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RESEARCH ARTICLE

One-Dimensional Convolutional Neural Network Model for Local Road Annual Average Daily Traffic Estimation

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ABSTRACT The focus of this research is to develop a robust model for accurately estimating link-level annual average daily traffic (AADT) of all the local functionally classified roads. The capabilities of one-dimensional convolutional neural network (1D-CNN), a deep learning architecture, and the domain knowledge pertaining to local road travel characteristics were combined to estimate local road AADT. The AADT based on traffic counts collected at 12,769 traffic count stations on local roads in North Carolina during 2014, 2015, and 2016 were considered for model training, validation, and testing. A total of eight existing state-of-the-art statistical, geospatial, and selected other machine learning models were compared with the 1D-CNN model to estimate local road AADT. These include ordinary least square (OLS) regression, geographically weighted regression (GWR), ordinary kriging, natural neighbor (NN) interpolation, inverse distance weighting (IDW), backpropagation artificial neural network (BP-ANN), random forest (RF), and support vector machine (SVM). The model development and test results showed that the 1D-CNN model performed better than the other considered models. The architecture of the 1D-CNN model can learn the intricate patterns in the local road AADT. The outputs from the methodological framework proposed in this research help practitioners perform safety evaluation, planning and implementing infrastructure improvements, fund allocation and prioritization, air quality estimates, and meeting Highway Safety Improvement Program (HSIP) reporting requirements.

INDEX TERMS Annual average daily traffic, AADT, convolutional neural networks, deep learning, local road, low-volume road, machine learning.

I. INTRODUCTION

The local functionally classified roads (local roads) constitute most of the total road network mileage in a state. The federally funded state-administered Highway Safety Improvement Program (HSIP) mandates state agencies to report annual average daily traffic (AADT) on all paved public roads. Most state departments of transportation (DOTs) cannot routinely count traffic for all public roads in the state, especially the local roads. In the case of North Carolina, count-based local road AADT is available for 12,769 traffic count stations, while count-based local road AADT estimates are needed for over 740,000 noncovered local road links. As state DOTs have to report local road AADT for all the public roads, they are looking into cost-effective methods for getting a better estimate of the local road AADT. Proposing a method that can accurately estimate AADT for all local roads helps practitioners in performing safety evaluation, planning and implementing infrastructure improvements, fund allocation and prioritization, and air quality estimates, in addition to meeting HSIP reporting requirements.

In general, most of the past studies and transportation agencies use the term 'estimating AADT' rather than 'predicting AADT'. Therefore, the term "estimation" was preferred over

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"prediction" and used in this paper. Researchers in the past have explored statistical models [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], time series methods [11], [12], [13], geospatial methods [14], [15], [16], [17], [18], [19], [20], [21], artificial neural network (ANN) and other machine learning approaches [22], [23], [24], [25], [26], [27], [28], [29], [30], and image processing [31], [32], [33] to estimate AADT at a road link-level. A few researchers explored probe vehicle data to estimate AADT [34], [35]. Most of these studies considered higher functionally classified roads in the AADT estimation process due to the availability of traffic counts. Only a few researchers estimated AADT on local roads using statistical methods [8], [10], [20], [21], geospatial methods like geographically weighted regression (GWR) and Kriging [14], [16], [20], [21], and ANN and machine learning [26], [29], [36], [37].

Many factors influence the travel characteristics of a local road. Per the American Association of State Highways and Transportation Officials (AASHTO) guidelines, local roads provide direct access to adjacent land. They often provide access to higher functionally classified roads (collector roads and above) [38]. Therefore, variables influencing local travel characteristics need to be incorporated in the AADT estimation process. A detailed illustration of the selection of those variables, also used in this research, are discussed in Mathew and Pulugurtha [21] and Pulugurtha and Mathew [39].

Recent advances in deep learning include powerful and robust tools like convolutional neural network (CNN) to train the deep architecture. CNN models have widespread applications in the field of image recognition and classification, image segmentation, and video processing [40], [41], [42]. Since an image has dimensional properties in the form of width and height, it can be interpreted as a matrix of pixel values with rows and columns. The tabular data processed for this research had the format of rows and columns, drawing a parallel to an image dataset. Therefore, the focus of this research is to apply the unique ability of a one-dimensional CNN (1D-CNN) model to understand the interdependencies between the features to accurately estimate local road AADT.

Although there are several methods of local road AADT estimation, a comprehensive comparison of statistical methods (ordinary least squares - OLS regression), geospatial methods (GWR, Kriging, natural neighbor - NN interpolation, and inverse distance weighting - IDW), artificial neural network and machine learning approaches (ANN, random forest - RF, and support vector machine - SVM), and deep learning algorithms like 1D-CNN was not performed in the past. Therefore, the intent of this research was also to compare outputs from 1D-CNN with other methods to estimate local road AADT using count-based local road AADT for 12,769 traffic count stations.

An assessment of the models' predictability and errors will help identify the best method/model to estimate AADT at noncovered (locations with no-count-based AADT estimates) local road links in North Carolina. Overall, this research aims to fill the methodological gap and add to the current body of knowledge by proposing a novel deep learning method and comparing it with statistical, geospatial, neural network, and selected other machine learning methods for estimating local road AADT.

II. LITERATURE REVIEW

In simple terms, AADT is the mean traffic volume across all days of a year for a given location along a roadway. Using the 'simple average method', AADT can be estimated using Equation (1) [43].

$$AADT = \frac{1}{n}\sum\nolimits_{k=1}^{n} Vol_k \tag{1}$$

where Vol_k is the daily traffic on kth day of the year, and n is the number of days in a year.

Past research on AADT estimation can be broadly classified into three categories: traffic count-based, non-traffic count-based, and travel demand model-based. Traffic counts are typically estimated using methods relying on data from continuous and short-duration traffic counters [44]. Agencies generally adopt stratified sampling procedures to estimate AADT at noncovered local road locations. The stratification is generally based on one or more attributes like the functional class type (say, urban or rural local road) [44]. Agencies collect traffic volume data at selected locations in each stratum and consider that as a representative of all the roads within the stratum [46], [47], [48], [49].

In non-traffic count-based methods, surrogate data like road characteristics, demographic characteristics, land use characteristics, temporal characteristics, etc. are used to estimate AADT [4], [8], [16], [20], [21]. In the case of travel demand model-based AADT estimation, trip generation, trip distribution, and traffic assignment are sequentially used to estimate AADT [50], [51], [52].

