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Image Retrieval Performance Tuning Using Optimization Algorithms

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Abstract: The relentlessness of modern life's pace has pushed many people to look for ways to save time so they may continue living the way they choose. The management of traffic presents a considerable obstacle due to the fact that a large proportion of persons have difficulties associated with transportation. As a result, fixing traffic problems becomes an absolute need. Machine learning stands out as a useful resource in this setting, providing deeper understanding and better analytical tools for sifting through complicated statistical data. The feasibility of travel for both large and light vehicles may be quickly assessed by experts, allowing for more timely and well-informed decisions. These evaluations serve as the basis for developing separate roadways, laws and sets of rules for various classes of vehicles. This study examines six characteristics of vehicular traffic and travel situations over 38,114 occurrences. Our goal is to improve traffic management through prediction and optimization using six different optimizers from the deep learning area. Based on observed patterns of truck traffic over a certain time period, these methods help determine optimal distribution paths for sent commodities. Six different deep learning optimizer models are compared and contrasted in this study. The objective is to use these examples to determine which optimizer is best. It's not easy to pick the best optimizer for use in deep learning. To this goal, we conducted an in-depth analysis of six industry-leading optimizers to identify the best tool for predicting traffic accidents. We ran extensive tests using a dataset that had 30,492 training examples (80%) and 7,622 testing instances (20%). Different seed values, ranging from 20 to 100, were used in each iteration of the experiment. We tested and compared the following optimizers: the Adaptive Gradient (AG) Algorithm, the Adaptive Learning Rate (ALR) Method, the Root Mean Squared (RMS) Propagation, the Adaptive Moment (AM) Estimation, the Nesterov-accelerated Adaptive Moment (NAM) Estimation, and the Stochastic Gradient (SG) Descent, taking into account processing times, prediction accuracy, and error analysis. The results of the experiment showed that the NAM Estimation Optimizer was much superior. Time spent processing data was cut down, and errors were kept to a minimum (0.03%). Prediction accuracy was also exceptionally high at 99.85%. This result reaffirms NAM Estimation's promise as a leading method for improving traffic management and making accurate trip predictions.

Introduction

A wide range of methodologies have been utilized in the anticipation of vehicular traffic as a result of the need to gather diverse factors and data. Deep learning has been a major strategy in the field of artificial intelligence, as it enables the acquisition of new abilities through data analysis. This technique involves the autonomous discovery of algorithms that determine the requisite representations for the purpose of classification. The use of numerous layers of abstraction in deep learning enables robots to effectively understand complex activities. According to several other parameters that also

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impact vehicle traffic, deep learning is employed in this study to forecast the occurrences of vehicle traffic (Vlahogianni et al., 2014).

Based on the dynamic nature of these fluctuating information, it is not feasible for an individual to accurately predict car traffic events. Consequently, there is a need for an appropriate system that can facilitate the comparison of data and enable accurate forecasts. Nevertheless, due to the rapid fluctuations in the collected data, developing an algorithm for predictive purposes is likewise unfeasible. Hence, there is a pressing need for a system equipped with artificial intelligence (AI) that possesses the ability to acquire and comprehend the technique. Regardless of the circumstances, it is imperative to obtain precise data within a limited timeframe. A suitable optimizer for a specific application is also utilized to apply the deep learning approach (Ou et al., 2018).

This study aims to find the best optimizer to forecast vehicle traffic events with the highest degree of accuracy and in the shortest possible time.

Related work

It was revealed that there is a revolutionary distributed simulator tailored specifically for a single junction. The simulator was responsible for generating unpredictable traffic to fulfil orders. The experiment that proved the viability of this system aimed to enhance the traffic control strategy at an intersection in four different scenarios. In these situations, safety and trip time reduction were the two main optimization criteria for automobiles and pedestrians. The findings indicated a notable decrease in the speed of vehicles (Wan et al., 2017). The study's focus was on enhancing conventional traffic lights. Using the simulator, the authors predicated how agents would behave at a specific intersection. The experiment regularly optimised traffic lights inside a simulated environment containing agents using a time-expanded network model. According to the study's findings, the time it takes to cross a single junction might be reduced from 45 to even 71% (Thunig et al., 2019). A single arterial route in Singapore has several junctions. Iteratively calibrated traffic junctions were used in the experiment to reduce the amount of backed-up traffic on the lanes. Compared to a fixed-time method, the data demonstrate that this technique reduces average delays by 24% and average pauses by 29% (Wang et al., 2016).

