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Distributed Multi-Intersection Traffic Flow Prediction using Deep Learning

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Abstract. Efficient traffic flow prediction is paramount in modern urban transportation management, contributing significantly to energy efficiency and overall sustainability. Traditional traffic prediction models often struggle in complex urban traffic networks, especially at multi-intersection junctions. In response to this challenge, this research paper presents a pioneering approach that not only enhances traffic flow prediction accuracy but also indirectly supports energy efficiency. This study leverages deep learning techniques, specifically the Gated Recurrent Unit (GRU), to analyze traffic patterns simultaneously at multiple intersections within a city. By treating the entire traffic network as a distributed system, the model provides real-time predictions, allowing for better traffic management and reduced fuel consumption. Moreover, the incorporation of data fusion techniques, which integrate data from various sources, including traffic sensors and historical traffic information, bolsters the accuracy and robustness of predictions. By predicting traffic flows with precision, this research aids in optimizing traffic signal timing, reducing congestion, and ultimately promoting more efficient transportation systems, which, in turn, reduces fuel wastage and emissions. This study, therefore, advances intelligent transportation systems and offers a promising pathway toward improved energy efficiency in urban mobility.

Keywords: Deep Learning, Traffic Flow, Energy Efficiency, Multi-Junction Traffic, Intelligent Transportation Systems

1 Introduction

In addressing the issue of traffic congestion in urban areas, a multitude of challenges arise, affecting diverse facets of societal and economic domains. Beyond the overt inconveniences such as prolonged travel times and heightened fuel consumption, this predicament engenders substantial environmental and public health concerns. A comprehensive resolution necessitates the incorporation of intelligent traffic management technologies and infrastructural enhancements[1]. At the core of these multifaceted endeavors lies the imperative of traffic dynamics prediction. While forecasting routine traffic congestion occurrences is relatively straightforward, attaining a high degree of precision in predicting

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traffic flow within specific temporal intervals presents a formidable task. Conventional statistical models are heavily reliant on predetermined structural expressions and underlying assumptions about variables, resulting in varying degrees of predictive accuracy[2]. The fundamental challenge lies in the inflexibility of these assumptions, rendering them ill-suited for accommodating the erratic and highly variable nature of traffic data. In this context, data-driven deep neural models have emerged as an influential paradigm for traffic flow prediction[3]. Among these models, Recurrent Neural Networks (RNNs) have garnered significant attention for their capacity to capture historical input data and thereby enhance predictive accuracy[4, 5]. Nonetheless, RNNs are plagued by the vanishing gradient problem, which causes them to lose track of longer temporal sequences over time. To address this inherent limitation, researchers have proposed various adaptations of RNNs, among which Long Short-Term Memory (LSTM)[6, 7] and Gated Recurrent Unit (GRU) have emerged as prominent solutions. Of particular note, the GRU model, tailored to alleviate the vanishing gradient problem, exhibits enhanced efficacy in modeling intricate temporal dependencies within traffic data.

The principal objective of this research is to advance the domain of traffic flow prediction, with a particular focus on the simultaneous prediction of traffic conditions at multiple intersections[8]. Our study centers on the analysis of a dataset encompassing information from four distinct nodes, each characterized by distinct traffic dynamics, temporal trends, and seasonal fluctuations. In line with our commitment to harnessing machine learning techniques, specifically the Gated Recurrent Unit (GRU) neural network model, we aim to achieve accurate predictions of traffic flow within this intricate multi-intersection milieu[9]. The significance of this research is underscored by the invaluable insights it offers into traffic behavior, thereby facilitating the development of infrastructure-oriented remedies to alleviate congestion[10]. Through the prediction of traffic patterns, our research equips city planners and policymakers with the essential information required for making informed decisions regarding traffic management strategies, road expansion initiatives, and the deployment of intelligent transportation systems. Notably, this paper yields a substantial contribution to the realm of energy efficiency in urban areas. Through the precise prediction of traffic flow and congestion patterns, it enables the implementation of more efficient traffic management practices, thereby curtailing wasteful idling times, superfluous acceleration and deceleration, and the ensuing traffic gridlock, all of which are deleterious to fuel efficiency. The ultimate result is a reduction in fuel consumption and greenhouse gas emissions, thereby harmonizing with the broader aspiration of fostering sustainable urban development. In the forthcoming sections, we expound upon our chosen approach, elucidate the data preprocessing techniques that we employ, and introduce the evaluation metrics utilized to gauge model performance. Additionally, we present the results derived from our experimental endeavors, illustrating the model's proficiency in capturing the intricate dynamics of traffic[11, 12]. Through this research endeavor, we aspire to make a substantive contribution to the ongoing initiatives aimed at refining traffic management strategies, mitigating challenges associated with congestion, while concurrently advancing energy efficiency and promoting environmental sustainability[13].