Blume et al. [46] proposed a methodology using census data and random sampling to estimate local road AADT. Their methodology includes dividing and categorizing the study area into regions based on population density, job density, and road density. Further, a minimum number of required samples (traffic counts) were proposed using the Highway Performance Monitoring System (HPMS) Field Manual requirement. Finally, the mean/median AADT was assigned to local roads within a region. Similarly, Frawley [53] proposed a random count-site selection process for local road vehicle miles traveled (VMT) estimation. It should be noted that VMT is the product of AADT and the corresponding local road length.

A few studies explored the application of ANN to estimate local road AADT from 48-hour sample counts [36], [37]. According to their findings, the ANN method outperformed the traditional factor-based method. Lowry [54] proposed spatial interpolation of traffic counts based on origin-destination centrality to estimate AADT.

Tsapakis et al. [44] improved the stratification process and estimated AADT accurately at local roads. Per their findings, having more strata and very homogeneous strata is preferable

TABLE 1. Past studies on local road AADT estimation.

Author	Study area	Method	Variables	Major findings
Xia et al. [4]	Florida, USA	Linear regression	Road characteristics, population, dwelling units, automobile ownership, employment, school enrollment, and hotel occupancy	Number of lanes, functional class, and area type are the most important predictors Socioeconomic variables are not significant predictors
Seaver et al. [5]	Georgia, USA	Cluster regression analysis	Population, education, travel time to work, income, employment, urbanization, housing	Stratifications by road type (paved or unpaved) and location (outside or within metropolitan statistical area) produce superior results
Wang and Kockelman [14]	Texas, USA	Kriging	Count-based AADT	Estimated AADT values for noncovered locations Median prediction error (MPE) is 31%
Yang et al. [7]	North Carolina, USA	Circuit network models and simulation	Number of households	Total entering traffic volume is strongly correlated with the total number of households in communities
Apronti et al. [8]	Wyoming, USA	Linear regression, logistic regression	Pavement type, access to highways, predominant land use types, and population	Linear regression; R-squared is 0.64, mean square error (MSE) is 73.4% Logistic regression; 88% of the local roads are accurately classified based on the predefined thresholds
Raja et al. [10]	Alabama, USA	Linear regression	Population, # of households, employment, population to job ratio, and access to higher functional class roads	R-squared for model validation (observed AADT vs. predicted AADT) is 0.80
Das and Tsapakis [29]	Vermont, USA	Linear regression, generalized linear regression, SVM, k-nearest neighbor	Population density, housing unit density, residence area characteristic density, work area characteristic density, distance of interstate roads, and distance to US routes	Machine learning based models outperformed conventional statistical methods Median root mean squared error (RMSE) is 360 for rural local roads and 889 for urban local roads
Pulugurtha and Mathew [20]	North Carolina, USA	OLS regression, GWR	Road density, distance to the nearest nonlocal road, AADT at the nearest nonlocal road, demographic data, and land use	GWR outperformed linear regression County-level models were used for estimating AADT at noncovered locations in each county
Mathew and Pulugurtha [21]	North Carolina, USA	OLS regression, GWR, Kriging, IDW, NN interpolation	Speed limit, road density, distance to the nearest nonlocal road, AADT at the nearest non-local road, and socioeconomic and demographic variables	GWR outperformed other considered statistical and geospatial methods GWR validation: RMSE is 733, mean absolute percent error (MAPE) is 82.1%, and MPE is -44.2%

than having fewer strata and more samples within each stratum.

The non-traffic count-based AADT estimation methods use different non-traffic data like population, employment, other socioeconomic characteristics, land use, etc. to estimate local road AADT. Table 1 summarizes the past studies on local road AADT estimation using the non-traffic count-based method.

Many researchers considered socioeconomic and demographic data along with road characteristics to estimate local road AADT. Population, population density, and the number of households are the demographic variables generally used to estimate AADT. A few researchers considered variables like land use [8], [20], [21] and access to a higher functionally classified road [10], [20], [21], [29]. The road density, which indicates the development density near the local road area, was considered in Pulugurtha and Mathew [20] and Mathew and Pulugurtha [21].

Zhong and Hanson [50] used travel demand models to estimate traffic on local roads in New Brunswick, Canada. Findings from their research indicated an average prediction error of less than 40% for the proposed method. Wang et al. [51] used a parcel-level trip generation model to estimate local road AADT and illustrated better predictability than statistical models.

Other state-of-the-art methods like Temporal Graph Convolutional Network (T-GCN) and Convolutional Long Short-Term Memory (Conv-LSTM) architecture were not explored in this research as temporal variations in AADT of local roads are limited and not widely captured or available.

In recent years, advanced image processing and machine learning approaches have been adopted by a few researchers to predict traffic flow and AADT [31], [32], [33]. The predictability of SVM over ANN in estimating AADT was illustrated in Khan et al. [27]. Das and Tsapakis [29] showed the predictability of SVM and RF models over conventional statistical models.

The statistical or machine learning methods like RF and SVM are prone to overfitting or underfitting based on the data. Deep learning methods like CNN were formed out of the necessity of modeling a growing number of data samples and being robust enough not to be susceptible to such biased predictions. The CNN models can handle a large dataset amounting to millions of records in contrast to the other models with overfitting or underfitting issues. CNN models are proven to be superior in many transportation engineering applications [56]. 1D-CNN is a newly developed variant of conventional CNN. Kiranyaz et al. [56] illustrated the predictability of 1D-CNN over traditional and conventional approaches.

The capability of CNN-based deep learning algorithm to estimate local road AADT was not explored in the past. Therefore, a local road AADT estimation method featuring 1D-CNN using count-based AADT obtained from the local road traffic count stations in North Carolina was explored in this research.

The contribution of this research is three-fold: 1) develop a novel 1D-CNN model for capturing data intricacies in a tabular dataset and estimating local road AADT by utilizing the advantages of CNN in image-based classification and enhancement; 2) a comprehensive comparison of statistical methods (OLS regression), geospatial methods (GWR, Kriging, NN interpolation, and IDW), selected other machine learning approaches (ANN, RF, and SVM), and the proposed 1D-CNN model to estimate local road AADT; and, 3) an error analysis to identify the locations with high prediction error for proactive planning.