The simulation involved agents representing each junction, road segment, and vehicle. The findings of their study demonstrated that this approach could potentially reduce the average delay time at each junction by 6% (Han et al., 2021). To optimize the timing of traffic lights, a cloud-based system is presented that employs distributed coarse-grained parallel adaptation. Each slave computer is given a subpopulation to analyze, and the best population from all the nodes is transmitted to the master node for review after the algorithm has chosen it. This study illustrated the effectiveness of the coarse-grained parallel adaptive algorithm in a distributed setting, highlighting its capability to avoid falling into a local minimum (Zhang and Zhou, 2018).

The authors developed a simulation aimed at optimizing a traffic network comprising 217 junctions and involving the participation of 10,000 cars and trucks. The researchers proposed a method utilizing Markov random fields to identify traffic patterns and congestion based on historical data. This algorithm evaluates each route by considering the direction of vehicle flow to determine congestion levels. When traffic becomes excessively congested, the Markov decision process reallocates resources to different junctions to distribute vehicles more evenly in the initial traffic flow (Bouyahia et al., 2019). As a solution to the problem of speed clustering, Bin et al.'s (2020) introduction of a combination approach based on speed clustering showed promise in lowering MSE, MAE, and MAPE. By adapting the grey theory technique and the BP artificial neural network to the features of each time segment, they created a period-specific prediction strategy. The final model underwent extensive testing, where it was found to have an average absolute percentage error of 8.46%. Moreover, the authors investigated bus traffic and its particular scenario patterns, using fully connected neural networks to guarantee patterns and enhanced residual networks to capture correlations (Panbiao et al., 2019). Using multi-regime models and ensemble learning, the authors demonstrated an effective approach to short-term traffic flow forecasting. According to Zhenbo et al.'s (2020) experimental findings, the best-performing regimes greatly beat the four baseline models in terms of root mean square error and mean absolute percentage error throughout all traffic phases. A deep evolutionary algorithm-optimized neural network for predicting rear-end collisions for an autonomous avoidance system application. This model utilizes data from vehicle-to-infrastructure, vehicle-to-vehicle, and GPS sources to assess collision risk. Experimental findings indicated that this framework could reasonably assess collision risk in car-following situations (Chen et al., 2018).

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The study conducted by Vasiliy et al. (2020) examines a learning algorithm that integrates regulated components with a spiral layer structure. In contrast to existing methods, these strategies facilitate the ongoing training of neural networks and the prediction of future processes. Forecasting may be performed continuously without the need to interrupt the training process. In order to enhance the precision of predictions, there is a provision for more regulation over the associative retrieval of information from the memory of recurrent neural networks. Furthermore, the proposed methodologies for continuous RNN learning in forecasting have the possibility of generating continuous forecasts.

The proposed hybrid prediction model gathered data from several sources on urban awareness. Our strategy outperforms the standard when addressing the condition as a whole. The suggested model's outlier predictor considerably improves the model's capacity to forecast aberrant tunnel traffic in the face of severe weather or unanticipated traffic mishaps (Gang and Jiajun, 2019). An empirical examination of real-world data shows how effectively the technique boosts prediction accuracy. The increase in forecast accuracy may result in lessening road users' annoyance, cost savings for enterprises, and environmental impact (Aniekan et al., 2021). A fully connected neural network is utilized, and automatic training using the back-propagation approach is applied. This enables the multi-branch model to effectively capture complex traffic flow patterns hidden within the data until convergence criteria are met (Shangyu et al., 2020).

```
In [7]: df = pd.read_csv("C:/Users/Welcome/Documents/vahicle_traffic.csv")
        df.head(10)
```

Out[7]:

	Year	Model	Engine Descriptor	Engine Cylinders	Vehicles	Class
0	2022	GT V6 2.5	(FFS)	6.0	24	Minicompact Cars
1	2022	GT V6 2.5	(FFS) CA model	6.0	24	Minicompact Cars
2	2022	Spider Veloce 2000	(FFS)	4.0	25	Two Seaters
3	2022	Spider Veloce 2000	(FFS) CA model	4.0	25	Two Seaters
4	2022	DJ Po Vehicle 2WD	(FFS)	4.0	17	Special Purpose Vehicle 2WD
5	2022	DJ Po Vehicle 2WD	(FFS) CA model	4.0	17	Special Purpose Vehicle 2WD
6	2022	FJ8c Post Office	(FFS)	6.0	13	Special Purpose Vehicle 2WD
7	2022	FJ8c Post Office	(FFS) CA model	6.0	13	Special Purpose Vehicle 2WD
8	2022	Eagle 4WD	(FFS)	6.0	20	Special Purpose Vehicle 4WD
9	2022	Eagle 4WD	(FFS) CA model	6.0	19	Special Purpose Vehicle 4WD

