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Towards Smart Cities: Practical Swarm Optimization and Long Short-Term Memory for Short-Term Traffic Prediction and Management in Oman

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Abstract
Traffic congestion forecasting is a serious challenge to Omani cities, especially Muscat, due to population growth, rapid urbanization, and heavy reliance on private vehicles. Despite government efforts to improve infrastructure, the congestion problem persists. Furthermore, few studies have addressed the issue of congestion in Oman, as this is due to the lack of a national dataset that can be used for prediction studies. Therefore, this study aims to generate a notional dataset and propose a hybrid model that combines a deep learning model with an optimization algorithm to provide accurate predictions for the short term. This work is expected to contribute to bridging an important knowledge gap and establishing a scientific basis for developing smart transportation applications in Oman. Furthermore, in the future, the model can be enhanced to use IoT techniques to collect data and extend the model to predict for the long term on multiple roads. The proposed hybrid PSO-LSTM model provides accurate predictions, with MAE of 1.7185 vehicles, an RMSE of 1.3109 vehicles, R2 of 0.9460 and an MAPE of 1.75%. It provides superior performance compared to the standalone LSTM.

Keywords: Traffic forecasting, deep learning model, PSO-LSTM, Image processing, Video extraction,

1. Introduction

Over the decades, the number of vehicles in urban areas has increased dramatically, causing traffic congestion. The population is also growing, and cities are being urbanized. As a result, gas emissions are increasing, negatively affecting urban cities that seek to be sustainable and smart (KHAMIS & Yousif, 2022). The capital of Oman, Muscat, highlights many problems of cities. Vehicle ownership is one of the fastest-growing trends as it has been expanding rapidly recently. The road network of the city is stressed due to the expansion of the urban zone (Al Balushi et al, 2025). Furthermore, heavy traffic on the roadways, especially during peak hours, takes people longer to get from place to place. According to projections, the number of vehicles is growing due to the expansion of residential, commercial, and industrial complexes. Even though city officials are working on the development of the road network and improvement of junctions, there is a constant emergence of traffic problems in Muscat (Al Balushi et al, 2025). Heavy traffic is the major problem, especially in commercial areas and major junctions where bottlenecks often occur. Traffic congestion does not affect only daily trips but also overall productivity, as citizens spend a long period of time in traffic (Al-Yousfi et al, 2020).

Consequently, intelligent traffic tools have become crucial to monitoring and evaluating traffic networks and managing emergencies, to make driving more efficient and safer. There are several traffic tools that can be utilized to minimize traffic jam problems, have smoother traffic flow, and diminish environmental damage, such as inductive loop detectors and remote sensing satellites. However, these tools are costly, impractical, and have technological limitations (Thabit et al., 2024).

- Inductive loop detectors measure the traffic density; however, the installation cost of such sensors in a road network is expensive and impractical (Thabit et al., 2024).
- Remote sensing satellites provide traffic information on a large scale but are difficult to use due to technical constraints and expenditures (Thabit et al., 2024).