The state-of-the-art statistical, geospatial, and selected other machine learning models are relatively simple compared to 1D-CNN and these models may not generalize well on a large dataset or data containing complex relationships between its features. Thus, this paper aims to contribute to the literature and minimizes the limitations of prior local road AADT estimation models by developing a novel 1D-CNN model.

III. METHOD

The methodological framework adopted involves the following steps.

- Data collection
- Data processing
- Descriptive analysis of local road data
- Develop local road AADT estimation models
  - 1D-CNN model for local road AADT estimation
  - Statistical, geospatial and selected other machine learning models for local road AADT estimation
- Model test and comparison

A. DATA COLLECTION

The local road count-based AADT data, road data, and socioeconomic and demographic data were obtained from the North Carolina Department of Transportation (NCDOT). In general, traffic volumes are collected at ~50% of the local road traffic count stations in odd years and at ~50% of the local road traffic count stations in even years. In other words, if local road AADT estimate is not available for the most current year at a traffic count station, it is available for the prior year. The growth factor estimates indicate that the count-based local road AADT does not seem to change significantly from year to year (average growth factor for the state is ~1.01 for the year 2016). Therefore, the average AADT at available local road traffic count stations collected in 2014 and 2016 in addition to AADT at local road traffic count stations collected in 2015 were used for the model training and validation. This helped increase the sample size for model training and validation.

B. DATA PROCESSING

The data was processed to extract the variables such as speed limit, road density, functional class type, population density, distance to the nearest nonlocal road, and AADT at the nearest nonlocal road.

The speed limit of the selected local road link was extracted from the road data shapefile obtained from the NCDOT. This data comes from traffic ordinances governing the speed limit.

The local road traffic count station is a point datum. The road density, defined as the length of all roads per unit area, was extracted by creating a 1-mile buffer around the traffic count station. This variable accounts for the development density, connectivity, and travel demand activity near the selected local road link.

The local road links are classified based on the functional class type, as urban local road links and rural local road links. Some of the local road links are located within the urbanized areas. Such links are identified by considering NCDOT guidelines (minimum population of a small urban boundary is 5,000). Other links are considered as rural local road links.

The statewide traffic analysis zone (TAZ)-level data was used to estimate population density near the subject local road link [20], [21].

A new network dataset using the road characteristics shapefile obtained from NCDOT was generated and used to estimate the distance to the nearest nonlocal road (Dis-nonlocal) and AADT at the nearest nonlocal road (AADT nonlocal). The origin-destination cost matrix analysis is performed to compute the distance between each local road and the nearest nonlocal road (collector roads and above). The count-based AADT at the nearest nonlocal road was estimated from the count-based AADT data for all the functionally classified roads.

C. DESCRIPTIVE ANALYSIS OF LOCAL ROAD DATA

A descriptive analysis was separately carried out to understand the influence of selected explanatory variables on the available count-based local road AADT. The minimum, 5th percentile, 25th percentile, median, mean, 75th percentile, 95th percentile, maximum, standard deviation, and variance of selected variables were computed and examined.

D. DEVELOP LOCAL ROAD AADT ESTIMATION MODELS

The 1D-CNN model was developed to estimate local road AADT and compared with the statistical, geospatial, and selected other machine learning methods. It should be noted that SVM and RF are the two widely adopted machine learning approaches to estimate AADT. The model was trained using the data for 7,926 local road traffic count stations and validated using the data for 2,966 local road traffic count stations.

The data used in this research has a fixed structure in the form of six input variables (explanatory variables) and one target variable (dependent variable). It is also assumed that the individual instances in the data are independent of one another. Thus, the data is interpreted as having a structure of m rows and n columns like an (m × n) image where m and n are the width and height of the image, respectively. In the case of graph neural network (GNN), as each node is related to others by links of various types, the aforementioned assumption does not hold. Therefore, GNN is not considered in this research. A general outline of the 1D-CNN architecture and brief overview of other selected modeling approaches are presented in the following subsections.

1) 1D-CNN

CNN comes under the domain of deep learning, a subset of artificial intelligence. As the name suggests, these networks are constructed to be deep and learn granular level information from the data. A convolution is a linear operation that involves the multiplication of a set of weights for the input variables, like in a traditional neural network. Given that the technique was designed for two-dimensional input, multiplication is performed between an array of input data and a two-dimensional array of weights, called a filter or a kernel. Using a filter smaller than the input is intentional as it allows the same filter (set of weights) to be multiplied with the input array multiple times at different points. Specifically, the filter is applied systematically to each overlapping part or filter-sized patch of the input data. The structure of the CNN model in the context of local road AADT estimation is shown in Fig. 1. CNN-based models are primarily made up of four basic layers: convolutional layer, pooling layer, rectified linear unit (ReLU) layer, and fully connected layer.

The convolutional layer is the core component of a CNN architecture. It consists of a set of learnable filters or kernels that have a small reception field but extend through the entire depth of the input. Each filter is convolved across the width and height of its input volume during the forward pass, and the resulting dot product is computed, producing a two-dimensional activation map of the filter. Through this process, the network learnable filters activate when a specific feature is detected at a particular location in the input.

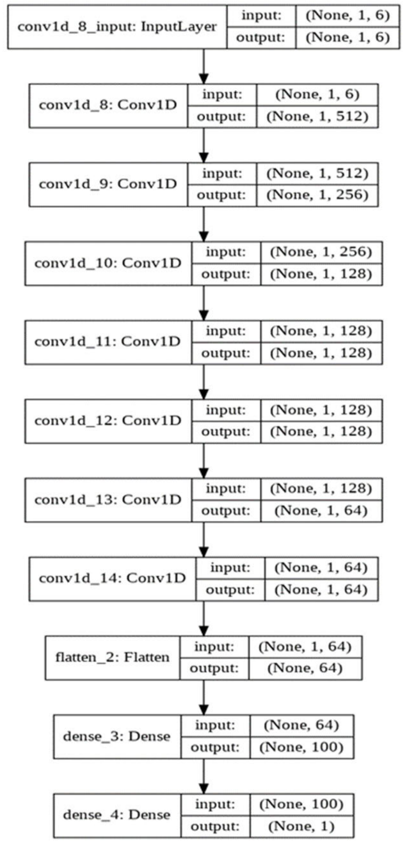


FIGURE 1. Overview of the proposed CNN model for local road AADT estimation.