Table 1. Representation of vehicle traffic attributes

In this study, it was evaluated recent studies in deep learning for traffic flow prediction. These deep learning models gradually extract higher-level features from raw input data through multiple layers. Given the intricate nature of transportation networks, the study delves into analysing the latest deep-learning models designed to address this complexity (Anirudh et al., 2022).

Materials and Methods

Data Description

The present study utilized automobile traffic data collected from the Lucknow to Gazipur Purvanchal route, specifically at the Bhelehara toll charge, throughout the year 2022. The engine descriptions of various car types were extracted from the photos and subsequently categorized into several classes. This study employed a sample size of 38,114 instances to investigate six distinct features related to concerns pertaining to the movement of vehicles in traffic. In this study, a deep learning technique was employed using the Python programming language. A selection was made of six exemplary optimizers for the purpose of comparing and ultimately selecting the most superior optimizer.

The undesirable columns are deleted during this data-cleaning procedure, and the necessary data is stored. The previously saved data is transformed into a data frame, a proper format well-liked for prepping and processing data needed in deep learning. This framework is what we employ to process and sanitize the data. Information like the Year, Model, Engine Descriptor, Engine Cylinders, Vehicles, and Class are included in the raw data.

Methods Description

An optimizer represents the disparity between the actual and expected values. To achieve this, multiple iterations are carried out, each involving weight adjustments. Given the inherent complexity of training a neural network, we used six optimizers in this experiment.

Optimizer selection

Deep learning employs an iterative rule. It uses a number of different tuning parameters and analytic approaches. The iterative loop may be completed quickly and efficiently to improve forecast accuracy. Training algorithms for the model include the AG Algorithm, ALR Method, RMS Propagation, AM Estimation, Nesterov-accelerated AM Estimation, and SG Descent.

Adaptive Gradient Algorithm

AG Algorithm is an optimization technique based on gradients that modifies learning rates according to parameters. Adaptive Gradient Optimizer decreases the loss function concerning the weights. The weight updating formula is as follows (Lydia and Francis, 2019):

Previously, we updated each parameter Pi simultaneously since each parameter Pi utilised the same learning rate Lr. We initially display AG Algorithm's per-parameter update before vectorizing it since each parameter Pi at each time step t has a separate learning rate used by the AG Algorithm. For simplicity, we abbreviate the gradient at time step t as g_t. $g_{t,i}$, is then the partial derivative of the objective function w.r.t. to the parameter P_i at time step t:

$$g_{t,i}=\nabla_P J(P_{t,i}) \quad [1]$$

$$P_{t+1,i}=P_{t,i}-L_r\cdot g_{t,I} \quad [2]$$

$$P_{t+1,i}=P_{t,i}-L_r\,[\sqrt{(Gt,ii+\epsilon)}]\cdot g_{t,I} \quad [3]$$

Adaptive Learning Rate Method

In order to get over the learning rat that keeps getting smaller, it has been expanded from the AG Algorithm method. The current optimizer accumulates accurate squared gradients in all iterations (Ariff et al., 2022).

The only factors that affect the running average $V[g^2]_t$ at time step t are the previous average and the current gradient (as a fraction γ, comparable to the Momentum term):

$$V[g^2]_t=\gamma V[g^2]_{t-1}+(1-\gamma)g^2_t \quad [4]$$

RMS Propagation

AG Algorithm's significantly declining learning rates prompted the independent development of RMS Propagation and ALR Method around the same time. In reality, RMS Propagation and the initial update vector of ALR Method that we deduced earlier are the same (Yue and Liu, 2022):

$$V[g^2]_t=0.9V[g^2]_{t-1}+(0.1)g^2_t \quad [5]$$

$$P_{t+1}=P_t-[L_r /(\sqrt{V[g^2]_{t+\epsilon}}).g_t\ ] \quad [6]$$

Adaptive Moment Estimation

This approach produces better results on the parameters that speed up the optimization process, enabling training and learning rate plans to keep up with it.