2 Related work

Traffic congestion is a pervasive and intricate predicament afflicting urban domains, exerting substantial ramifications on transportation infrastructures, economic systems, and the general well-being of urban inhabitants. Over the past years, considerable interest has been directed towards the creation of efficacious models for forecasting traffic flow, with a pronounced emphasis on the integration of deep learning paradigms. This comprehensive review undertakes an examination of pivotal scholarly contributions and prevalent trajectories within the domain of traffic flow prediction, centering its attention on the utilization of deep learning methodologies. Within this context, a multitude of strategies has been propounded by researchers to substantiate and assess the veracity of traffic prognostications [14, 15, 16]. Traffic flow prediction models are commonly categorized into two primary classes: parametric and non-parametric models [17]. Parametric models entail predefining a structured expression, which involves making assumptions about the variables [18]. The effectiveness of a parametric algorithm hinges on the accuracy of these assumptions; otherwise, its performance may deteriorate. Within the realm of parametric models, discussions frequently revolve around linear regression, Auto-regressive Integrated Moving Average (ARIMA) models [19], Kalman Filtering (KF) models, and maximum likelihood estimation techniques [20]. Despite their historical application in characterizing traffic features, parametric models exhibit limited adaptability. Furthermore, their efficacy diminishes due to the inherent non-linearity and fluctuations within traffic data [21]. This inadequacy has prompted the exploration of alternative approaches, specifically rooted in Artificial Intelligence (AI), which outperform conventional statistical models by capitalizing on their capacity to glean insights from complex, multidimensional traffic data. To address these challenges, researchers have delved into non-parametric prediction models characterized by their flexibility in accommodating varying numbers of parameters. Notably, these parameters expand as the model acquires additional data. Consequently, non-parametric algorithms are computationally more demanding and, albeit computationally slower, represent a promising avenue for improving traffic flow prediction. In contrast to parametric models, non-parametric models embrace a more flexible approach by making fewer a priori assumptions about the underlying data distribution. This category encompasses diverse protocols, including Support Vector Machine (SVM) [22], K-nearest Neighbor (KNN) [23], Neural Networks [24], among others. Notably, the emergence of deep learning techniques has revolutionized the field of traffic prediction, garnering widespread recognition for their superior capacity to capture intricate traffic dynamics. Diverging from conventional shallow architectures, deep learning models employ multi-layer nonlinear structures to encapsulate distributed and hierarchical features within complex traffic flow datasets. Some researchers have introduced clustering methodologies, such as Deep Belief Networks (DBN), into the realm of traffic flow prediction [25]. Moreover, [26] have devised an intelligent swarm-based optimization framework for parameter tuning in DBN, augmenting its predictive prowess for multiple time steps ahead. Additionally, a novel attention-based model akin to Stacked Auto-Encoder (SAE) has been proposed, exhibiting superior performance when compared to Random Walk (RW), Feed-Forward Neural Networks (FFNN), and Radial Basis Function (RBF) approaches [27]. Fully-connected neural network models represent another facet of non-parametric modeling, characterized by their dense interconnections, whereby each neuron within a given layer establishes connections with every neuron in the subsequent layer. This architecture inherently refrains from imposing any assumptions regarding feature representations, allowing for automatic feature extraction directly from the dataset [28]. Furthermore, it has been empirically observed that RNNs and their variants excel in capturing the stochastic and nonlinear temporal dependencies inherent in traffic data. Nonetheless, the utilization of RNN in traffic flow prediction poses certain challenges of academic significance. One notable issue is the occurrence of the vanishing gradient problem, a well-documented phenomenon in RNNs, which constrains their ability to handle long sequences effectively. This limitation stems from the inherent short memory retention characteristic of RNNs, rendering them less suited for capturing temporal dependencies in extended sequences. Furthermore, RNNs demonstrate suboptimal performance when confronted with specific features inherent