After the activation maps are generated from the convolutional layer, pooling is the next step in the architecture. It is a form of nonlinear downsampling. While there are different nonlinear methods to implement the same, max pooling is the most common method. It partitions the filter into rectangular subregions and generates the maximum output from each region. The idea behind this is that the exact location of the feature is less important compared to its rough location relative to other features. This kind of downsampling also helps to reduce the spatial representation in the network, thereby reducing the computation time, memory and simultaneously tackling the problem of overfitting.

ReLU is the layer which applies the non-saturating activation function, $f(x) = \max(0,x)$. ReLU is preferred as it is proven to train the neural network faster. After several convolution operations in the layers, the final classification is done using a fully connected layer. The neurons in this layer have connections with the activation functions of the previous layer.

In this research, a 1D-CNN model is developed to estimate local road AADT. The processed dataset is in the form of rows and columns with the input variables (columns) such as the

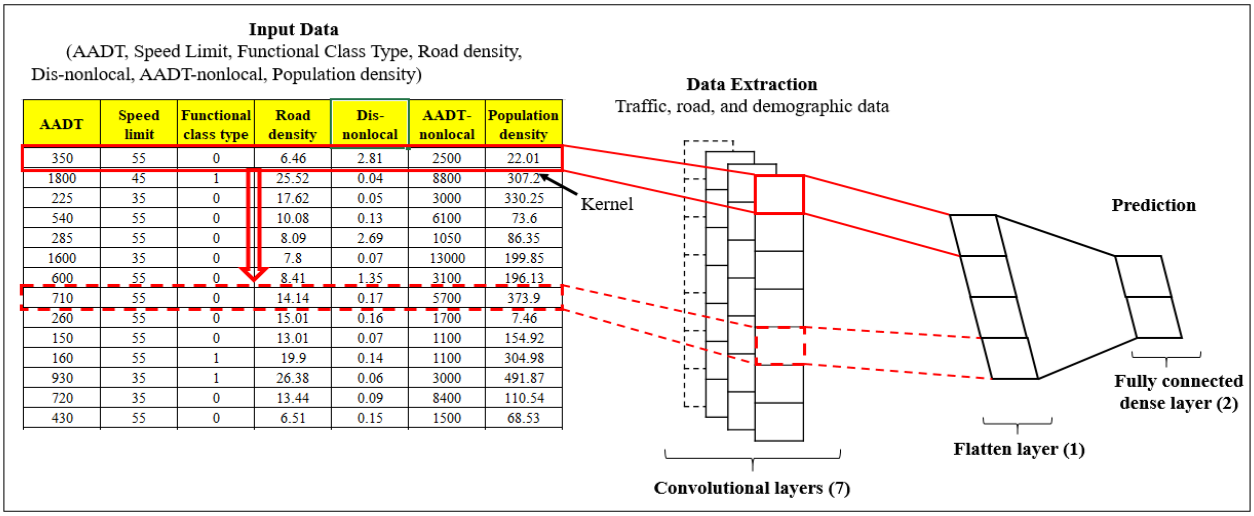


FIGURE 2. 1D-CNN architecture for local road AADT estimation.

speed limit, functional class type, road density, distance to the nearest nonlocal road (Dis-nonlocal), AADT at the nearest nonlocal road (AADT-nonlocal), and population density (Fig. 1). With a kernel size = 1, this forms the filter, which is used to take each individual row in the data as input i.e., this filter slides in only one direction from top to bottom, thus covering the training dataset in each iteration. 1D-CNN takes input data in the form of three dimensions: samples, time steps, and features.

About 85% (10,892) of the local road traffic count stations were randomly selected for modeling. Python programming language was used to train the 1D-CNN model. There are six features (explanatory variables) and are sliding the kernel over each row, making the time steps = 1. On the other hand, the samples are the total number of rows in the training data, which in this case is 10,892 (∼85% of the data). Thus, the input is in the form of [10892, 1, 6].

The model's hyperparameters are initialized at random. During the process of model training, the optimum set of hyperparameters are generated when the model is providing the most accurate results (the lowest error – mean squared error (MSE) value). The convolution operation is performed on the input and the filter. As the filter slides over the rows of data in the training dataset, a matrix multiplication is performed at each step, and the result is summed up to build a feature map. This process is applied for all the convolution layers in the network resulting in multiple feature maps. The final output is obtained by putting together all the feature maps. The 1D-CNN architecture for the local road AADT estimation is illustrated in Fig. 2.

The AADT-net architecture consists of 7 convolutional layers with 512 neurons in the first layer and goes down to 64 neurons in the final convolutional layer and uses the ReLU activation function in all the layers. The max pooling layer is not used as it is redundant since the filter size here is (1,1). The convolutional layers are followed by two fully connected dense layers, which assemble the output shape to one prediction, which is the local road AADT. The selection of the proper loss function is critical for training an accurate 1D-CNN model.

The MSE loss function was used to compute the deviation between the count-based AADT and the estimated AADT from the model. MSE is the sum of the squared difference between the count-based AADT (CAADT) and the estimated AADT (EAADT), as shown in Equation (2). It indicates the training process and the direction in which the network learns and estimates local road AADT.

$$Mean\ Squared\ Error\ (MSE) = \frac{1}{N}\sum\nolimits_{j=0}^{N}(CAADT - EAADT)^2 \tag{2}$$

2) OLS REGRESSION

OLS regression computes the best fitting line for the observed data by minimizing the sum of the squares of the residuals. The dependent variable is the count-based AADT. Pearson correlation coefficients were computed to perform correlation analysis for selecting potential explanatory variables and developing the OLS regression model. The methodological framework adopted to develop a valid OLS regression model for local road AADT estimation is illustrated in Pulugurtha and Mathew [20] and Mathew and Pulugurtha [21].

3) GWR

GWR allows the dependent and independent variables to vary locally. In other words, GWR develops a separate OLS regression model for each local road traffic count station. It incorporates count-based AADT and explanatory variables of locations falling within the bandwidth of a target traffic count station. More details on the GWR model framework and calibration for local road AADT estimation are presented in Pulugurtha and Mathew [20] and Mathew and Pulugurtha [21].