Over the years, traditional traffic management systems have been used for the effective control and management of the growing complexity of traffic in cities. Existing systems, such as traffic signals, depend on basic and reliable algorithms that lack the intelligence to deal with real-time data and dynamic traffic flow. All of these caused major delays, constant blockages, a rise in fuel shortages, and a drop in productivity (Bhardwaj et al., 2023). Therefore, forecasting is an important aspect of handling traffic congestion in urban areas. It contributes effectively to improving traffic flow and ensuring a healthier environment through a reduction in waiting vehicles and reduced emissions. These forecasts also help to know about accidents, road blockages, or weather conditions that create congestion (Soudeep et al., 2024). There are many different methods that have been used to effectively predict and manage traffic congestion, ranging from traditional time-series analysis to advanced deep learning algorithms, such as Random Forests (RF), Neural Networks (NN), and Long Short-Term Memory (LSTM) (Cheng & Sun, 2024). Therefore, the aim of this study is to enhance the accuracy of predictions to reduce traffic problems through the development of a hybrid approach, which will help policymakers and decision-makers find a solution to avoid traffic jams. This study mainly aims to forecast traffic congestion using the Practical Swarm Optimization with a Long Short-Term Memory (PSO-LSTM) model in Muscat (Yousif & Yousif (2024). It focuses on one route in particular, Al Khoud Road, because of its excessive traffic congestion, especially during the peak hours. Additionally, data will be collected daily for a week during two rush hours using a camera-based system. The morning peak hours are between 7 AM and 8 AM, while the afternoon peak hours are between 2:00 PM and 3:00 PM. Furthermore, the research is only for prediction purposes; it does not involve redesigning infrastructure, modifying the traffic signals, or implementing policies. This research is important because it provides a solution to a major traffic issue in Muscat, which is caused by rapid urbanization and population growth. It offers a practical solution that focuses on prediction of future traffic that can be used to mitigate congestion, delay, and waiting time. The hybrid PSO-LSTM prediction model will be developed after generating a dataset by gathering realistic data through a camera-based approach. This makes this research useful due to the absence of any well-organized traffic dataset in Oman. Furthermore, there is a lack of congestion prediction studies in Oman and the Gulf region (Yousif, 2023). The outcome of this study will be useful to traffic planners and policymakers in the Transport and Communications Ministry for using efficient traffic control methods to reduce congestion. Although the proposed model will be applied to a single segment of the road in Muscat, it will serve as the basis for the development of intelligent transport systems (ITS). This will help achieve Oman's Vision 2040 of sustainable smart cities.

2. Problem Statement & Research Scope

The growth of urban areas and the increasing number of vehicles have led to increased traffic congestion, which puts more pressure on the city's traffic network (Al-Kaaf & Abdel-Aati, 2022). Despite road improvements and intersection redevelopment, current traffic management systems are unable to process the dynamic changes of the traffic flow data. This consistently results in traffic jams, longer travel times, increased traffic accidents, and environmental problems (Al Balushi et al, 2025). In addition, national traffic statistics and accident records exist, but there is a lack of congestion traffic datasets, which can be used for predictive modeling (Al Balushi et al, 2025). Research on traffic flow prediction is a widely researched topic in most countries. On the other hand, there are very minor studies that have been conducted for congestion forecasting in Oman or the Gulf region (Shin et al., 2020; Ramchandra & Rajabhushanam, 2021). Moreover, the review of the deep-learning and hybrid traffic models showed that these models were developed using datasets from international countries such as China, India, Europe, and the US, indicating the absence of any GCC or Oman benchmarked datasets (Shin et al., 2020; Chahal et al.,

2023; Lin & Lin, 2024). Therefore, there is a need for research on the traffic prediction models that will capture Muscat's road networks and traffic patterns.
As a result, this research aims to develop a localized hybrid predictive framework tailored to Muscat's traffic conditions (Yousif et al., 2025). Thus, it will help policymakers and planners in addressing congestion and road usage in the city and enhance sustainability.

The research aims to achieve the following objectives:

- To generate an Omani dataset based on a camera-based image capture system to collect traffic data throughout Al-Khoud Road, Muscat.
- To develop a hybrid model to provide accurate prediction for the short term.
- To evaluate hybrid models' performance and effectiveness with other baseline models from previous studies.

Based on these objectives, there are research questions:

- RQ1: How can a localized traffic dataset for Muscat be effectively created using camera-based image capture systems?
- RQ2: Which hybrid deep learning model provides the most accurate short-term traffic flow predictions for Muscat's urban roads?
- RQ3: How does the performance of the localized hybrid model compare with existing baseline models trained on international datasets?