to traffic data, wherein Convolutional Neural Networks (CNNs) exhibit superior capabilities. The specialized requirements of traffic flow prediction, which often demand the analysis of distant temporal features, pose an additional challenge to RNNs, as they tend to lose the capacity to retain such remote information over extended time intervals. Another practical challenge associated with RNNs lies in the determination of the optimal size for the sliding window data. Unlike some models that can adaptively adjust this parameter, RNNs necessitate a predetermined window size, presenting a practical impediment to achieving optimal model performance. In response to these challenges, a viable alternative emerged in the form of the GRU architecture, introduced by [29]. GRU architecture was specifically designed to mitigate the vanishing gradient problem associated with traditional RNNs. Empirical investigations within the realm of transportation, particularly traffic-flow estimation, have demonstrated the superiority of GRU models over alternative techniques, including Stacked Autoencoders (SAE), Feedforward Neural Networks (FFNN), and SVM[30]. Notably, the GRU model shares conceptual similarities with the LSTM architecture and exhibits comparable predictive performance. Both models effectively address the vanishing gradient and overfitting issues commonly encountered with traditional RNNs. GRU's streamlined internal structure expedites training, featuring two crucial control gates—the reset and update gates. The update gate plays a pivotal role in preserving pertinent historical information, mitigating the risk of vanishing gradients, while the reset gate governs the degree of forgetfulness regarding past data. Various external factors, such as weather conditions, shifting population dynamics, and socio-economic events, can significantly impact traffic flow patterns. While traffic exhibits consistent temporal patterns throughout day and night cycles, these external factors introduce notable deviations. Notably, [31] highlighted a limitation in existing LSTM studies, emphasizing the underutilization of temporal features for traffic prediction. In response, they introduced a specialized variant of LSTM known as Temporal LSTM (T-LSTM) to predict traffic speed within a single road section. However, this approach primarily enhances temporal dependencies and lacks consideration of spatial dependencies. In traffic flow data collected via Roadside Units (RSUs), a unique temporal and spatial correlation emerges. RSUs continuously transmit real-time measurements to the Intelligent Transportation System (ITS), reflecting the dynamic nature of traffic conditions, particularly during rush hours. To efficiently capture this spatiotemporal correlation, some researchers have turned to SVM. [32] presents the Adaptive Multi-Kernel SVM with Spatial–Temporal Correlation (AMSVM-STC) for short-term traffic prediction. This model aims to discern the nonlinear and stochastic aspects of traffic flow at Points of Interest (POIs) primarily through probabilistic models. Although the study claims superiority over existing models, it lacks comparative evaluations with deep learning approaches. Furthermore, [33] introduces the STANN model, inspired by attention-based models, incorporating spatial and temporal attention mechanisms for traffic flow prediction. Preliminary results indicate the model's promise in enhancing prediction accuracy. Additionally, CNNs have gained popularity in traffic flow prediction due to their robust spatial feature modeling capabilities [34]. Nonetheless, there is a limitation in capturing temporal attributes within the existing framework. Recognizing the superior capability of RNNs in exploiting temporal characteristics, some scholars have advocated for the integration of CNNs with RNNs to mitigate prediction errors. The hybrid CNN-RNN model is designed to capitalize on historical data to discern temporal characteristics while concurrently utilizing image data to delineate spatial attributes. Consequently, it facilitates the exploration of spatio-temporal features inherent in the input sequence [35]. In a pertinent development, Kong et al. have expounded upon the burgeoning significance of real-time traffic flow data as a constituent of the realm of big data [36]. This realization aligns with the evolving landscape of Intelligent Transportation Systems (ITS), which is progressively transitioning into a data-driven paradigm characterized by the escalating heterogeneity, volume, and intricacy of data samples generated by the Internet of Things (IoT) [37]. The primary objective of ITS resides in the establishment of an advanced, well-informed, and more intelligent utilization of transportation network systems, catering to the needs of both citizens and governing authorities.