4) KRIGING

The Kriging method uses a weighted sum of the count-based AADT at local road traffic count stations to estimate AADT at noncovered local road locations. It assumes that the distance between local road traffic count stations reflects the spatial autocorrelation, explaining the variation in local road AADT. More detailed discussion on the selection of a best-fitted Kriging model for estimating local road AADT are found in Eom et al. [57], Selby and Kockelman [16], and Mathew and Pulugurtha [21]. This research followed the methodology illustrated in Unnikrishnan et al. [52] to identify the best Kriging model for the local road AADT estimation.

5) NN INTERPOLATION

The NN interpolation method uses the Thiessen polygon developed over each local road traffic count station to estimate AADT at a noncovered location. The boundaries of polygons are defined such that the edges are equidistant from the local road traffic count station in the adjacent polygons. A new Thiessen polygon is generated at each noncovered location, and the proportion of overlap between the new polygon and the initial polygon is used as the weights. A more detailed discussion on NN interpolation along with mathematical formulation for estimating local road AADT is presented in Mathew and Pulugurtha [21].

6) IDW

To predict AADT at a noncovered location, IDW uses count-based AADT from the surrounding local road traffic count stations. IDW allows higher weights to the closer local road traffic count stations than the farther ones. Mathew and Pulugurtha [21] estimated local road AADT using the IDW method. More discussion on IDW implementation for estimating local road AADT is presented in Mathew and Pulugurtha [21].

7) ANN

A multilayered, feed-forward, backpropagation artificial neural network model (BP-ANN) was used in this research for estimating local road AADT. The multilayer perceptron consists of the input, hidden, and output layers. The developed algorithm fine-tunes the model by learning the error rate obtained from the previous epoch (backward propagation of errors). The difference between 1D-CNN and the BP-ANN is the involvement of convolution operations in the 1D-CNN. Convolutional layers take advantage of the local spatial coherence of the input meaning that spatially close inputs are corelated. Using this property, CNNs are able to reduce the number of parameters in comparison to a fully-connected multilayered perceptron by sharing weights making them extremely efficient in processing. The BP-ANN model was a shallow network compared to the 1D-CNN and the number of epochs were reduced consequently to reduce the training time and avoiding overfitting.

8) RF

RF is a supervised machine learning algorithm that uses decision trees to estimate the output and produces the average output value. The data is segregated into many random samples to construct decision trees separately. Each decision tree runs parallel to others for estimating the local road AADT at the noncovered locations. The tree-based approach accounts for the stochastic variation through random sampling, which also eliminates the problem of over-fitting.

9) SVM

A few researchers considered SVM models to estimate AADT [23], [27], [28], [29]. SVM is a supervised learning model for classification and regression analysis. The straight line that is required to fit the data is referred to as the hyperplane. The objective of SVM is to find a hyperplane in Z-dimensional space (Z is the number of features) that distinctly classifies and estimates the local road AADT.

E. MODEL TEST AND COMPARISON

Count-based AADT data for selected local functionally classified public road links (~15%) was set aside for testing. The 1D-CNN model was trained using data for 7,926 local road traffic count stations and validated using data for 2,966 local road traffic count stations (data set aside for tuning the model's hyperparameters) for 100 epochs. The model was then tested using data for 1,877 local road traffic count stations. The predictive performance was assessed using the mean absolute percentage error (MAPE), mean percentage error (MPE), and root mean square error (RMSE). They are mathematically represented as shown in equations (3), (4), and (5).

$$MAPE = \frac{1}{N}\sum\nolimits_{j=1}^{N}\left|\frac{CAADT_j - EAADT_j}{CAADT_j}\right| \tag{3}$$

$$MPE = \frac{1}{N}\sum\nolimits_{j=1}^{N}\left(\frac{CAADT_j - EAADT_j}{CAADT_j}\right) \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{j=1}^{N}(CAADT_j - EAADT_j)^2}{N}} \tag{5}$$

where N is the number of local road traffic count stations kept aside for testing, CAADT is count-based AADT, and EAADT is estimated AADT.

MPE was used to understand if each developed model generally underestimates or overestimates. MAPE was also used as there could be a mix of positive and negative errors. However, RMSE was favored as MPE and MAPE failed with a mix of positive and negative errors and may result in biased outcomes if range of errors is large. The use of RMSE is also in alignment with the past studies on local road AADT estimation.

IV. RESULTS

The results from descriptive analysis and modeling are discussed in this section.

TABLE 2. Descriptive analysis.

Variable	Minimum	Q1	Median	Mean	Q2	Maximum	Std. Dev.
Count-based AADT	10	260	495	824	1,000	5,000	884
Speed limit	20	45	55	49	55	55	8.90
Road density	2.00	7.49	11.09	13.70	17.75	74.00	8.40
Dis-nonlocal	0.01	0.10	0.20	0.54	0.66	9.48	0.77
AADT-nonlocal	50	1,600	3,300	5,490	6,800	151,000	6,837
Functional class type	0	0	0	0.24	0	1	0.42
Population density	0.81	61.81	116.95	231.86	277.35	5,798.78	312.65

Note 1: Q1 is 25th percentile and Q2 is 75th percentile.
Note 2: Dis-nonlocal is distance to the nearest nonlocal road and AADT-nonlocal is AADT at the nearest nonlocal road.

TABLE 3. Correlation matrix.

Variable	Count-based AADT	Speed limit	Road density	Dis-nonlocal	AADT-nonlocal	Functional class type
Speed limit	-0.33					
Road density	0.47	-0.55				
Dis-nonlocal	0.19	0.21	-0.28			
AADT-nonlocal	0.31	-0.22	0.38	-0.09		
Functional class type	0.43	-0.42	0.63	-0.18	0.35	
Population density	0.41	-0.34	0.61	-0.17	0.33	0.61

Note 1: Dis-nonlocal is distance to the nearest nonlocal road and AADT-nonlocal is AADT at the nearest nonlocal road.

A. DESCRIPTIVE ANALYSIS

The descriptive statistics of all the selected variables are summarized in Table 2. The median count-based AADT is 495, and the standard deviation is 884. The higher variations in count-based AADT are mainly attributed to the local road travel characteristics. The functional class type of most of the local road traffic count stations is rural, and they account for about 76% of the total local road traffic count stations. Most rural local roads have a speed limit of 50 mph or 55 mph. However, urban local roads generally have a speed limit less than or equal to 35 mph. The correlation between count-based AADT and selected explanatory variables is summarized in Table 3.

