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Neural Network-Driven Road Traffic Forecasting for Optimized Smart Network Infrastructure

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Abstract - *Road traffic forecasting is the process of predicting future traffic conditions and patterns using data analysis. It is crucial for the better traffic management, safety enhancement, congestion reduction, and urban mobility. Current road transport forecasting approaches are limited by inaccuracies in real-time data, poor handling of complex traffic dynamics and unpredictable human behavior. In order to forecast traffic flows using radar and meteorological sensor data, this study evaluates the efficacy of three advanced deep learning approaches: convolutional neural networks (CNN), long short-term memory (LSTM) and autoregressive LSTM (AR-LSTM). The system demonstrated that they accurately predict traffic patterns by including weather as an essential element. The study shows how weather has a big influence on traffic flow, which makes it crucial for predictive modeling. In terms of computational efficiency and prediction accuracy, the CNN model performed better than both LSTM and AR LSTM. CNN demonstrated its suitability for real-time applications by achieving the lowest mean absolute error and require a small amount of execution time to create predictions. The study demonstrates the potential of these models to assist traffic management, which shows that it is feasible to estimate traffic flows with a high degree of accuracy across one-hour intervals. The importance of implementing advanced deep learning techniques for more intelligent and responsive traffic systems is highlighted by these findings.*

Key Words *Road traffic forecasting, convolutional neural networks, mean absolute error, deep learning.*

1.INTRODUCTION

Road traffic forecasting can optimize route planning, enhance decision-making, and improve overall transportation efficiency. The rise in traffic congestion is one of the main problems that drivers, highway operators, and municipal managers are currently dealing with. It worsens the traveller experience by adding complexity to everyday travel and having harmful effects on the environment, users' time, and financial expenses. Road and city operators may also find it useful to use traffic flow forecasts when putting traffic planning and management techniques into practice. Traffic state estimation (TSE) is the technique of using noisy and partially observed traffic data to infer traffic state parameter such as speed, flow, and other similar factors, on road parts. Because the TSE topic is useful to public authorities, road workers, and the general people, there is a lot of interest in investigating it in the ITS field [1].

Road traffic situation problems are a typical occurrence in all major cities globally. For more than 50 years, governmental and private organizations have worked to reduce the social, economic, and environmental issues caused by traffic congestion. Three methods used to lessen the effects of traffic congestion: controlling traffic flows, promoting transportation alternatives, and building more infrastructure. The second is primarily a subject of public policies, while the first is constrained by topographical, financial, and social factors. The latter has been improving steadily over the past few years due to the data growth provided by sensors in vehicles and roads, as well as the technology required for using that data. In order to create advanced traveller information systems (ATIS) and advanced traffic management systems (ATMS), it is helpful to be able to monitor, analyze, and understand traffic factors like flow, occupancy, or travel times. Early investigations of Kalman filtering techniques and time-series approaches using various approaches comprised the majority of the initial efforts to predict traffic flows. Figure 1 depicts the road traffic forecasting model.

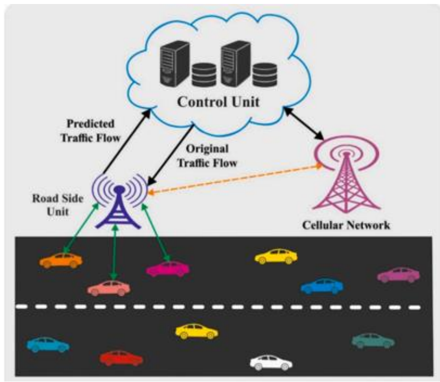


Fig – 1: Road traffic forecasting model

Short-term prediction horizons have been used in many methods to forecast traffic features. The research community's interest in this area has grown considerably, as have the availability of data, analysis techniques, and processing power. Predicting traffic details is one of the pillars of the dynamic field of research, policymaking, and technological development known as Intelligent Transportation Systems (ITS) nowadays. In addition to being stored in frequently updated public repositories, road sensor data is also made available with fine-grained resolution in the form of floating automobile data, people's mobility traces, traffic counts of bicycle, and traffic signal operation conditions. Forecasting methods have developed at a comparable rate; while time-series analysis continues to be a major component of the most recent research contributions, machine learning approaches are also receiving a lot of interest. The use of simulation tools has increased. The proposed study evaluated the utilization of several DL approaches and data characteristics to predict traffic patterns.