3 Methodology and Implementation

In this research, we aimed to predict traffic flow at four different junctions using a GRU neural network model. The proposed architecture to predict the future traffic flow at an intersection is defined below in Fig. 1. In order to analyse pre-processed data and evaluate the effectiveness of traffic flow prediction models, the neural network model based on the GRU architecture was employed for model training and evaluation. Prior to the training and evaluation process, the data underwent preprocessing steps such as normalization, and principal component analysis. It's important to note that the same preprocessing techniques were applied consistently to the data before training and evaluating each algorithm.

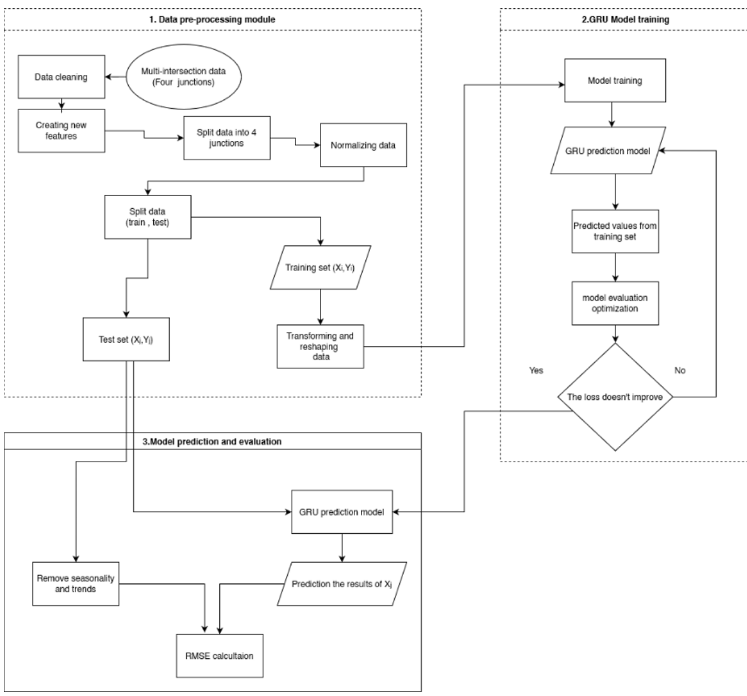

Fig. 1. Flowchart of proposed architecture

3.1 Data Collection and Preprocessing

Beginning our analysis with exploratory data analysis is consistently a wise decision as it helps us understand important dataset properties such as data format, number of samples, and data types. In this case, the dataset we are working with contains more than 48000 data points with 4 attributes. Table 1. shows a sample of the data, providing a visual representation. The dataset comprised hourly counts of vehicles at four junctions, each represented by features such as DateTime, Junctions, Vehicles, and ID.

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Table 1. Sample Data Illustration and Dataset Overview.