The results indicate that road density, functional class type, and AADT at the nearest nonlocal road have a positive correlation with count-based local road AADT. In general, local roads are designated for land access, and most travel is based on land access to the nearest nonlocal road. Hence, nonlocal roads with higher AADT have a higher level of interaction with local roads. Contrarily, there is a negative correlation between local road AADT and speed limit. Most rural local roads have a speed limit of 50 mph or 55 mph from the road database. However, urban local roads with a lower speed limit have a higher AADT. The negative correlation between local road AADT and speed limit can be attributed to this factor.

B. MODEL DEVELOPMENT

The cross-validation approach was used to find the best Kriging model. The ordinary kriging model with exponential semivariogram performed better in the cross-validation process. Fig. 3 shows the MSE loss over the training epochs for the training and validation datasets in the 1D-CNN model development process. The model converged, and both training and validation performance remained equivalent for 100 epochs.

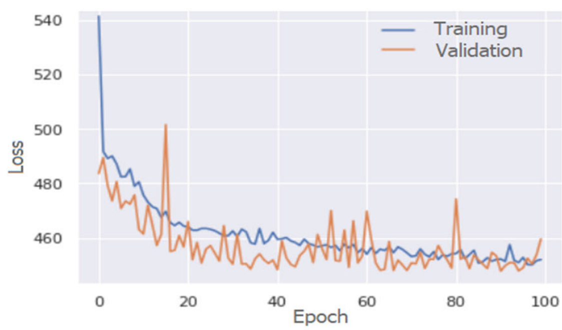


FIGURE 3. MSE loss over the training epochs.

The learning rate = 0.001, batch size is none, dataset is small enough to fit in the central processing unit (CPU), and training time is ~8 minutes for 100 epochs for the 1D-CNN model, compared to the learning rate = 0.001, batch size is none, and training time is ~2 minutes for 50 epochs for BP-ANN model.

C. MODEL TEST

Count-based AADT data for selected local functionally classified public road links (~15% of the sample) were set aside for testing. Sample predictions for ten randomly selected traffic count stations are summarized in Table 4. In general, test results indicated that GWR performed better at majority of local road traffic count stations with count-based AADT less than 400, while 1D-CNN performed better at majority of local road traffic count stations with count-based AADT more than 400 (as illustrated in Table 5).

TABLE 4. Estimated AADT at selected test traffic count stations.

Traffic count station	Estimated AADT									Count-based AADT
	OLS Regression	GWR	Ordinary kriging	NN interpolation	IDW	BP-ANN	RF	SVR	1D-CNN	
1	340	249	340	292	271	367	233	406	320	180
2	364	398	433	449	377	318	522	364	368	355
3	406	300	262	277	398	363	396	404	404	500
4	611	615	372	339	342	647	831	629	728	710
5	530	622	533	679	685	815	806	741	804	745
6	843	951	854	1196	834	1022	1798	866	995	940
7	801	705	493	445	621	849	885	860	1152	1,000
8	955	1334	565	1219	1027	1792	1226	1047	1294	1,400
9	2011	1828	1932	3140	2631	2019	2230	2443	1695	2,100
10	1735	1903	1741	1429	1242	1296	1656	1387	2287	2,900

