ENHANCING URBAN TRAFFIC MANAGEMENT THROUGH PREDICTIVE MODELLING AND DRONE-Captured IMAGE ANALYSIS FOR SMART TRAFFIC LIGHTS

Aatmaj Amol Salunke*1

*1Bachelor Of Technology, Department Of Computer Science & Engineering, School Of Computer Science And Engineering, Manipal University Jaipur, India.

DOI : https://www.doi.org/10.56726/IRJMETS44052

ABSTRACT

This research paper explores the utilization of predictive modelling and drone-captured image analysis to enhance urban traffic management in the context of smart traffic lights. The study focuses on employing advanced machine learning techniques, including LSTM and GRU architectures, to predict traffic flow patterns. Comparative analysis is conducted by evaluating the performance of these deep learning models against traditional algorithms such as Linear Regression, Gradient Boosting Regressor, and Random Forest Regressor. Metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared values are utilized to quantify the predictive accuracy of these models. Experimental results reveal that the LSTM model achieves an MAE of 6.32 and an RMSE of 12.76, while the GRU model yields an MAE of 6.50 and an RMSE of 13.12. These values outperform traditional algorithms, emphasizing the effectiveness of the proposed models in improving traffic flow predictions. The dataset comprises drone-captured images of urban traffic scenes, enabling the extraction of relevant features for accurate predictions. Findings underscore the potential of the proposed models in advancing intelligent traffic management systems.

Keywords: Traffic Flow Prediction, Predictive Modelling, Drone Captured Images, Smart Traffic Lights, Deep Learning, LSTM and GRU Architectures, Urban Traffic Management.

I. INTRODUCTION

Traffic congestion in urban areas poses significant challenges to efficient transportation and environmental sustainability. To address this issue, emerging technologies like smart traffic lights have gained attention for their potential to optimize traffic flow. This research paper investigates the synergy of predictive modelling and drone-captured image analysis in enhancing urban traffic management through intelligent traffic light control. By leveraging advanced machine learning techniques, including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, the study aims to predict traffic flow patterns with improved accuracy. Comparative evaluation against conventional algorithms such as Linear Regression, Gradient Boosting Regressor, and Random Forest Regressor provides insights into the effectiveness of the proposed models. The integration of drone-captured images as a data source enables the extraction of relevant features, contributing to the enhancement of traffic flow predictions. This paper thus presents a comprehensive exploration of the potential for data-driven strategies to revolutionize traffic management systems.

Fig.1. Flowchart of the proposed method
II. RELATED WORK


III. METHODOLOGY

1. Dataset

The dataset employed in this study comprises a collection of drone-captured images offering a unique vantage point from directly above Surat streets and key junctions. These images provide a comprehensive spatial perspective of the traffic dynamics. The dataset encompasses various time intervals, allowing analysis of traffic patterns across different hours of the day. Each image is associated with corresponding traffic flow data, enabling the extraction of temporal and spatial features. These images encompass diverse traffic scenarios, encompassing varying congestion levels, road occupancy, and traffic light states. The inclusion of drone imagery enriches the dataset, enhancing the potential to capture intricate traffic behaviours. This dataset forms the foundation for training, validation, and testing of predictive models, ultimately contributing to the advancement of intelligent traffic management strategies.
2. Data Preprocessing

2.1 Data Cleaning

The collected dataset underwent meticulous data preprocessing to ensure its quality and suitability for analysis. This involved the removal of any outliers or erroneous entries that could distort results. Additionally, missing values were addressed through imputation methods. The drone-captured images were subjected to noise reduction and enhancement techniques to enhance their clarity and utility. The resultant refined dataset serves as a reliable foundation for subsequent modelling and analysis, facilitating accurate traffic flow predictions.

2.2 Data Transformation

The dataset underwent comprehensive preprocessing to enhance its suitability for modelling. This involved handling missing values through imputation and addressing outliers that could skew results. Additionally, raw images were transformed into feature vectors using techniques like image segmentation and feature extraction. Numeric features were scaled for uniformity, and categorical variables were encoded. The resultant transformed dataset serves as a structured foundation for subsequent analysis, ensuring accurate and meaningful traffic flow predictions.
2.3 Data Normalization

In the data preprocessing phase, normalization techniques were applied to standardize the dataset's feature values. This process ensured that numeric attributes, including traffic density, vehicle speed, and road occupancy, were scaled to a common range. By normalizing the features, algorithms were able to treat each attribute equally, preventing any undue influence due to differing scales. This step contributed to improved convergence and accuracy during the subsequent modelling and analysis stages.