	DateTime	Junction	Vehicles	ID
0	2015-11-01 00:00:00	1	15	20151101001
1	2015-11-01 01:00:00	1	13	20151101011
2	2015-11-01 02:00:00	1	10	20151101021
3	2015-11-01 03:00:00	1	7	20151101031
4	2015-11-01 04:00:00	1	9	20151101041
5	2015-11-01 05:00:00	1	6	20151101051
6	2015-11-01 06:00:00	1	9	20151101061
7	2015-11-01 07:00:00	1	8	20151101071
8	2015-11-01 08:00:00	1	11	20151101081
9	2015-11-01 09:00:00	1	12	20151101091

Variations in data collection times across different intersections introduced disparities in traffic data periods and sparsity issues, necessitating comprehensive data exploration and preprocessing procedures. Our preparatory steps encompassed the following phases:

3.2 Data Exploration

Commencing with the analysis, we initially plotted the vehicle count against the date variable. This preliminary examination revealed distinct trends, notably an upward trajectory in the data pertaining to the first intersection. In contrast, the fourth intersection exhibited significant data sparsity, with records only becoming available after 2017. Seasonal patterns were not readily apparent in the initial plots, prompting us to delve deeper into the exploration.

3.3 Feature Engineering

A critical component of our data analysis involved feature engineering. We derived additional features from the DateTime variable, including Year, Month, Date within the month, Day of the week, and Hour. This feature engineering approach uncovered recurring yearly, monthly, daily, and weekly patterns spanning all intersections, contributing valuable insights to our subsequent data preprocessing endeavors.

3.4 Data Transformation

Recognizing the non-stationary nature of the time series data, we applied differencing transformations aimed at eliminating trends and seasonality effects specific to each intersection. It is worth noting that distinct differencing strategies were employed for intersections one and two, aligning with their unique data characteristics.

3.5 Model Development

Our model construction centered on the implementation of a neural network model based on the GRU architecture, tailored for traffic flow prediction. To facilitate model fitting for each intersection, a dedicated function was formulated. These models were trained using the transformed training datasets, accounting for the differential preprocessing requirements dictated by each intersection's distinct data profile.

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3.6 Model evaluation

Upon concluding the model training phase, it becomes imperative to assess the accuracy of the prediction model utilizing distinct testing data. In the context of comparing forecasting techniques operating on the same unit scale, a prevalent and robust metric employed is the Root Mean Square Error (RMSE). The RMSE is computed through a defined mathematical expression, quantifying the magnitude of disparities between the predicted values generated by the model and the ground truth values present in the testing dataset. This evaluative metric offers a quantitative gauge of the model's predictive prowess, facilitating substantive juxtapositions among various forecasting methodologies.

$$\mathrm{RMSE}(y, \hat{y}) = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1}(y_i - \hat{y}_i)^2} \quad (1)$$

Where:
n : Number of samples
y : Observed traffic flow
$\hat{y}$: Predicted traffic flow

4 Results and discussion

4.1 Model Fitting

Our traffic flow prediction model is constructed using a deep learning architecture with specific configurations for GRU layers, dropout layers, and output layer, followed by a meticulous compilation and training process. The model architecture and training details are outlined below.

4.1.1 GRU Layers

The model incorporates four GRU layers, each with varying numbers of units to capture hierarchical features in traffic patterns:

- First GRU layer: 150 units
- Second GRU layer: 150 units
- Third GRU layer: 50 units
- Fourth GRU layer: 50 units

All GRU layers utilize the hyperbolic tangent (tanh) activation function and are configured to return sequences (return_sequences=True), as they are stacked to allow for comprehensive traffic pattern analysis.

4.1.2 Dropout Layers

To mitigate overfitting and enhance generalization, a Dropout layer with a dropout rate of 0.2 is added after each GRU layer. Dropout randomly omits a fraction of input units during training, contributing to a more robust and reliable model.

4.1.3 Output Layer

The model concludes with a Dense layer comprising a single unit. This architecture aligns with the regression nature of the task, where the goal is to predict a continuous value representing traffic flow.

4.1.4 Compilation

The model is compiled using stochastic gradient descent (SGD) as the optimizer. The SGD optimizer is augmented with a small weight decay (decay=1e -7) and momentum (momentum=0.9) to enhance training stability. The mean squared error (MSE) is employed as the loss function during training, a suitable choice for regression problems.