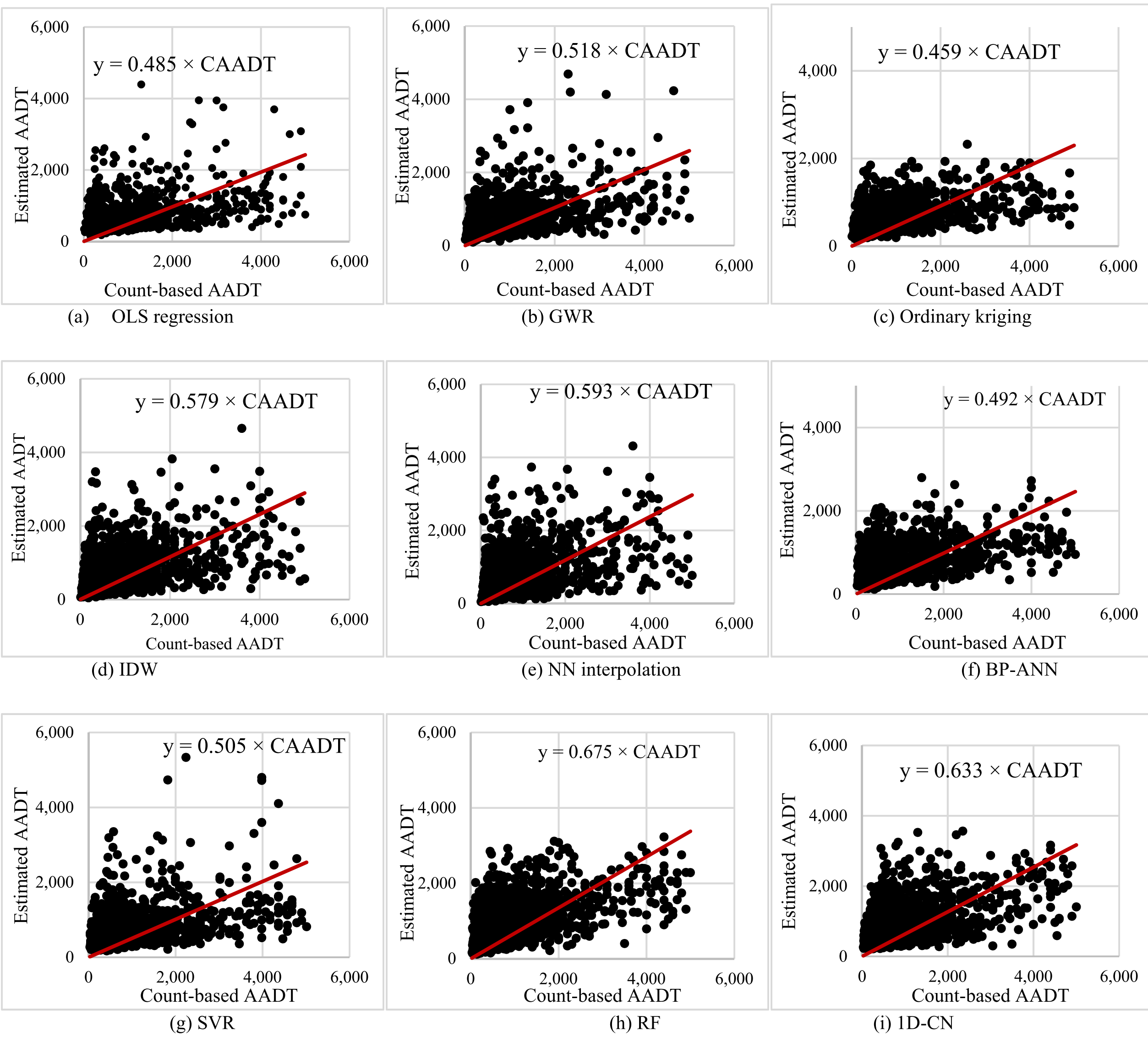


FIGURE 4. Estimated AADT vs. count-based AADT.

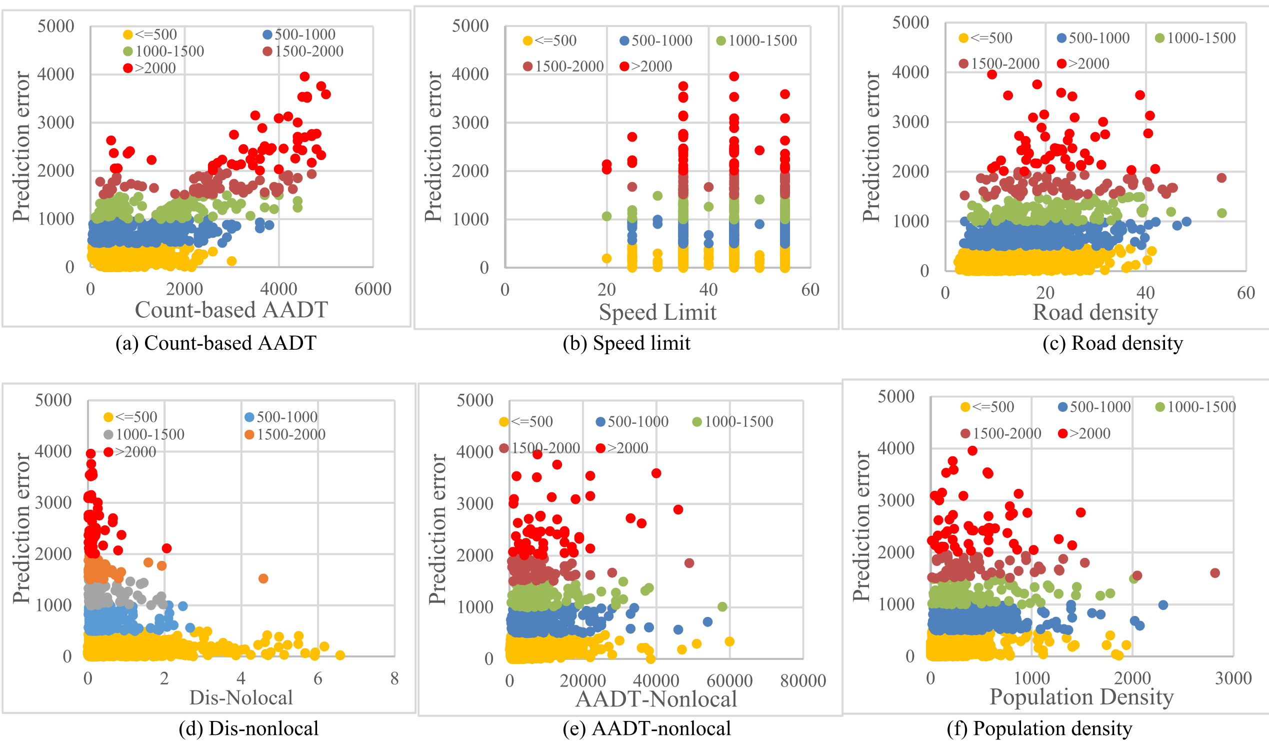
1D-CNN model was tested using MAPE, MPE, and RMSE. Table 5 summarizes the validation results of the 1D-CNN and all the other selected models.

From Table 5, 1D-CNN and RF models performed better in terms of RMSE. However, GWR and ordinary kriging models also better estimate local road AADT when assessed using

TABLE 5. Model test results.

Method/model	AADT<=400			AADT>400			All Data		
	MAPE	MPE	RMSE	MAPE	MPE	RMSE	MAPE	MPE	RMSE
OLS regression	151.11	-149.40	335.47	45.15	25.87	967.88	90.1	-48.4	765
GWR	139.11	-136.12	329.26	43.92	21.60	782.12	84.1	-45.2	729
Ordinary kriging	143.11	-140.12	336.62	40.87	23.59	933.51	84.5	-45.4	735
NN interpolation	152.21	-139.19	456.94	48.86	11.42	890.04	93.1	-53.2	738
IDW	149.40	-139.12	424.34	46.55	12.32	879.46	90.1	-51.5	722
BP-ANN	150.92	-147.51	348.76	46.64	19.94	950.12	89.1	-48.3	764
RF	198.58	-195.92	474.78	50.26	-7.26	836.91	105.2	-84.1	712
SVM	148.49	-146.70	344.68	48.58	20.86	972.19	89.8	-47.4	749
1D-CNN	163.61	-162.46	376.32	48.44	3.10	776.28	89.1	-60.1	712

Note 1: AADT<=400: test sites with observed AADT <= 400, Note 2: AADT>400: test sites with observed AADT > 400



(a) Count-based AADT (b) Speed limit (c) Road density
(d) Dis-nonlocal (e) AADT-nonlocal (f) Population density

FIGURE 5. Relationship between prediction error and explanatory variables.

all the measures. As MAPE and MPE divide each error individually by the observed count-based AADT, high prediction errors at locations with low AADT significantly impacted the MAPE and MPE of 1D-CNN. Geospatial methods like GWR and Kriging can accommodate the spatial variability in data. The travel characteristics on a local road are generally location-specific. Hence, methods addressing the nonstationary relationship between the AADT and other explanatory variables may yield better results. In this research, 1D-CNN architecture is developed without considering any spatial weights.