3. Feature Engineering

**Selected Features and Rationale:**

**Traffic Density:** Quantifying the number of vehicles present in an image provides insights into road congestion and traffic flow at specific intervals.

**Time-Related Features:** Incorporating time-based features, such as the day of the week and hour of the day, captures periodic traffic patterns and peak hours.

**Vehicle Class Distribution:** Leveraging the annotation of around 5000 drone images classified into vehicle classes, enhances predictive accuracy. Different vehicle types impact traffic flow uniquely, contributing to the prediction model's granularity.
Different class names:
1. Truck
2. Bus
3. LCV
4. Cars
5. Rickshaw
6. M2W
7. MAV

Vehicle Type Counts: Counting the occurrences of different vehicle classes within an image contributes to understanding road occupancy and composition, influencing traffic flow predictions.

Spatial Features: Spatial analysis of vehicle distribution in different lanes and sections of the road provides insights into bottlenecks and congested areas.

Fig. 7. Dataset split into Train-Validation-Test after annotations.

Domain-Specific Insights:
Annotating around 5000 drone images with vehicle classes allowed the integration of vehicle type information directly into the model. This domain-specific insight acknowledges that different vehicle classes behave diversely in traffic scenarios. For instance, the presence of larger vehicles like Trucks or Buses might indicate slower-moving traffic, while the presence of smaller vehicles like Cars or Rickshaws might signify higher agility and potentially faster traffic.

The utilization of these features aligns with the research's goal to enhance traffic flow predictions using both quantitative and visual information from the drone-captured images. This comprehensive approach amalgamates domain knowledge and data-driven insights, resulting in a robust predictive model capable of capturing intricate traffic dynamics.

4. Deep Learning Models VS Traditional Machine Learning Algorithms:
LSTM and GRU Architectures: Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are specialized Recurrent Neural Network (RNN) variants designed for sequence modelling and time series prediction. These architectures overcome the vanishing gradient problem by incorporating memory cells and gating mechanisms that retain long-term dependencies in sequential data.

RNN Theory and Suitability: Recurrent Neural Networks (RNNs) are well-suited for sequential data due to their inherent ability to maintain memory of previous time steps. They process data in a sequential manner, making them effective for tasks such as time series prediction, where temporal dependencies are crucial.
LSTM vs. GRU: LSTM and GRU are variations of RNNs that address the challenge of capturing long-range dependencies. LSTM introduces explicit memory cells, input, output, and forget gates, allowing it to retain and update information for longer periods. GRU simplifies this architecture by merging input and forget gates, reducing computational complexity while maintaining comparable performance.

Advantages: LSTMs excel in capturing complex temporal patterns, making them suitable for intricate traffic flow prediction. GRUs offer similar capabilities with reduced computational demands, enhancing training efficiency.

Comparative Models

Linear Regression, Gradient Boosting Regressor, and Random Forest Regressor: These traditional algorithms serve as comparative models due to their widespread use and interpretability. Linear Regression provides a baseline, while Gradient Boosting Regressor and Random Forest Regressor offer ensemble learning for enhanced accuracy and robustness.

Choice of Comparison: This selection allows for an insightful comparison between deep learning models (LSTM, GRU) and traditional algorithms, aiding in evaluating the effectiveness of cutting-edge techniques against established methods in the context of traffic flow prediction.

Fig. 8. Code Snippet for Training the LSTM Model

```python
from keras.models import Sequential
from keras.layers import LSTM, Dense

# Prepare data for time series prediction
# (reshape input data if needed)

# Build LSTM model
model = Sequential()
model.add(LSTM(64, input_shape=(time_steps, num_features)))
model.add(Dense(1)) # Output layer for prediction

# Compile and train the model
model.compile(optimizer='adam', loss='mean_squared_error')
model.fit(X_train, y_train, epochs=num_epochs, validation_data=(X_val, y_val))
```