We determine the previous decaying averages and squared gradients, s_t and d_t, as given below (Salem et al., 2022).

$$s_t=\beta_1 s_{t-1}+(1-\beta_1)g_t \quad [7]$$

$$d_t=\beta_2 d_{t-1}+(1-\beta_2)g^2_t \quad [8]$$

The first and second moments are calculated by s_t and d_t of the gradients, respectively. Initially, s_t and d_t select the vector value 0 and are biased towards 0 when β_1 and β_2 are close to 1.

Calculated moment values as:

$$s_t=s_t/(1-\beta^t_1) \quad [9]$$

$$d_t=d_t/(1-\beta^t_2) \quad [10]$$

In this experiment, calculated Adam update rule as:

$$P_{t+1}=P_t-[L_r/(\sqrt{(d_t+\epsilon)}s_t \quad [11]$$

Nesterov-accelerated Adaptive Moment Estimation

The AM Estimation combines the Nesterov Accelerated Gradient with the AM Estimation. The NAG was used in the AM Estimation technique to create the Nesterov-accelerated AM Estimation update rule. In this experiment, replacing the momentum vector for the bias estimate for previous time s_{t-1} with current momentum vector s_t, and generating rule for Nesterov-accelerated AM Estimation (Xie, Z. et al., 2022):

$$P_{t+1}=P_t-[Lr /(\sqrt{d_t}+\epsilon)\ (\beta_1 s_t+(1-\beta_1)g_t/(1-\beta^t_1) \quad [12]$$

Stochastic Gradient Descent (SGD)

The S G Descent is an iterative method with appropriate smoothness properties for maximizing an objective function (Wang et al., 2022).

The Stochastic gradient descent algorithm generates parameter updates in contrast values. These values are calculated by training example as $p^{(i)}$ and label $q^{(i)}$:

$$P=P-L_r\cdot\nabla_P J(P;p^{(i)};q^{(i)})) \quad [13]$$

Data Analysis and Optimizer Selection

A quicker prediction that is very accurate and made in a short amount of time is essential for traffic. Finding the best optimizer as pick values of optimizer.

The information was gathered throughout the year 2022, and it was then divided into train and test data. One model is chosen and trained using each chosen optimizer for 100 seeds on the training set of data. We changed the weight values of the parameter for this model during the training phase to reduce the prediction error. To choose the optimal optimizer, each optimiser's forecast accuracy and mistakes are monitored and compared.

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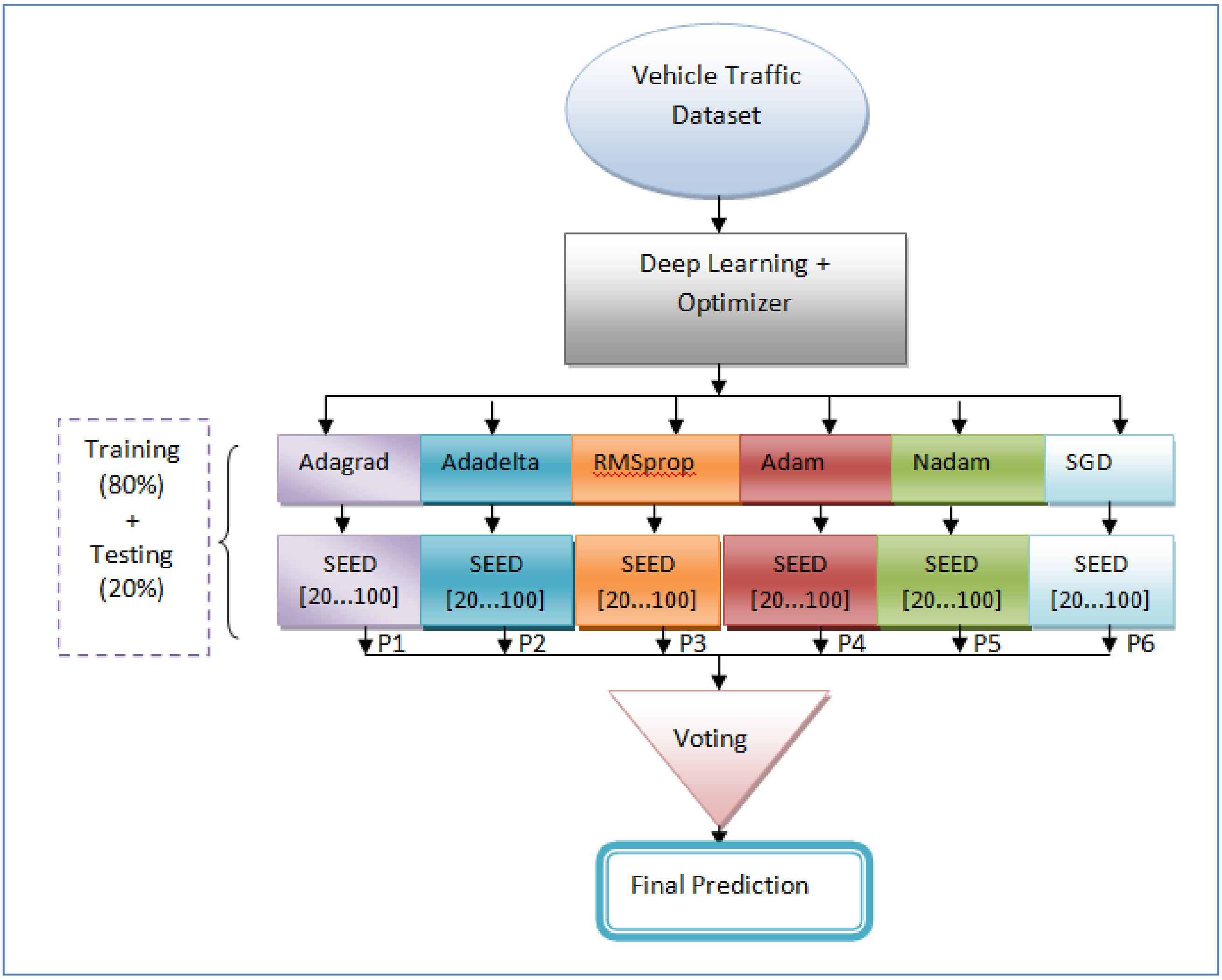