4.1.5 Training

The model undergoes training for 50 epochs, with the training data partitioned into batches of size 150. Early stopping is implemented as a callback, monitoring the validation loss. Training halts if the validation loss does not improve by at least 0.001 for 10 consecutive epochs. The model with the best validation loss is restored, ensuring optimal predictive performance.

The transformed training datasets for all four junctions were meticulously tailored to align with the specific requirements of the corresponding model, as illustrated in the accompanying Fig. 3, Fig. 4, Fig. 5 and Fig. 6. These figures provide a visual representation of the intricate relationship between the transformed training data and the model architecture. Each junction's distinct characteristics and data intricacies were taken into account during the model fitting process, ensuring a precise alignment between the data and the predictive models. This meticulous approach to model-data integration served as a foundational element in our endeavor to develop accurate and context-aware traffic flow prediction models for urban intersections.

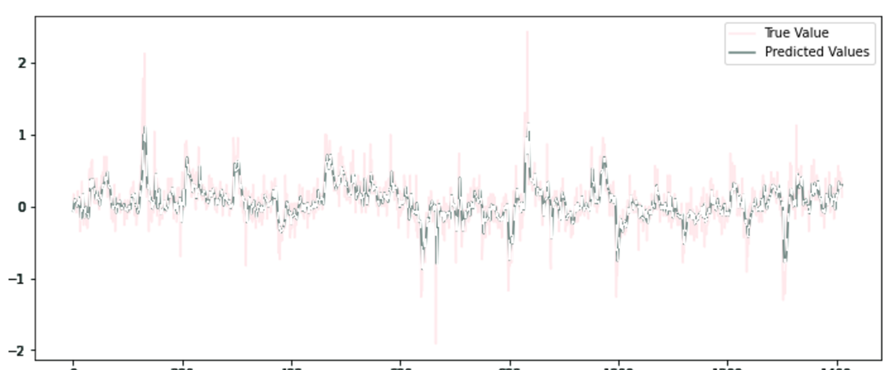

Fig. 3. plot of the first junction (predicted vs actual values)

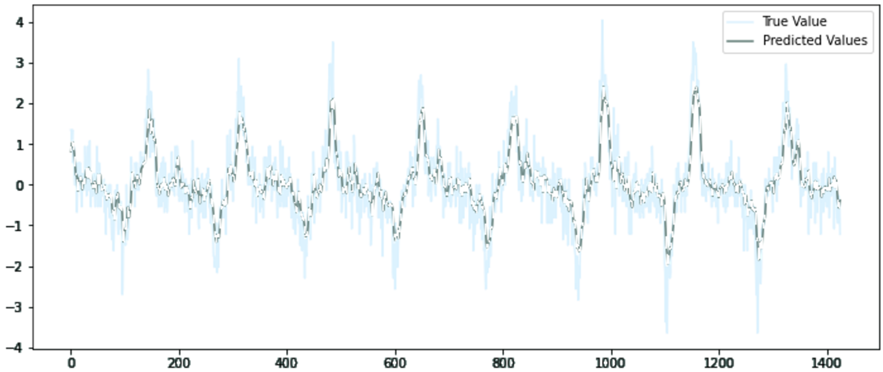

Fig. 4. plot of the second junction (predicted vs actual values)

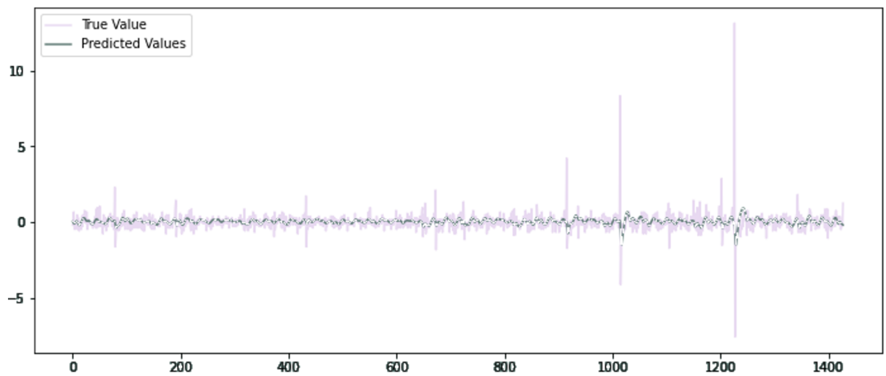

Fig. 5. plot of the third junction (predicted vs actual values)