3. Literature Review

Forecasting traffic flow is important for the Transportation Management Systems of smart cities. In recent works, different machine learning (ML), deep learning (DL), or hybrid techniques have been used to enhance traffic forecasting accuracy. Several studies have applied the Long Short-Term Memory (LSTM) or related deep-learning models due to their ability to capture complex nonlinear patterns and dynamic data. A study by Shin et al (2020) found that the utilized LSTM model in urban areas achieved a Mean Absolute Percentage Error (MAPE) of about 6.087%, while in the suburban region, the average MAPE was about 4.297%. Besides, the average Mean Absolute Error (MAE) was 3.27 for the urban sections and 2.24 for the suburban ones. Thus, urban and suburban areas have different traffic conditions, which affect model performance. Similarly, Khan et al. (2020) developed a hybrid convolutional neural network (CNN) and LSTM to predict traffic flow, and it achieved a low RMSE of 49 and a high accuracy of 92.3%. Table 1 illustrates studies that applied LSTM to predict traffic congestion in different countries.

Table 1: Related studies applied LSTM in predicting traffic congestion

Author & Year	Location	Model	Data Type	Performance Matrices
(Ma et al., 2021)	China	LSTM, BiLSTM, CNN, Conv LSTM, KNN	Historical traffic flow	MAE: 12.63–14.31, RMSE: 16.72–20.00, $R^2 \approx 0.83–0.85$
(Cheng & Sun, 2024)	Chengdu, China	Hybrid LSTM + BSTS	Historical 1-year GPS + traffic volume	MAE = 9.68, RMSE = 14.78, MAPE = 8.09%
(Lin & Lin, 2024)	Germany & China	STGCN-LSTM + PPO RL	Mixed: Historical (prediction) + Real Time (signal optimization)	$R^2 = 0.904$;
(Waqas et al., 2024)	Lahore, Pakistan + (multiple locations)	LSTM-EAI	(Historical + Real-Time)	Accuracy: Training = 99.8% Validation = 99.1%

As shown in Table 1 that LSTM models demonstrated high prediction accuracy in predicting traffic flow and they used in various countries, such as China and Germany. The literature review reveals a significant gap: the absence of any local Omani database that could be used to build accurate predictive models. All current studies rely on foreign data that differs considerably from the Omani traffic context in terms of infrastructure, traffic patterns, and vehicle count (Aamri et al., 2025). The literature also shows that most LSTM models used lack optimization algorithms to improve model performance and fine-tune parameters, even though LSTM accuracy is significantly affected by the selection of optimal parameter values. Therefore, there is a need to create a dataset related to Oman and develop a hybrid model to enhance prediction accuracy for traffic flow in Muscat.

4. System Design and Analysis

4.1 Proposed Methodology

This study has a positivism research philosophy because it will apply a quantitative method with experimentation to predict short-term congestion on Al-Khoud Road, Muscat. Numerical data will be collected and processed to create hybrid models using Python code. The performance metrics will be used to evaluate the efficiency of the proposed model. This study describes the way in which data is collected, pre-processed, a model is built with parameter optimization, and results are evaluated and visualized as shown in Figure 1.