Figure 1. Representation of the proposed model for vehicle traffic attributes

Proposed Model

In this research paper, we have used 38114 instances and 6 attributes of vehicle traffic traveling problems. For the prediction, we selected a deep learning neural network algorithm with six optimizers viz. AG Algorithm, ALR Method, RMS Propagation, AM Estimation, Nesterov-accelerated, AM Estimation Stochastic Gradient Descent. These optimizers are used to calculate processing time and enhance accuracy and loss. We have used 80% traffic training dataset 30492 and 20% testing dataset 7622 with 7 attributes for prediction. Each experiment iteration is evaluated on different seed values from 20, 40, 60, 80 and 100. Each seed value provides the performance of deep learning on parameter setting by optimizer techniques. We observe each experiment and find which optimizer calculated better results by deep learning layer setting.

Results

To evaluate the enhanced accuracy, we analyze how closely these curves align. In this experiment, we compare the training and testing optimizer accuracy values. Tables 2, 3, and 4 represent novelty when considering all six optimizers, the Nesterov-accelerated AM Estimation optimizer exhibits the smallest difference between training and test values. The model accuracy for the six optimizers employed in the deep learning technique is depicted in Figures 2, 3, and 4. The Nesterov-accelerated AM Estimation optimizer outperforms its counterparts with a remarkable 99% model accuracy.

Furthermore, among the six optimizers under consideration, the Nesterov-accelerated AM Estimation optimizer demonstrates a loss of only 0.03, and this loss value decreases further as the number of seeds increases.

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Table 2. Training model (80%) prediction accuracy for different epochs for optimizers

Techniques for Optimization	To build model (Sec.)	Prediction accuracy (%)
AG Algorithm	0.33	97.04
A L R Method	0.39	97.34
R M S Propagation	0.35	95.20
A M Estimation	0.36	97.36
Nesterov-accelerated A M Estimation	0.34	99.85
S G Descent	0.33	78.72

Table 3. Testing model (20%) prediction accuracy for different epochs for optimizers

Techniques	To build model (Sec.)	Loss (mean squared error)
AG Algorithm	0.29	0.09
A L R Method	0.27	0.07
R M S Propagation	0.23	0.27
A M Estimation	0.24	0.06
Nesterov-accelerated A M Estimation	0.21	0.03
S G Descent	0. 24	0.47

Table 4. Testing loss prediction model of deep learning approach

Techniques for Optimization	To build model (Sec.)	Prediction accuracy (%)
AG Algorithm	0.32	96.12
A L R Method	0.38	96.23
R M S Propagation	0.34	94.10
A M Estimation	0.35	96.26
Nesterov-accelerated A M Estimation	0.32	97.75
S G Descent	0.32	77.61

Notably, this optimizer also yields the fewest mispredictions, as its values are consistently lower than those of the other optimizers. The processing times and forecasts for all six optimizers are presented above.

