0	0	303	63	0	0	0	0	427	0.78
Class 9	0	1	0	8	0	0	18	4286	3	0	0	2	4318	0.99
Class 10	0	0	0	0	0	0	3	20	5	0	0	1	29	0.36
Class 11	0	0	0	1	1	0	0	1	0	267	6	0	276	0.96
Class 12 & 13	0	0	0	0	0	0	1	1	0	13	50	1	66	0.81
Class 14	0	0	0	0	0	0	0	4	1	1	0	169	175	0.97

Note: Yellow cell indicate correct classifications by class. Grey cells highlight significant misclassifications

These three classes are also hard to distinguish using current classification sites (*8*). As Figure 10 and Figure 11 present, some Class 3, 5 and 8 trucks share very similar body types and axle configurations. Therefore, it remains a challenge to classify these vehicles accurately using either inductive loops or any axle sensors.

Figure 10. Class 3 vs. Class 5 (8).

Figure 11. Class 3 vs. Class 8 (8).

The main differences across Classes 8, 9 and 10 lies in the number of the axles that the truck-trailer combination has. Since inductive loop signatures do not have ability to directly capture the axle number of each truck-trailer, correctly distinguishing these classes has been a challenge for signature-based models (10). Nevertheless, the performance of bagging DNN model represented a significant improvement over Jeng et al.'s approach (10). However, misclassified vehicles were still observed among those classes due to the overlapping body types across FHWA classes. As Figure 12 shows, a Class 8 enclosed van (Figure 12a) was misclassified as a Class 9 (Figure 12b) vehicle, where Class 8 and Class 9 enclosed vans share similar shapes. Likewise, the bagging DNN model was found to misclassify a Class 10 drop frame van in Figure 13c into a Class 9, which is also a common axle configuration among drop frame vans.