The higher prediction error is mainly attributed to the high variations in traffic volumes on local roads. The count-based AADT values range from less than 100 to 5000. Similar observations were also reported in past research efforts. Das and Tsapakis [29] used the SVR model to estimate local road AADT. Their research reported a mean RMSE of 420 for rural local roads and 1,066 for urban local roads. This research reported (marginally) lower RMSE. Consultations with the NCDOT staff also indicated an expected error of ∼100% in local road AADT estimation.

The relative improvement in local road AADT estimates from the 1D-CNN model in comparison to all the other selected models in terms of % RMSE are: OLS regression (7.40%), GWR (2.40%), ordinary kriging (3.23%), NN interpolation (3.70%), 1DW (1.50%), ANN (7.30%), RF (0%), and SVR (5.10%). The MPE is negative (EAADT > CAADT) for all the models.

Fig. 4 shows the relationship between count-based and estimated AADT at test traffic count stations. A linear fitted model was developed. A better relationship between estimated and count-based AADT is observed in the case of

RF and 1D-CNN. However, the MAPE and MPE values in Table 4 show that estimates from 1D-CNN are better than from RF.

Apart from comparing the performance of 1D-CNN model with other selected models, a reverse engineering approach was applied to uncover the 1D-CNN black box. The relationship between selected explanatory variables and prediction error was assessed using the scatter plots (Fig. 5). The prediction error was observed to increase with an increase in the count-based local road AADT. Similarly, the prediction error was observed to increase with an increase in road density and population density. Further, a Pearson correlation coefficient analysis was carried out to analyze the relationship between the prediction error and selected explanatory variables for all the selected modeling techniques. The correlation between the prediction error and count-based local road AADT, speed limit, functional class type, road density, Dis-nonlocal, AADT-nonlocal, and population density was examined. The Pearson correlation analysis results indicated a similar trend for all the selected models.

The prediction error has a highly positive correlation with the count-based AADT. Similarly, there is a positive correlation between the prediction error and the functional class type. It indicates that the prediction error is higher on urban local roads than rural local roads. The road density has a positive correlation with the prediction error. Likewise, the links with lower speed limits have a higher prediction error. Overall, the prediction error analysis indicates that there are unknown parameters (other factors or variables like land use, socioeconomic characteristics, etc.) that influence the local road AADT at many traffic count stations with higher count-based AADT. Hence, there is a need to collect more samples from areas with higher local road AADT to improve the model predictability. The 1D-CNN model used in this research has a fixed parameter size, however it can be changed depending on the availability of additional data.

The findings from the past studies indicated improved prediction with GWR over statistical and other geospatial methods like Kriging, IDW, and NN interpolation [21]. In this research, GWR performed quite well (MPE is -45.2, MAPE is 84.1, and RMSE is 729) and offered the added benefit of accommodating the spatial variations in data in the modeling process. GWR also provides insights into the relative effect of different explanatory variables on local road AADT.

V. CONCLUSION

Reliable estimation of AADT is central to road improvement and funding prioritization, safety performance assessment, and developing calibrated travel demand forecasting models.

Due to resource limitations, state DOTs and other regional/local transportation agencies need cost-effective methods for accurately estimating local road AADT.

Variables such as speed limit, road density, functional class type, population density, distance to the nearest nonlocal road, and AADT at the nearest nonlocal road were extracted and considered as the potential explanatory variables. This gives the data a fixed structure in the form of input variables and a target variable as well as the individual instances in the data being independent of one another. Consequently, this data structure is interpreted as an image of the format width x height.

Deep learning algorithms like CNNs have been proven to perform exceedingly well on structured data (images for example) and thus are applicable for AADT estimation discussed in this research. The results of the proposed 1D-CNN model were compared with eight existing state-of-the-art statistical, geospatial, and selected other machine learning models. The proposed 1D-CNN architecture was fine-tuned using the MSE loss function. The performance of the selected models was evaluated using MAPE, MPE, and RMSE. The comparison results indicated that the 1D-CNN approach improves the local road AADT estimation accuracy. Although 1D-CNN and RF have the same RMSE, 1D-CNN performed significantly better than RF in terms of MPE and MAPE. Also, the prediction error for 1D-CNN is found to be less than 50% for more than half of the traffic count stations used for testing.

The effect of the explanatory variables on the prediction errors was also quantified for the 1D-CNN model. The findings indicated that collecting count-based local road AADT data from urban local roads, locations with high road density, locations with high population density, and locations with low-speed limits can improve the predictability of models.

There are nearly 418,000 urban local road links (typically between two adjacent intersections; small lengths) in North Carolina. However, local road traffic count stations are available for only ∼0.72% of the urban local road links in North Carolina. On the other hand, there are nearly 328,000 rural local road links and traffic counts are available for ∼3% of the links. Collecting more data at urban local roads will help improve the model accuracy.

Statistical and machine learning methods did not show any significant improvement in their accuracy once they are trained on a certain amount of data. Hence, there lacks a scope for improvement in the accuracy with such methods. On the contrary, deep learning models can account for a large number of training samples and thus have higher scope for improvement in accuracy scores over the existing ones. As the purpose of this research was to accurately estimate local road AADT rather than looking into the effects of potential explanatory variables and their effect on local road AADT, the implementation of 1D-CNN was deemed appropriate. The explanatory variables considered in this research are significant variables among a set of road and socioeconomic and demographic variables identified through the Pearson correlation analysis and the OLS regression as part of a research project [21]. The model test and prediction error analysis indicated that 1D-CNN is equally good in learning the intricate pattern in the local road AADT and adequately estimating AADT at noncovered local road links.

To the best of the authors' knowledge, this research is the first attempt to use the 1D-CNN model to estimate local road AADT. Although this method is computationally intensive, the training speed could get faster with better processers. Past studies indicated that incorporating spatial weights may improve the predictability of the local road AADT estimation model. Developing a geographically weighted 1D-CNN algorithm may improve predictability, which merits further investigation.

1D-CNN model implementation was performed for experimental reasons to examine, even with less data and information to solve transportation problems like estimating local road AADT, if a deep learning model works well in comparison to statistical and machine learning methods. The results indicate that a dataset with similar data distributions, larger in size compared to the one used in this experiment, should significantly improve accuracy. Similarly, incorporating statewide land use data may also help improve the model accuracy.

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