A Multi-Phase Deep Learning Methodology for Short Term Traffic Flow Prediction

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1 INTRODUCTION

Accurate traffic state prediction is important for effectively managing traffic flow during peak hours or in the event of an accident or road closure. The quest for accurate traffic forecasts faces challenges due to the spatial and temporal dependencies that characterize traffic flow across different network segments. Whereas traditional deep learning methods mainly rely on traffic data from isolated sections of the road network for traffic forecasting, recent advancements leverage information from the entire road network to enhance prediction accuracy. This study aims to predict traffic flow using historical traffic flow data, spanning from August 1st 2023 to February 1st 2024 (six-month period), from traffic detectors located at the city of Ioannina, Greece. Employing a phased deep learning approach, we initially explore traffic predictions using basic deep learning models and 1-minute resolution data from a single detector. Subsequently, we employ a Graph Convolutional Network (GCN) to harness 1-minute resolution data from three detectors. In a final effort to refine our predictions, we aggregate the original data into 5-minute intervals and reassess the GCN model's performance.

2 METHODOLOGY

This study employs a phased deep learning approach to predict traffic flow, leveraging six months of historical traffic data at 1-minute resolution from the city of Ioannina, Greece. To optimize model training and performance, data are normalized within a [0,1] range. Our dataset is methodically partitioned into training (130 days), validation (40 days), and testing phases (14 days) to establish a comprehensive framework for evaluating the models' real-world applicability and accuracy.

Initially, our analysis focuses on traffic prediction at the level of individual traffic detectors, employing input windows of up to 30 timesteps for forecasting the immediate future timestep. This phase is inspired by the studies Wang *et al.* (2021) and Ma *et al.* (2022) that explore the potential of hybrid deep learning models in short-term traffic flow prediction. Subsequently, our research advances to incorporate sophisticated architectures, including a Graph Convolutional Network (GCN) model. Inspired by seminal works Kipf & Welling (2016), Zhao *et al.* (2020), and Yin *et al.* (2021), this model leverages 30-timestep sequences from three detectors and employs a dynamically calculated Laplacian matrix based on the correlation across detectors for each 30-timestep sequence. This innovative approach enables our GCN model to adeptly capture evolving spatial dependencies and patterns, offering an adaptable framework for accurately predicting traffic flow amidst changing conditions. The exploration of deep learning architectures includes:

- Baseline Model: An elementary approach that forecasts based on the last observed value.
- Linear Model: A single-layer model designed for capturing linear data relationships.
- Dense Model: A multi-layer model that allows for the modeling of non-linear dependencies through adjustable neuron counts and activation functions.
- LSTM Model: Specialized for capturing temporal dynamics, this model addresses the vanishing gradient problem common in recurrent neural networks.
- CNN Model: Utilizes convolutional layers for efficient feature extraction and reduction, helping to mitigate overfitting.
- CNN + LSTM Hybrid Model: Combines CNN's spatial analysis capabilities with LSTM's temporal pattern recognition.
- Custom Model: A configuration integrating Dense, CNN, and LSTM layers with Maxpooling and Dropout strategies to analyze complex data patterns comprehensively.
- GCN model: An advanced configuration (Graph Convolutional Network) that leverages historical data from three detectors concurrently to predict traffic flow at each detector location.

Mean Absolute Error (MAE) is selected as the primary evaluation metric to emphasize the practical relevance of prediction accuracy in traffic management. TensorFlow served as the foundational platform for developing and evaluating our models, chosen for its extensive support for deep learning applications.

In the methodology's concluding phase, we examine the effects of data aggregation on model accuracy, transitioning from 1-minute to 5-minute intervals. This strategy aimed at reducing data noise and elucidating more pronounced traffic trends, potentially enhancing model performance. Direct comparison of model outcomes with original and aggregated data sets intends to pinpoint the optimal data resolution for precise traffic flow predictions, underlining our commitment to refining predictive models for urban traffic management.

3 RESULTS

3.1 Mean Absolute Error Comparison of basic Deep Learning Models

This subsection evaluates basic deep learning models' performance on predicting traffic flow using Mean Absolute Error (MAE). Ranging from simple Baseline to complex Custom models, their comparative effectiveness is illustrated in Figure 1, utilizing 1-minute resolution data from one detector.

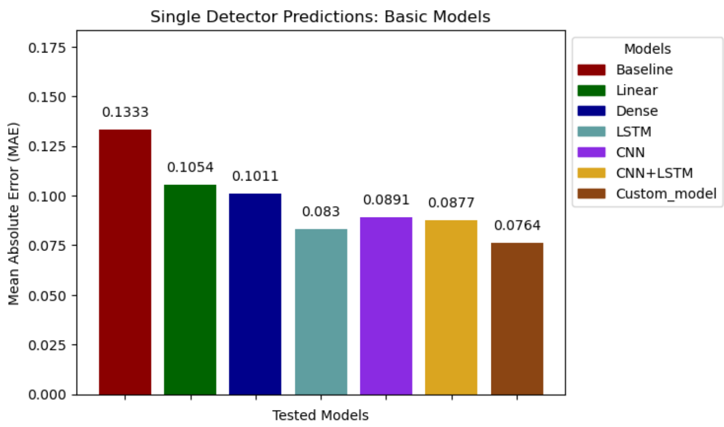

Figure 1 – *Mean Absolute Error of basic models on 1-minute resolution data from a single detector*

The custom model outperforms others, with LSTM exhibiting slightly inferior performance compared to the custom one, indicating its effectiveness in capturing complex traffic patterns. This outcome is likely due to its sophisticated architecture, combining Dense, CNN, and LSTM layers, with Maxpooling for dimensionality reduction and Dropout to mitigate overfitting.