Fig. 9. Code Snippet for Training the GRU Model

```python
from keras.models import Sequential
from keras.layers import GRU, Dense

# Build GRU model
model = Sequential()
model.add(GRU(64, input_shape=(time_steps, num_features)))
model.add(Dense(1)) # Output layer for prediction

# Compile and train the model
model.compile(optimizer='adam', loss='mean_squared_error')
model.fit(X_train, y_train, epochs=num_epochs, validation_data=(X_val, y_val))
```
5. Training Process for LSTM and GRU Models

**Model Architecture:** The model architecture utilized LSTM and GRU networks for traffic flow prediction. These architectures are specialized Recurrent Neural Network (RNN) variants designed to handle sequential data. They consist of multiple layers, including input, hidden, and output layers. The key components are memory cells with gating mechanisms that enable the models to capture long-term dependencies in time series data. LSTM features explicit memory cells and separate gates for input, output, and forget operations. GRU simplifies this by merging input and forget gates, streamlining computations while preserving performance.

![Architecture of the RNN – LSTM and GRU](image)

**Training:** The training process involved optimizing the LSTM and GRU models for traffic flow prediction. Backpropagation and gradient descent were employed to adjust the models’ internal parameters iteratively. The dataset was split into training and validation subsets to ensure effective generalization. This separation facilitated the models’ ability to learn underlying patterns without memorizing the data. During the model compilation phase, the mean squared error (MSE) is employed as the loss function. The optimizer used is RMSprop from the Keras library with its default parameters. As for the evaluation metric, mean absolute error (MAE), RMSE and R-squared is employed. The training process utilizes a batch size of 128 and is run for 50 epochs, with 5% of the training data allocated for validation. The experiments are executed within the Google Collaboratory environment, with tracking facilitated by Weights & Biases.
**Fig. 11.** Training performance of both neural networks – Loss and MAE

**Epochs:** Epochs refer to the number of times the entire dataset is passed through the model during training. The choice of epochs is crucial to prevent both underfitting and overfitting. Too few epochs may result in the models not capturing complex patterns, while too many epochs could lead to the models memorizing noise. A suitable number of epochs was determined based on monitoring the models’ performance on the validation set. This iterative process allowed the models to progressively refine their predictions by learning from the data’s temporal characteristics.

**Fig. 12.** Comparison of Training Times for Different Models

1. **Outcome Analysis**

Linear Regression exhibits moderate predictive capabilities, suitable for basic forecasting. Gradient Boosting demonstrates improved predictions due to its ensemble learning nature, aggregating multiple models’ insights. Random Forest excels further, providing enhanced accuracy by effectively handling non-linear relationships within the data. LSTM stands out with remarkable performance, excelling in capturing intricate temporal dependencies due to its specialized memory cells and gating mechanisms. GRU yields a similar performance to LSTM while maintaining computational efficiency with merged gating structures. This analysis underscores the
strengths and trade-offs associated with each algorithm, guiding their application in diverse traffic flow prediction scenarios.

Table 1. Performance Analysis of the various Models used.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Regression</td>
<td>Moderate predictive capabilities</td>
</tr>
<tr>
<td>Gradient Boosting</td>
<td>Improved predictions, ensemble learning</td>
</tr>
<tr>
<td>Random Forest</td>
<td>Enhanced accuracy, handles non-linearity</td>
</tr>
<tr>
<td>LSTM</td>
<td>Remarkable performance, captures dependencies</td>
</tr>
<tr>
<td>GRU</td>
<td>Similar performance to LSTM, computational efficiency</td>
</tr>
</tbody>
</table>

2. Performance Evaluation

Linear Regression attains a Mean Absolute Error (MAE) of 12.34, Root Mean Squared Error (RMSE) of 18.56, and R-squared value of 0.678, indicating moderate predictive capabilities. Gradient Boosting exhibits enhanced accuracy, with an MAE of 8.21, RMSE of 15.43, and R-squared value of 0.765, signifying improved predictions attributed to ensemble learning. Random Forest excels with an MAE of 8.45, RMSE of 16.21, and R-squared value of 0.743, showcasing its ability to handle non-linearity. LSTM demonstrates remarkable performance, achieving an MAE of 6.32, RMSE of 12.76, and an impressive R-squared value of 0.845, capturing complex dependencies. Similarly, GRU achieves comparable results with an MAE of 6.50, RMSE of 13.12, and R-squared value of 0.832, underlining its computational efficiency.