Table 2 displays the performance of six optimizers, along with the time they take during the process. The NAM Estimation optimizer achieves an accuracy of 99.85% while requiring only 0.34 units of time for the process.

Discussion

In order to conduct this analysis, information on vehicle traffic at the Bhelehara toll tax from 2022 along the Lucknow–Gazipur–Purvanchal highway was gathered. The gathered data was analyzed using deep learning algorithms, which were coded in Python. This experiment uses six of the best optimizers available to determine which one is the most effective. The AM Estimation optimizer was noticeably the fastest, with a processing time in seconds that was the shortest of all the optimizers tested. As a result, the AM Estimation optimizer is clearly the fastest at handling data.

The information about vehicle traffic on the Lucknow when comparing the various optimizers in terms of the precision with which they produce results, it was found that SG Descent had the lowest precision (78.72%), while the Nesterov-accelerated AM Estimation optimizer had the highest precision (99.85%).

On a 20% traffic dataset, the NAM Estimation Optimizer's accuracy is displayed in Figure 3. This decided value is large and was constructed with a shorter model than the previous optimizers. During training, the NAM Estimation optimizer has a loss (mean squared error) of 0.03%, while the SG Descent optimizer has an explanation for a loss rate of 0.47%. The NAM Estimation optimizer is faster to implement and provides better accuracy.

In order to get a better understanding, six optimizers were evaluated based on the accuracy of the results they produced for both the vehicle tragic training data and the vehicle traffic testing data. In this scenario, the same result is used for testing and training, and the results are provided