3.2 Performance of the GCN Model for Different Data Granularities

We have also examined the GCN model's performance using data from three detectors to assess the impact of data granularity on traffic prediction accuracy (1-minute and 5-minute resolutions). Figure 2 shows a bar plot of the GCN model's MAE for both datasets, highlighting how data granularity influences predictive performance.

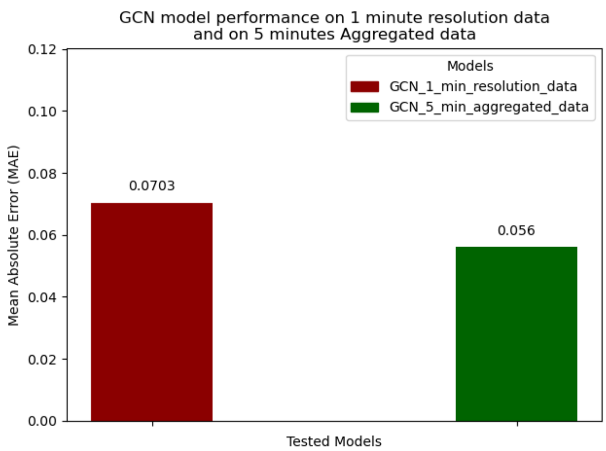

Figure 2 – *Mean Absolute Error of the GCN model on 1-minute vs 5-minutes data*

The bar plot in Figure 2 shows that the GCN model exhibits a superior performance when utilizing 5-minutes aggregated data compared to 1-minute data, suggesting that slightly coarser temporal resolutions may enhance prediction accuracy by smoothing out noise and capturing more significant traffic trends.

The performance of the GCN model on 5-minutes aggregated data is visually represented in Figure 3 for two consecutive days respectively (26th and 27th January 2024). The predicted values closely track the actual traffic flow, indicating the model's capability to capture the underlying temporal patterns across the three detectors. Despite minor discrepancies, the overall trend and fluctuations in traffic flow counts are well-reproduced by the model, showcasing its potential for real-world traffic prediction applications.

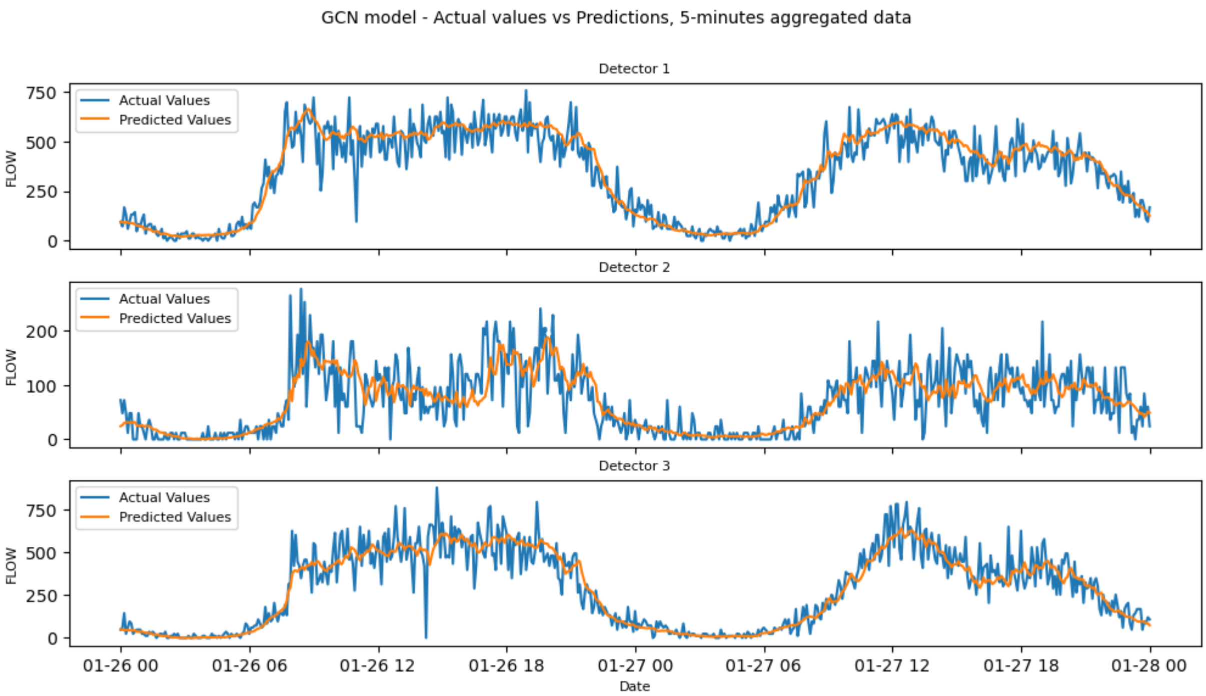

Figure 3 – *GCN model predictions on 5-minutes aggregated data*

4 DISCUSSION

This study demonstrates the significance of data preprocessing and advanced neural network architectures, like GCNs, in predicting traffic flow for varying data resolutions. Limitations include the narrow focus on a few detectors installed in the city of Ioannina, Greece, and reliance solely on traffic flow data, omitting factors like weather or detector occupancy. Future efforts should broaden the data scope to enhance model accuracy for traffic forecasting.

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