Table 2. Evaluation metrics of the models used.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>MAE</th>
<th>RMSE</th>
<th>R-squared</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Regression</td>
<td>12.34</td>
<td>18.56</td>
<td>0.678</td>
</tr>
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<tr>
<td>GRU</td>
<td>6.50</td>
<td>13.12</td>
<td>0.832</td>
</tr>
</tbody>
</table>

These metrics illuminate the varying strengths and accuracy levels of each model, providing valuable insights into their performance in traffic flow prediction tasks.

Fig.13. Comparison of the Evaluation Metrics for all the Models involved.
Discussion of Trends and Patterns:
Both LSTM and GRU consistently outperform traditional algorithms in terms of MAE and RMSE, indicating their superior predictive accuracy.

The R-squared values for LSTM and GRU are notably higher than those of Linear Regression, Gradient Boosting, and Random Forest, underscoring their ability to capture a larger portion of the variance in the traffic flow.

The results exhibit a clear trend of deep learning models (LSTM and GRU) excelling in capturing the intricate temporal patterns inherent in traffic flow data. This suggests their suitability for modeling complex sequential data compared to traditional algorithms.

The minor difference between the performance of LSTM and GRU implies that GRU, with its simpler architecture, can achieve comparable results with less computational complexity.

3. Comparison of Algorithms

3.1 Analysing Performance of LSTM and GRU Models:
Both LSTM and GRU models exhibited impressive predictive performance in traffic flow prediction. They outperformed traditional algorithms such as Linear Regression, Gradient Boosting, and Random Forest, as indicated by lower error metrics (MAE, RMSE) and higher R-squared values. This suggests their ability to capture the intricate temporal patterns inherent in traffic data.

3.2 Strengths and Weaknesses:
LSTM's strengths lie in its capacity to capture long-term dependencies and intricate patterns, rendering it suitable for complex temporal sequences like traffic flow. However, its architecture complexity can demand substantial computational resources. GRU offers similar performance while being computationally efficient due to its simplified design. Its limitation lies in handling highly complex patterns. Balancing computational efficiency and pattern capturing ability, the choice between LSTM and GRU depends on the application's demands. Both models demonstrate the potential of deep learning in traffic flow prediction, each catering to different computational and pattern complexity requirements.

3.3 Contributions of Underlying Architectures:
Both LSTM and GRU architectures address the vanishing gradient problem associated with traditional RNNs, allowing them to capture long-term dependencies. LSTM’s separate memory cells and input, output, and forget gates enable it to hold information for extended intervals, crucial for modelling complex traffic flow patterns.

GRU’s merged gating mechanisms simplify computations, resulting in faster training times. While it may not capture as intricate patterns as LSTM, GRU remains adept at handling short and medium-term dependencies, making it suitable for real-time traffic flow prediction.

Fig.14. Code snippet for comparison of models and visualising the results obtained.
V. DISCUSSION

The findings of this study highlight the effectiveness of LSTM and GRU models in accurate traffic flow prediction. Their ability to capture intricate temporal dependencies contributes to improved predictions compared to traditional algorithms. This research underscores their significance in shaping smart traffic light systems, offering the potential to reduce congestion and enhance urban mobility. The study’s outcomes also underscore their implications for urban planning, enabling informed decisions on infrastructure development. While this research sheds light on the transformative impact of deep learning, further investigations could delve into hybrid model architectures, explore novel algorithms, and consider real-time data integration for even more accurate predictions and dynamic traffic management. Ultimately, these insights pave the way for data-driven solutions that could alleviate traffic-related challenges in urban environments.

In this visualization, each point represents a data point’s true traffic flow value and the predicted value by different models. The black dashed line represents perfect predictions. Observing the distribution of points relative to the dashed line helps you identify where models are accurate or deviate.

Interpreting the Graph:

- Points closer to the dashed line represent accurate predictions.
- Points deviating from the line indicate prediction errors.

Instances where deep learning approaches (LSTM and GRU) excel over traditional models (Linear Regression, Gradient Boosting, Random Forest) are shown when the points from LSTM and GRU are closer to the dashed line compared to the points from traditional models. This signifies the superior ability of deep learning models to capture complex temporal patterns, leading to more accurate traffic flow predictions in diverse scenarios.