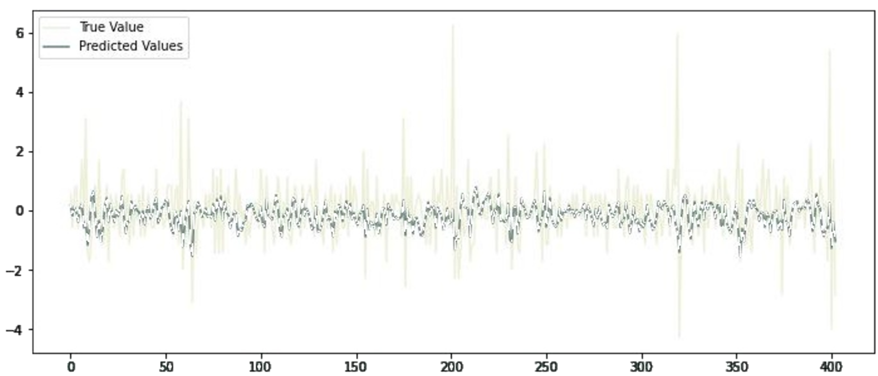

Fig. 6. plot of the fourth junction (predicted vs actual values)

The assessment of our traffic flow prediction models has yielded insightful performance metrics. Specifically, for Junction 1, the model has demonstrated robust predictive capabilities, characterized by a RMSE of 0.245881, which indicates a high degree of accuracy in its predictions. In the case of Junction 2, while the RMSE is marginally higher at 0.558597, the model has still exhibited commendable predictive performance. Junction 3 has similarly demonstrated competitive predictive prowess, with an RMSE of 0.606137, affirming its capacity to generate reliable forecasts of traffic flow. However, Junction 4, which presented inherent challenges due to limited data availability, has registered a comparatively elevated RMSE of 1.024198. Nevertheless, it is worth noting that the model has consistently displayed

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a noteworthy level of performance across all four junctions, emphasizing its ability to furnish valuable traffic flow prognostications showns in Table 2.

Table 2. Performance Metrics of Traffic Flow Prediction for Different Junctions.

Junction	**RSME**
1	0.245881
2	0.558597
3	0.606137
4	1.024198

4.2 Inverting the Data Transformation

In order to ensure that our predictive outputs remain consistent with the original data scale, we meticulously reversed the transformations that had been initially employed to mitigate the impact of seasonality and trends within the datasets. This pivotal undertaking serves to realign our predictions with the authentic traffic flow values, thereby bolstering the practical utility and interpretability of our predictive models. By reinstating the data to its original scale, we enable stakeholders to readily comprehend and employ the model outputs within the real-world context of traffic management and decision-making.