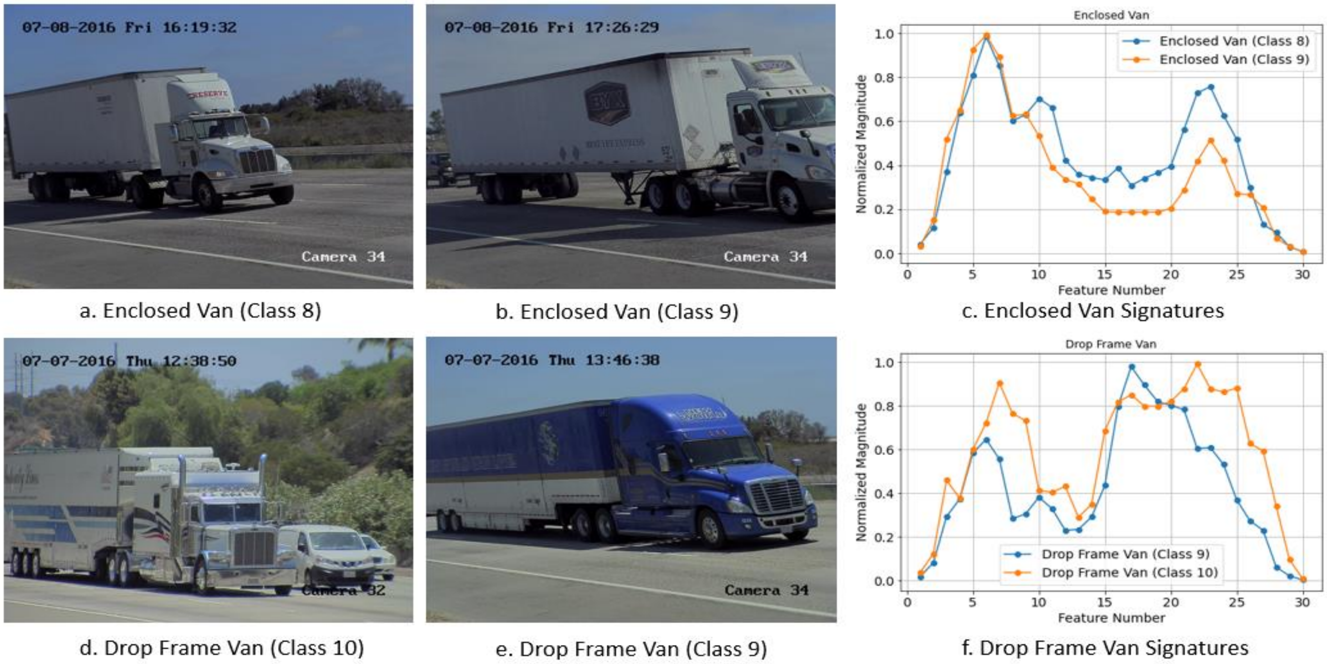


Figure 12. Overlapping body type across FHWA classes.

Compared to conventional axle detectors, inductive loop signature data have demonstrated the ability to distinguish the body type of trucks with relatively high accuracy (31). Therefore, errors associated with overlapping axle configurations of different vehicle body types (refer to Figure 13) which are a major source of confusion at classification sites, were better managed by the signature-based bagging DNN model proposed in this study.

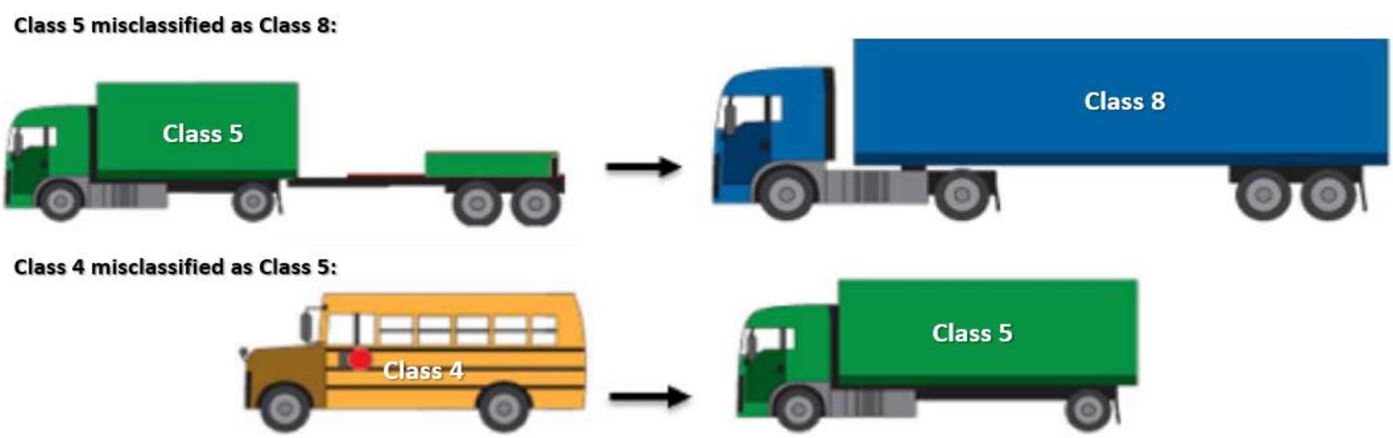


Figure 13. Error cases for piezoelectric sensors (14).

Traffic Census Reporting Dashboard

The Traffic Census Reporting Dashboard was designed and developed as an enhancement of the Truck Activity Monitoring System (TAMS, http://freight.its.uci.edu/tams) – an interactive web-based interface to provide access to on-demand summary truck classification reports using a combination of Java, JavaScript and Java Server Pages technology.

System Architecture

Figure 14 summarizes the system architecture of TAMS. The main components comprise edge computing units that reside in the field at existing inductive loop detector sites, and servers located at the University of California, Irvine Institute of Transportation Studies (UCI-ITS) that receive, archive and provide data access to end users via a web interface.