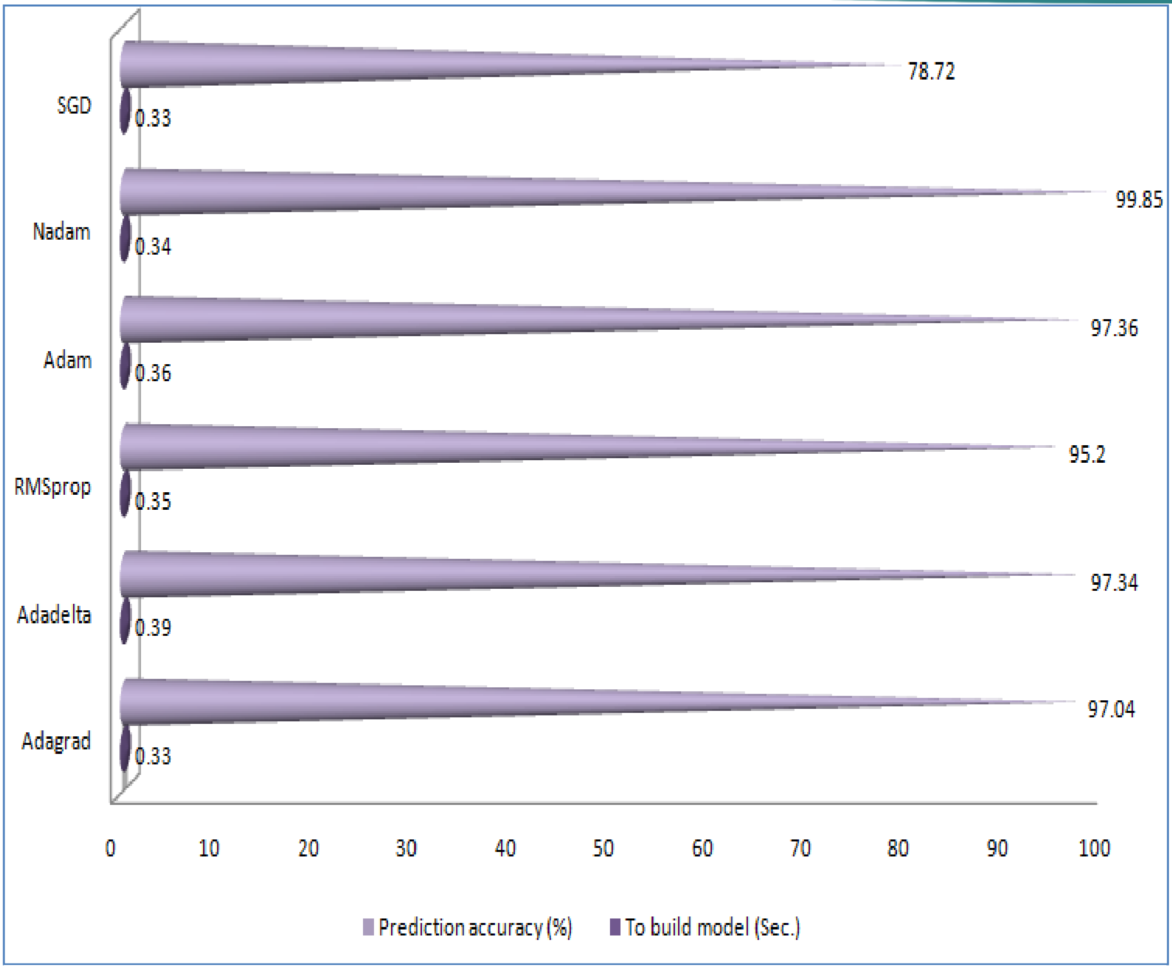

Figure 2. Analysis of training model for vehicle traffic attributes

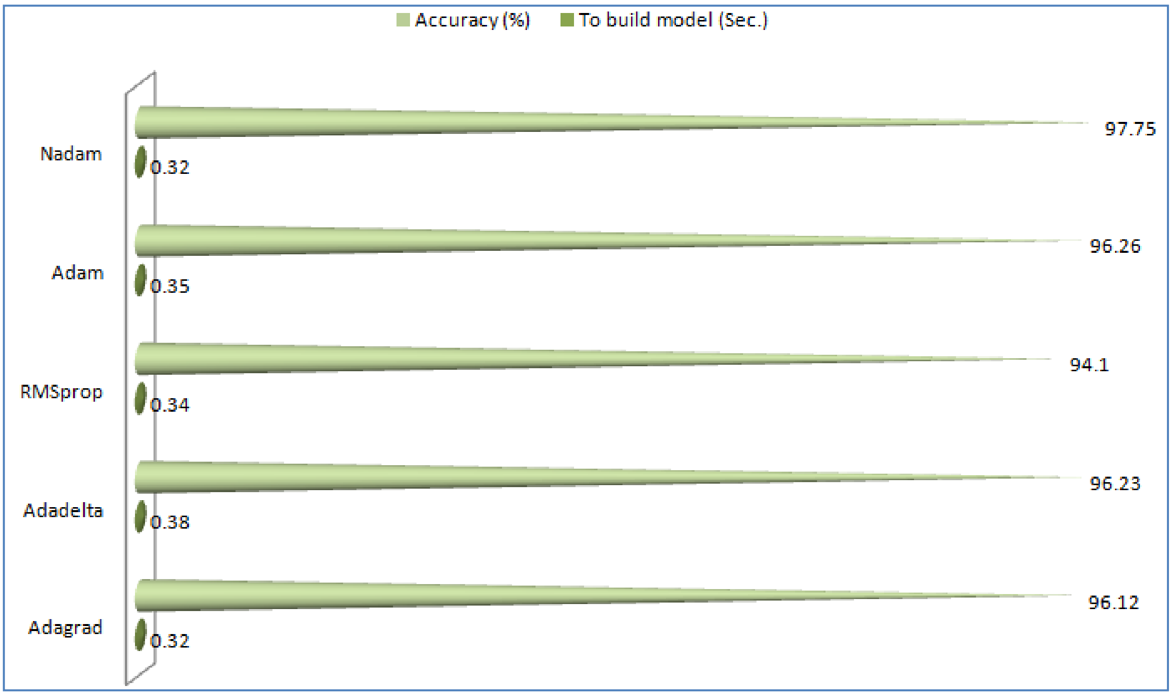

Figure 3. Analysis of testing model for vehicle traffic attributes

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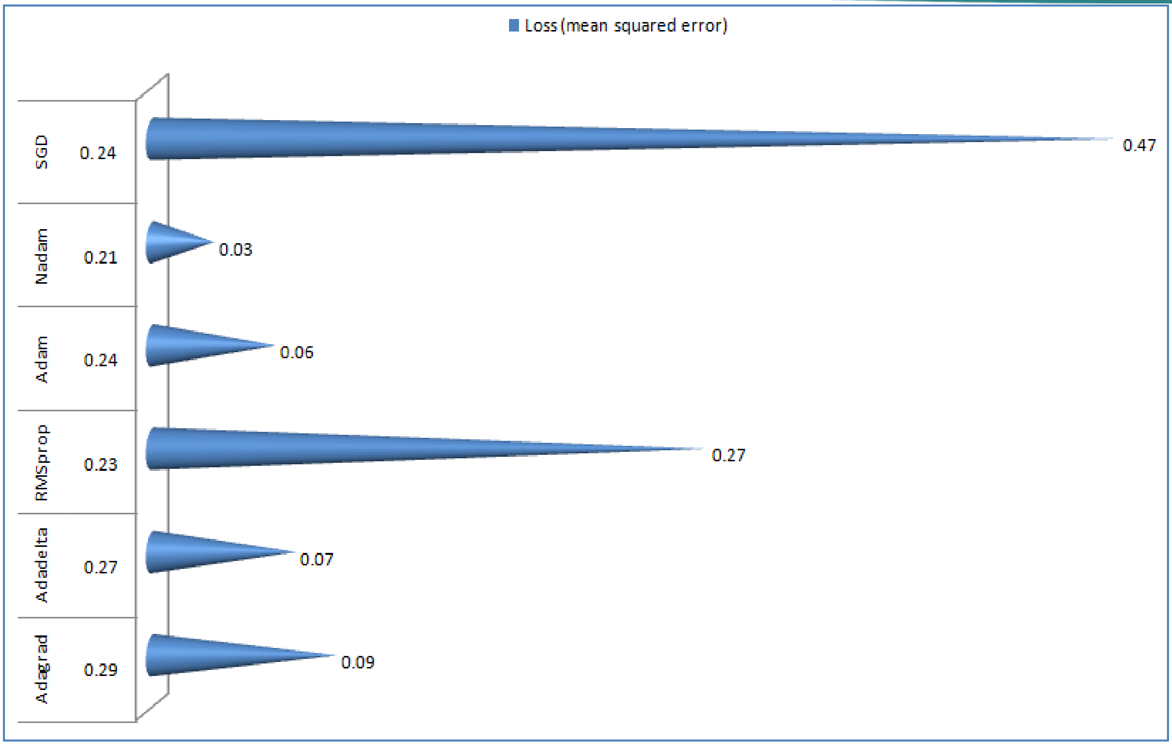

Figure 4. Analysis of loss model for vehicle traffic attributes

in a graphical manner for comparison so that spectators can easily evaluate how each optimizer performs in both scenarios. The AM Estimation, NAM Estimation, and other utilized optimizers have closer test and training outcomes compared to the SG Descent, RMS Propagation, and ALR

Method optimizer. Further investigation revealed that the test and training values of the optimizer and the results of the deep learning algorithm look more comparable for both AM Estimation and NAM Estimation. Therefore, the NAM Estimation optimizer provides more precise outcomes than AM Estimation and other optimizers.

Conclusion

The fast and constant rhythm of contemporary society has emphasized the crucial necessity for efficient methods that save time, particularly when dealing with the complexities associated with traffic control. The significance of addressing traffic problems cannot be emphasized, given the considerable number of individuals experiencing transportation challenges. Machine learning has become a great asset in this particular setting, providing more profound insights and improved analytical tools for effectively traversing intricate statistical data. The objective of this research was to enhance traffic management by utilizing six different deep learning optimizers to anticipate and optimize six significant features of vehicle traffic and trip situations. The study analyzed a dataset consisting of 38,114 occurrences. These methodologies facilitated the identification of the most efficient distribution routes for transported commodities, specifically in relation to truck congestion within a designated time period.

The NAM Estimation Optimizer demonstrated superior performance compared to other optimizers that were evaluated. The implementation not only resulted in a substantial decrease in processing durations but also upheld an exceptional level of prediction precision, achieving an accuracy rate of 99.85% and minimizing mistakes to a negligible 0.03%. The aforementioned results highlight the potential of the NAM Estimation approach to significantly transform traffic management and offer precise trip estimates. Therefore, this research validates the potential of the NAM Estimation Optimizer as a prominent tool for tackling traffic issues and promoting enhanced efficiency and informed decision-making within the transportation domain. In future, we will employ a variety of retrieval photographs taken from various perspectives and improve several crucial parameters using deep learning optimizers.

Conflict of Interests

The authors have no conflict of interest in this study.

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