2. LITERATURE REVIEW

Traffic flow prediction has evolved as a crucial aspect of transportation engineering and urban planning, aiming to enhance the efficiency and safety of transportation systems. Early research in this domain relied heavily on traditional statistical models like the AutoRegressive Integrated Moving Average (ARIMA) model, which became a standard tool for short-term traffic forecasting. ARIMA models utilize historical traffic data to predict future trends by identifying and extrapolating linear patterns within the data. However, despite their utility, these models have limitations, particularly when faced with non-stationary data or abrupt changes in traffic behavior, which are common in dynamic urban environments [1], [2].

Recognizing these limitations, researchers began to explore machine learning techniques that could offer more robust and flexible prediction capabilities. One such technique is the Random Forest model, an ensemble learning method that improves prediction accuracy by combining the results of multiple decision trees. When applied to traffic flow prediction, particularly using data from GPS, Random Forest models have been shown to outperform traditional statistical approaches. These models, however, require substantial computational resources and careful tuning of parameters to achieve their full potential [3], [4].

Another machine learning approach that gained prominence is the Support Vector Machine (SVM). SVMs are particularly adept at capturing non-linear relationships in data, which are often present in traffic patterns. Their ability to model complex, non-linear trends makes them highly effective for traffic flow prediction. However, the computational demands of SVMs and the need for precise parameter selection can pose challenges, particularly in real-time traffic management scenarios where speed and efficiency are critical [5].

The introduction of deep learning has further revolutionized traffic flow prediction, particularly with the development of advanced neural network models like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks. LSTM networks, which are designed to capture long-term dependencies in sequential data, have been particularly successful in modeling the temporal dynamics of traffic flows. These networks excel at handling time-series data, where understanding the order of events is crucial for accurate predictions. Studies have demonstrated that LSTM models significantly outperform traditional methods by effectively capturing the complex, non-linear patterns inherent in traffic data [6], [7].

While LSTM networks are powerful, their complexity can make them computationally expensive. To address this, GRU networks were developed as a more streamlined alternative. GRUs simplify the architecture of LSTMs by merging some of the gates, thereby reducing the computational load while

maintaining a similar level of performance. This efficiency makes GRUs particularly attractive for scenarios where faster model training is necessary, without a significant trade-off in accuracy [8], [9].
In addition to these sequential models, Convolutional Neural Networks (CNNs) have also been explored for traffic prediction, especially in capturing spatial dependencies within traffic networks. CNNs are highly effective at processing grid-based spatial data, which makes them well-suited for modeling the spatial distribution of traffic across urban networks. However, their ability to capture temporal dynamics is limited unless they are combined with models like LSTMs or GRUs that are designed for sequential data processing [10], [11].

To harness the strengths of different neural network architectures, researchers have developed hybrid models that integrate various approaches. For example, by combining CNNs with LSTMs, it becomes possible to capture both the spatial and temporal dependencies in traffic data, leading to more accurate predictions. These hybrid models have proven particularly effective in improving the overall performance of traffic flow prediction systems by addressing the specific limitations of each individual model [12], [13].

More recently, Graph Neural Networks (GNNs) have emerged as a novel approach for traffic flow prediction, particularly in complex urban environments. GNNs are designed to model both spatial and temporal dependencies within traffic networks, making them highly suitable for urban traffic prediction. However, despite their potential, challenges related to the implementation and scalability of GNNs have hindered their widespread adoption [14].

Incorporating real-time and crowdsourced data into traffic prediction models has also gained importance in recent years. Real-time GPS data and crowdsourced information from platforms like Waze offer valuable insights that can enhance the accuracy and timeliness of predictions. However, these data sources present challenges such as data sparsity, privacy concerns, and the need for effective integration methods to ensure that the predictions remain reliable and accurate [15].

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