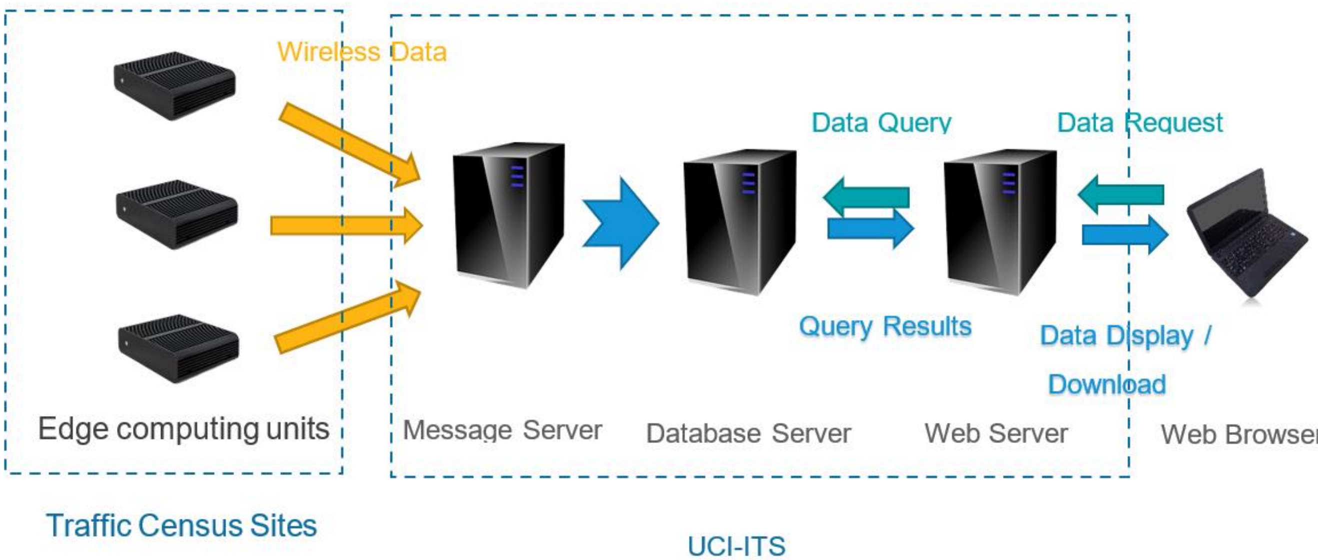


Figure 14. System architecture of TAMS.

The edge computing units at each location are connected to advanced loop detector cards. After a vehicle traverses the inductive loop sensor, data retrieved from the advanced loop detector is parsed and translated into a raw inductive signature vehicle record. The signature record is subsequently preprocessed to generate inputs to downstream predictive models embedded within the field edge computing unit, such as the FHWA axle-based classification model developed in this study. The edge computing[3] framework allows an operational

[3] Edge computing is a distributed information technology diagram which deploys the computing and storage resources closer to the sources of the data.

system to perform the majority of data processing in the field, which reduces data transmission latency and costs, and improves the data security and scalability of this system. The real-time transmission of data is achieved by utilizing the MQ Telemetry Transport (MQTT), which is a lightweight, publish-subscribe, machine-to-machine network open messaging protocol that has been designed for Internet of Things (IoT) applications. MQTT follows the Pub/Sub messaging principle of publishing messages and subscribing topics, which exchanges data between publishers and subscribers relying on a message broker that resides in the message server. The protocol is capable of packing messages efficiently to save bandwidth and enables TAMS to be deployed on a large scale. The database server operates on the PostgreSQL platform and subscribes all vehicle signature records from the message server, and archives the incoming data in real-time, while simultaneously computing and archiving hourly aggregations of vehicle counts by class. The web server hosts the interactive TAMS web-based interface and serves as a broker between end users and the database server by performing data queries requested by users through the web interface.