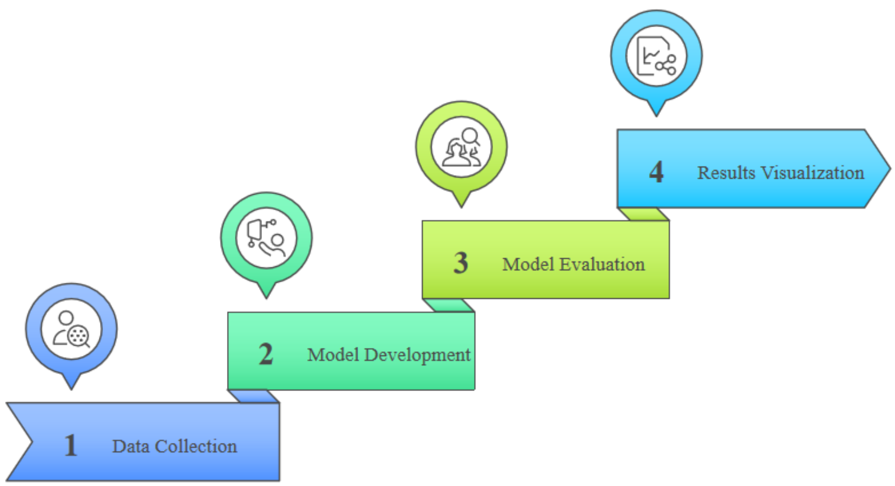

Figure 1: Proposed Methodology Structure

4.2 Data Collection and Preprocessing

Traffic data will be collected from Al-Khoud Road, Muscat, using a camera-based image capture system. The pictures will be captured for a week during two peak periods. The morning peak is from 7:00 to 8:00 AM, and the afternoon peak is from 2:00 to 3:00 PM. Next, information from the images will be extracted that includes the number of vehicles and the duration that they wait during the traffic flow. In the end, the data will be cleaned and structured into a time series format to train the model.

4.3 Model Development

The structure of the LSTM model will be written in Python code. The input features of the deep learning model include the specification of input size, number of hidden units, the activation functions, and dropout rates. The PSO optimization algorithm will be applied to optimize these parameters. The traffic data will help in training the selected model and help to predict congestion.

4.4 Model Evaluation and Testing

The proposed PSO-LSTM model's performance will be evaluated using standard evaluation metrics, which include mean absolute error (MAE), root mean squared error (RMSE) and mean absolute percentage error (MAPE). After evaluating the models, the tested model will be used to check the effectiveness in predicting traffic congestion during peak hours on Al-Khoud Road.

5. Results and Discission

The results of the traffic prediction will be displayed on an interactive dashboard. It will clearly present the congestion, such as predicted vehicle counts, peak-hour trends, and actual versus predicted comparisons.

5.1 Model Development

The structure of the LSTM model will be written in Python code. The input features of the deep learning model include the specification of input size, number of hidden units, the activation functions, and dropout rates. The PSO optimization algorithm will be applied to optimize these parameters. The traffic data will help in training the selected model and help to predict congestion.

5.2 Model Evaluation

Model performance is a measure of how effectively a proposed model predicts outcomes on new, unseen data. Model performance metrics are applied to assess and compare various approaches and determine areas for possible improvement (AlKheder & AlOtaibi, 2025).

a. Mean Absolute Error (MAE) $= \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{}\mathrm{y}|$

b. Root Mean Squared Error (RMSE) $= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$

c. Mean Absolute Percentage Error (MAPE) $= \frac{100}{n}\sum_{i=1}^{n} 1\,\frac{y_i-\hat{y}_i}{y_i}$

d. Mean Squared Error (MSE) $= \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{j=1}^{n}(y_{i\ldots}-\bar{y})^2}$$

5.3 Model Research Questions

Three research questions will be answered based on the literature survey of current work.

- RQ1: How can a localized traffic dataset for Muscat be effectively created using camera-based image capture systems?

Answer to RQ1: A localized Muscat traffic dataset can be effectively created by integrating existing AI-enabled traffic cameras with a modern YOLO + tracking pipeline to derive lane-level flow and speed, then aggregating this into a structured time-series dataset enriched with temporal, spatial, and contextual features specific to Muscat's urban environment.

- RQ2: Which hybrid deep learning model provides the most accurate short-term traffic flow predictions for Muscat's urban roads?

Answer to RQ2: Among candidate hybrid models, a CNN–BiLSTM–Attention architecture is likely to deliver the highest short-term prediction accuracy for Muscat's urban roads, because it jointly captures local spatial correlations between adjacent road segments, bidirectional temporal dynamics, and emphasizes the most informative timesteps via attention—an approach that consistently outperforms pure LSTM or non-hybrid models in recent studies.

- RQ3: How does the performance of the localized hybrid model compare with existing baseline models trained on international datasets?