Deep learning approaches, such as LSTM and GRU, excel over traditional models in instances where intricate temporal patterns play a pivotal role in accurate predictions. Their ability to capture complex dependencies and learn from sequential data empowers them to outperform traditional models, like Linear Regression, Gradient Boosting, and Random Forest, in scenarios involving dynamic and evolving systems, such as traffic flow. Deep learning models thrive when confronted with non-linear relationships and sequences with long-range interdependencies, making them superior choices for tasks that demand nuanced insights from vast and evolving datasets, as observed in the dynamic and multi-dimensional nature of traffic patterns.

VI. CHALLENGES AND LIMITATIONS

During experimentation, a challenge arose from the dataset's noise and irregularities, leading to suboptimal model performance. Noise in traffic data, caused by external factors like weather or accidents, can obscure underlying patterns. Additionally, insufficient feature engineering hindered the models' ability to capture intricate temporal dependencies accurately. To mitigate this, refining feature selection and engineering methods, such as incorporating historical traffic data and weather information, could enhance predictions.
Moreover, fine-tuning hyperparameters like the number of hidden units and training epochs for LSTM and GRU could potentially yield better results. Addressing these challenges and adopting more comprehensive data preprocessing strategies could lead to improved accuracy and better real-world applicability.

VII. IMPLICATIONS AND APPLICATIONS

1. Real-World Applications
Accurate traffic flow prediction is pivotal for smart traffic light systems, revolutionizing urban mobility. Precise predictions enable adaptive signal timing, minimizing congestion by synchronizing lights to actual traffic demand. Improved traffic management leads to reduced travel times, fuel consumption, and greenhouse gas emissions. This fosters sustainable urban environments, mitigating environmental impact. Real-time data-driven decisions empower cities to optimize traffic flow dynamically, responding to congestion in real-time. Enhanced traffic management ultimately transforms the commuting experience, promoting efficient mobility, reduced congestion, and greener cities, aligning with sustainable urban development goals.

Fig. 16. Proposed usage of the system.

Fig. 17. Real-life scenario of the proposed system.

2. Urban Planning and Infrastructure
Accurate traffic flow prediction holds substantial influence over urban planning decisions, shaping future city infrastructure development. Reliable predictions aid in optimizing road network design, lane configurations, and traffic flow patterns. Data-driven insights enable urban planners to anticipate traffic bottlenecks, strategically positioning highways, roads, and public transport hubs. This minimizes congestion and enhances
overall transportation efficiency. Accurate predictions inform the creation of pedestrian-friendly zones, bike lanes, and intelligent parking solutions, promoting sustainable mobility options. By integrating predictive analytics into urban planning, cities can proactively address traffic challenges, optimize land use, and design resilient transportation systems. Ultimately, precise traffic flow predictions are indispensable tools for developing cohesive, efficient, and liveable cities that cater to present and future mobility needs.

VIII. CONCLUSION

In conclusion, this research demonstrates the superiority of LSTM and GRU models in predicting traffic flow compared to traditional algorithms. Their adeptness in capturing complex temporal patterns showcases their potential in revolutionizing urban mobility. Accurate traffic flow prediction emerges as a crucial factor in driving the efficiency of smart traffic light systems and informing urban planning decisions for optimized infrastructure development. The study’s insights underline the transformative power of deep learning in addressing traffic-related challenges. As cities continue to evolve, leveraging advanced modelling techniques and integrating real-time data holds the promise of ushering in a new era of sustainable and efficient urban transportation systems, leading to reduced congestion, improved traffic management, and enhanced environmental sustainability.

IX. CONTRIBUTIONS AND FUTURE WORK

The study’s outcomes underscore the transformative potential of advanced deep learning models like LSTM and GRU for traffic flow prediction. Their superior accuracy holds promise for enhancing smart traffic light systems, reducing congestion, and optimizing urban mobility. Further research could explore hybrid architectures that combine LSTM and GRU strengths, investigate novel algorithms that integrate spatial and weather data, and focus on real-time data integration to bolster prediction accuracy and enable real-time traffic management. These avenues hold the potential to revolutionize urban traffic systems and contribute to sustainable and efficient city planning.

X. REFERENCES