Web Interface

Figure 15 shows the layout of the TAMS Traffic Census Reporting Dashboard. The TAMS interface allows the user to query data within various spatial regions, including Caltrans districts, major Metropolitan Planning Organizations (MPO), and eight air basins in California. An interactive interface based on Open Street Map allows users to intuitively search truck classification results by location. All historical data are accessible to facilitate direct access to archived truck count data. Each site initially provides the breakdown of daily volumes by lane and aggregated by vehicle class categories according to the FHWA scheme (e.g. see Box A in Figure 15). A further breakdown of hourly volume counts can be obtained by clicking on the individual daily volume entries (e.g. see Box B in Figure 15). With the hourly volume table, a cell color scheme is implemented to represent variations of the daily hourly volume patterns. This facilitates a quick assessment of the predominant truck volumes at each location and the peak hourly volumes corresponding to each truck configuration.

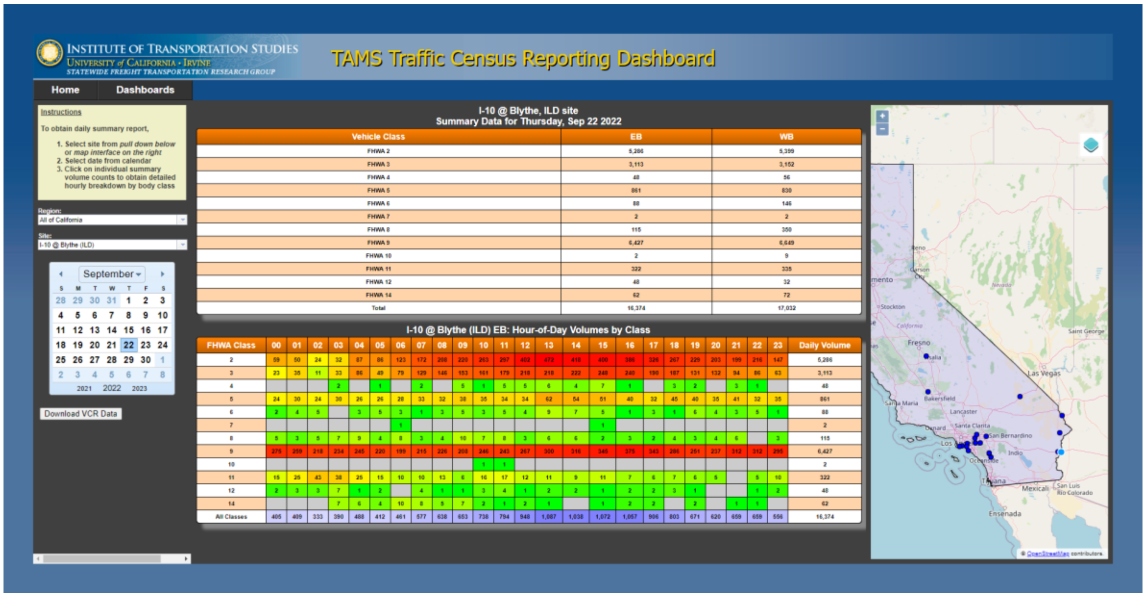


Figure 15. TAMS Traffic Census Reporting Dashboard.

The “Download VCR Data” feature (as shown in Figure 16) was also developed as a part of the dashboard to streamline traffic census reporting operations. Data across any desired reporting period for each instrumented site can be processed on-demand from the system and downloaded in the standard traffic census reporting data format known as the “Vehicle Classification Record” or VCR.