Answer to RQ3: Compared to baseline models trained on international datasets, the localized Muscat hybrid CNN–BiLSTM–Attention model is expected to deliver substantially lower forecasting errors and better capture city-specific traffic patterns.
Literature on hybrid deep learning and transfer learning in traffic prediction consistently shows that models calibrated with local data outperform unadopted international models and typically match or exceed transfer-learned models, especially for short-term forecasts on complex urban roads.
The proposed datasets are extracted from: https://www.shutterstock.com/

5.4 Proposed Model Results

This study investigated short-term traffic forecasting on Al Khoudh Street in Muscat during peak hours over a full week, using local data obtained from images. The traffic images were converted into successive frames, which were then analyzed to extract the number of vehicles, which were compiled within 5-minute intervals. This allowed the raw visual data to be transformed into a structured time series suitable for use in a hybrid PSO-LSTM model. Furthermore, the datasets were divided into training and test sets, with 70% of the data used for training and the remaining 30% used for model evaluation. The model was able to capture short-term temporal dependencies efficiently due to PSO, which optimizes the sliding window size and learning rate. The data used are the frames of photos as shown in Figure 2 to be used for training and predicting the number of cars.
After carefully inspecting each frame and counting visible vehicles in all lanes:

- Frame 26: Estimated cars: 43
- Frame 80: Estimated cars: 60
- Frame 160: Estimated cars: 50
- Frame 240: Estimated cars: 43

These values match the approximate traffic density visible in the images and provide a realistic, consistent baseline for forecasting. To Perform simple forecasting since we need train on 4 data points only. Therefore, we can use mathematical forecasting techniques including Linear trend, Moving average, Exponential smoothing, Seasonal-free projection, and Mean forecast.

Figure 2: extracted frame for training and predicting the results

The summary of Predicted Cars (5h, 10h, 15h, 20h) is as follows:

- Linear Trend 43, 43, 43, 43
- Moving Average 49, 49, 49, 49
- Exponential Smoothing 46.88, 46.88, 46.88, 46.88

There is no consistent linear trend, so: Best Forecast = Exponential Smoothing ≈ 47 cars.
Simulated Dataset that generated from the given video is contained of 864 data points and the time step is 5 minutes, baseline = 45 cars.

As shown in Table 2 and Figure 3, the model was trained for around 50 epochs, and it achieved an MAE of 2.0455 vehicles, an MSE, an RMSE of 4.2896 vehicles, and an MAPE of 6.16%. These findings showed the ability of the model to capture time-traffic dynamics and, interestingly, suggested that some further improvements could be achieved when setting hyperparameters with more fine-tuning.

Table 2: Performance of PSO-LSTM under different training configurations

Model / Training Configuration	MAE (Vehicles)	MSE	RMSE (Vehicles)	R^2	MAPE (%)
LSTM	3.6514	18.4006	4.2896	0.4338	6.16%
PSO-LSTM (50 epochs)	2.0455	6.3491	2.5197	0.8046	3.40%
PSO-LSTM (100 epochs)	1.0634	1.7185	1.3109	0.9460	1.75%