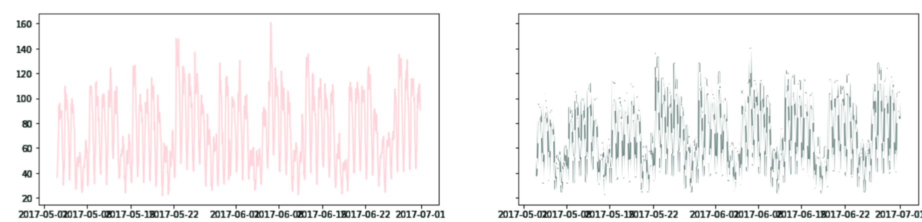

Fig. 7. The inverse transform on the first junction

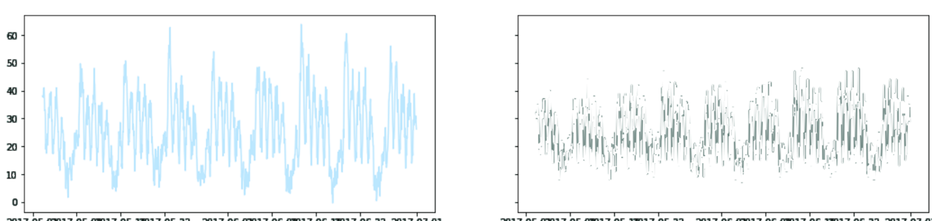

Fig. 8. The inverse transform on the second junction

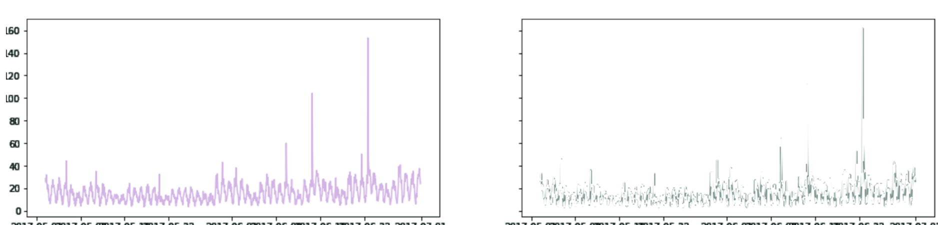

Fig. 9. The inverse transform on the third junction

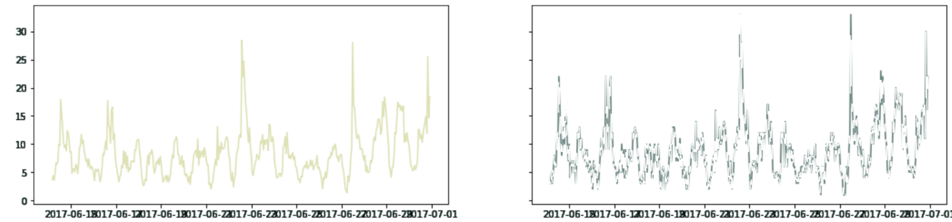

Fig. 10. The inverse transform on the fourth junction

Upon reverting the data transformations, a salient observation comes to the fore. Our predictive accuracy experiences a substantial enhancement. This pivotal step not only reverts our forecasts to their original data scale but also underscores the precision and reliability intrinsic to our predictive models. In our endeavor to anticipate traffic dynamics at four distinct intersections, we harnessed the capabilities of a GRU Neural network. The process of rendering the time series stationary involved employing a combination of normalization and differencing transformations, tailored individually to each intersection due to their unique trends and seasonality patterns.

5 Conclusion

In the present study, we have adeptly harnessed the capabilities of a neural network, specifically a GRU model, to undertake the intricate task of predicting traffic flow dynamics across four distinct junctions. To achieve this objective, we judiciously applied a range of data preprocessing techniques, including data normalization, and differencing transformations, to ensure the uniformity and appropriateness of the time series data for each junction, accounting for their idiosyncratic trends and seasonality patterns. Our meticulous scrutiny of the dataset has yielded noteworthy insights into the traffic dynamics. It is of particular significance to note that Junction 1 displayed a marked surge in vehicular volume when compared to Junctions 2 and 3, although conclusive inferences regarding Junction 4 remained elusive due to data constraints. Moreover, Junction 1 exhibited conspicuously pronounced hourly seasonal patterns, distinguishing it from the remaining junctions. This research constitutes a substantial contribution to the field of traffic flow prediction by elucidating essential techniques for both model development and evaluation. Notably, it underscores the paramount significance of data preprocessing in mitigating the intricate nuances intrinsic to junction-specific traffic datasets, with potential implications for the reduction of energy consumption in the realms of traffic management and urban planning.

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