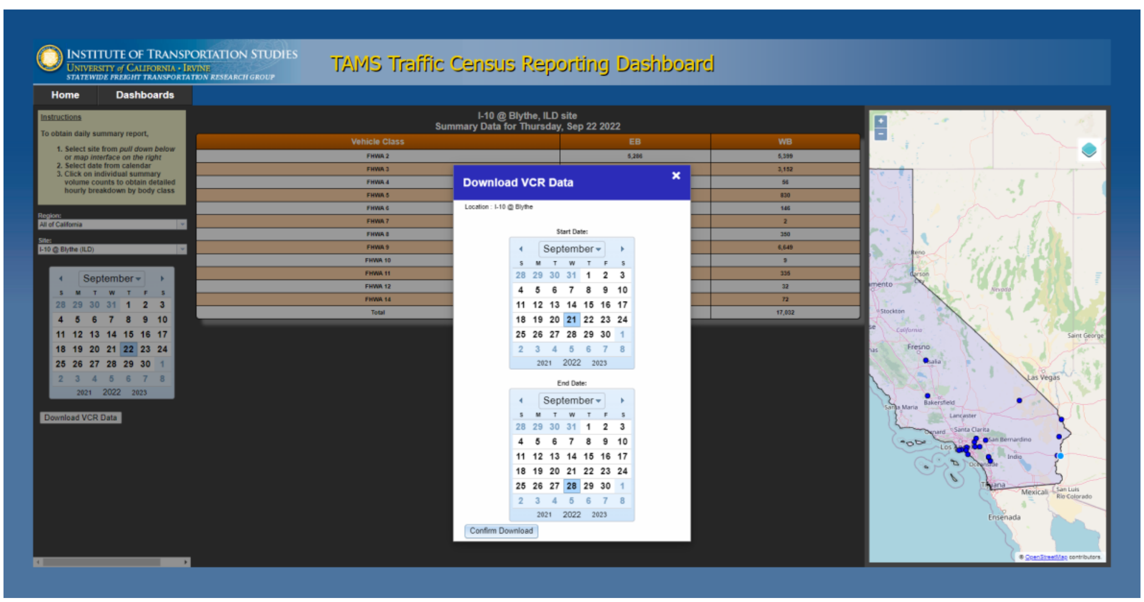


Figure 16. Requesting data in VCR format for traffic census reports.

Conclusion and Discussion

This project presents the development of an accurate vehicle classification model to classify vehicles based on the FHWA-CA classification scheme using single inductive loops and the corresponding Truck Activity Monitoring System (TAMS) Traffic Census Reporting Dashboard purposefully built for accessing the operational data from the deployment of this model and TAMS-instrumented sites to support Caltrans Traffic Census Reporting operations. The model was developed on a truck-focused dataset and utilized a bagging ensemble technique to resolve the classification challenges of accommodating a dataset with uneven class distribution – which is typically observed using the FHWA classification scheme. The modeling process involved three major steps. First, the dataset used for model development was partitioned using the stratified sampling approach to retain a proportional number of samples from minority classes for both the training and testing sets. Then, a DNN model was constructed to assign signatures to their corresponding FHWA-CA classes. Dropout regularization was applied during the fine-tuning process, which successfully alleviated overfitting of the DNN model. Finally, a bagging ensemble technique was used to address the imbalanced dataset issue. This bagging DNN model significantly outperformed a state-of-the-art FHWA classification model using inductive loop signature data (10) for all truck-related classes. The bagging DNN model was able to achieve an F1 score of 0.83, where the comparable model obtained a value of 0.50. The error analysis showed that the majority of error cases came primarily from the overlapping body types across the FHWA classes. For instance, both Classes 8 and 9 shared common body types such as semi-trailer enclosed van. In addition, semi-trailer drop frame vans exists in both Classes 9 and 10. According to the error analysis, the model likely inferred the FHWA classes through the majority class associated with the corresponding body types. Notwithstanding, the overlapping axle configurations with different general body types, which is a common type of error at classification sites (14) were still generally well-managed in the signature-based bagging DNN model.

Inductive loop sensors remain the most widely deployed detector infrastructure in California and the United States, and inductive signature-based classification models have been widely deployed in California (32). This project demonstrates that the improvements in the inductive signature-based model described in this report is a cost-effective solution that can provide accurate classification performance across FHWA truck categories, while concurrently addressing common body configuration confusion issues experienced by axle-based detection systems.

The enhancement of TAMS web interface with the Traffic Census Reporting Dashboard provides Caltrans with an efficient operational tool to utilize the data generated by the model in TAMS edge processing units that have been deployed at existing inductive loop detector sites. The dashboard is equipped with user-interactive features such as a GIS-enabled map for selecting desired site locations to review and report data to support Caltrans traffic census operations.

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