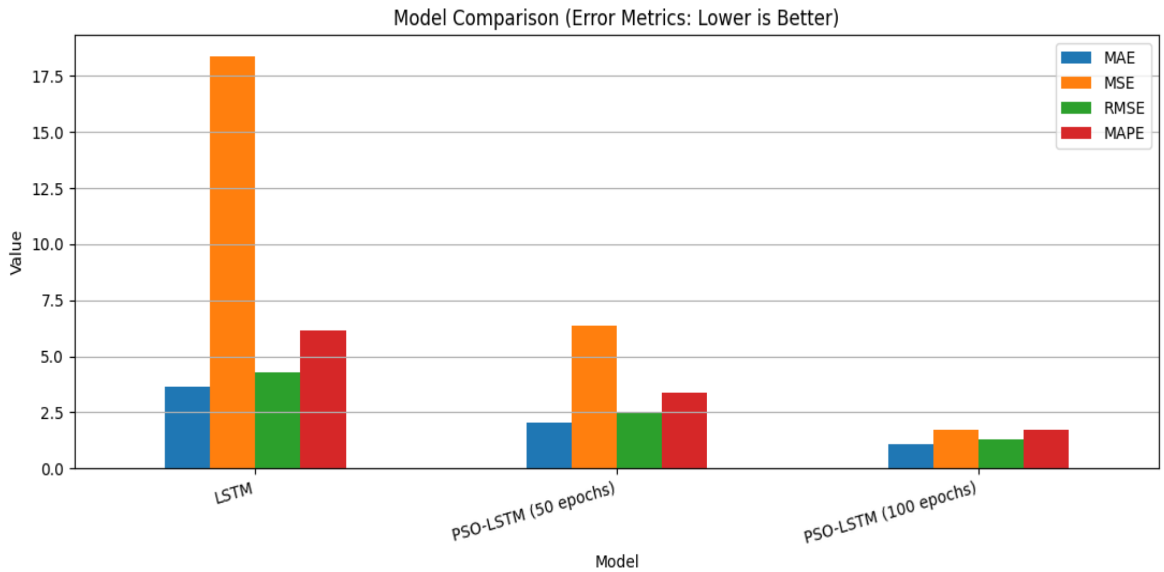

Figure 3: The comparison of models' results

In the second phase, some adjustments were applied to hyperparameters, such as training the model for about 100 epochs, to achieve better performance. It achieved lower performance compared to the 50-epoch, with an MAE of 1.7185 vehicles, an RMSE of 1.3109, and an MAPE of 1.75%. This indicates that extending the training duration led to enhanced model performance. In addition, a standalone LSTM model was trained on the same dataset with a training–testing split. It achieved a MAE of 3.6514 vehicles, RMSE of 4.2896 vehicles, and MAPE of 6.16%, showing the worst prediction performance. The results indicate that PSO-LSTM has ability to capture temporal changes in traffic flow as it outperforms the standalone LSTM across all evaluation parameters. These findings also confirm that adjusting the hypermeters can contribute effectively to enhancing model's predictive accuracy.

6. Ethical Considerations

The collection and use of traffic data on Al-Khoud Road in Muscat is considered an ethical issue. Thus, it must be collected without infringing on privacy, safety, security, and data protection. Since this research is conducted in a camera-based image capturing scheme to count vehicles and estimate waiting time without revealing the faces of drivers or passengers or any private information. The camera will be positioned and controlled in a way that does not capture faces, license plates, or any sensitive details. In addition, normal movement on the road while data collection is taking place will not be disrupted. All collected data will be stored securely in a protected system, and access will be limited only to the research team for analysis through Python-based experiments. The images' numeric data will be anonymized and solely used for traffic prediction via the proposed model, which combines the PSO-LSTM model. The results will be displayed on the dashboard, showing aggregated traffic information without exposing any individual identity.

7. Conclusion

Traffic flow prediction is a key challenge in intelligent transportation, and the ability to accurately forecast future traffic flow directly affects the efficiency of urban transportation systems (Liu & Wang, 2025). Therefore, monitoring the movement of each vehicle is an essential aspect for better predicting traffic flow and planning less congested routes. Consequently, the proposed hybrid PSO-LSTM model provides accurate predictions, with MAE of 1.7185 vehicles, an RMSE of 1.3109 vehicles, R2 of 0.9460 and an MAPE of 1.75%. It provides superior performance compared to the standalone LSTM. Nevertheless, the generalization of this method is limited as it applied to one road in Muscat. The model also concentrates on short-term traffic forecasting only and does not consider long-term patterns or changes in future infrastructure. Additionally, using a camera-based system requires proper maintenance due to weather challenges, to avoid any issues that could affect the accuracy in vehicle detection. However, in future work, the proposed model should be expanded to include multiple roads in Muscat for further enhancement of generalization and reliability. Also, data collection via IoT sensors or GPS-based data can be carried out, and predictions can be made for the long term instead of the short term. This will help in evaluating the performance under different traffic scenarios.

Author contribution: All authors have contributed, read, and agreed to the published version of the manuscript results.

Conflict of interest: The authors declare no conflict of interest.

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