The aims of the study are as follows:

- To utilize deep learning (DL) methods such as LSTM, CNN and AR LSTM for the road transport forecasting effectively.
- To access the system performance in terms of execution time and mean absolute error.

2.RELATED WORKS

A hybrid multimodal DL framework (HMDLF) was proposed by Du et al. [2] for predicting short-term traffic flow. Within an auxiliary attention mechanism, the model employed gated recurrent units (GRU) with 1D CNN. While the GRU modelled long temporal relationships, the CNN extracted local trend aspects. In order to learn deep nonlinear relations between traffic modalities, including speed, flow, weather, and pass time, a multimodal representation and fusion learning framework were created using several CNN-GRU-Attention modules. The findings confirmed that the model performed well in a range of traffic scenarios, including weekdays, weekends, and anomalies. When learning spatial-temporal interdependence and allowing for errors at peak and trough points, the method achieved good performance. However, limitations included reliance on large datasets and challenges in collecting diverse traffic data.

Essien et al. [3] developed a DL model using a bi-directional LSTM stacked autoencoder (SAE) for urban traffic prediction. It integrates tweets from traffic officials with weather and traffic data to enhance accuracy. Tested on Chester Road, Greater Manchester, UK, the model outperformed traditional machine learning methods. However, scalability remains a challenge due to high processing costs and uneven traffic sensor distribution, limiting its application to a single arterial road rather than a broader urban traffic network. Formosa et al. [4] introduced a DL approach with a centralized digital architecture to predict traffic conflicts. They collected disaggregated traffic data and in-vehicle sensor data from the UK M1 motorway. Using an R-CNN model, they analyzed video data to track vehicles and identify lane markers relative to the ego-vehicle. A Deep Neural Network (DNN) was then developed by combining traffic factors like density and speed with surrogate safety measures (SSMs) such as time-to-collision (TTC). The DNN achieved real-time predictions at 15Hz with 94% accuracy, making it suitable for Advanced Driver Assistance Systems (ADAS). It also demonstrated low false alarm rates, with sensitivity ranging from 71% to 78%. However, the model's reliance on high-quality sensor data and challenges in managing various traffic scenarios posed limitations.

Boukerche et al. [5] analyzed machine learning (ML) models for traffic prediction by categorizing them based on their theoretical foundations and modifications. Recurrent Neural Networks (RNNs), CNNs, and Conv-RNN were widely used, while seq2seq and attention-based architectures improved efficiency. Combining Graph-Convolutional Networks (GCNs) with attention-based seq2seq models effectively captured spatial and temporal correlations. However, predicting traffic on extensive road networks remained computationally expensive. Ahmed et al. [6] proposed a graph neural network-based on information fusion. By integrating temporal and geographical data into a graph structure, the model identified complex patterns in traffic flow. GNNs effectively captured spatial relationships, improving prediction accuracy. However, challenges included the need for substantial datasets and difficulty in precisely modeling dynamic traffic conditions.

Ma et al. [7] proposed a neural network autoregressive integrated moving average (NN-ARIMA) model for traffic state prediction. By combining the ARIMA method with a neural network multilayer perceptron, the model extracted location-specific features and nonlinear traffic patterns while capturing network-wide co-movement trends. Validated on a six-month highway dataset, NN-ARIMA reduced mean squared error (MSE) by 8.9–13.4% compared to standalone MLP and ARIMA models. However, it faced challenges in handling large networks and long time-series datasets. Zhang et al. [8] proposed a Hybrid Graph Convolutional Network (HGCN) to forecast traffic flow at highway toll stations, integrating date-type, meteorological, spatial, and temporal factors. Using GCN, the model effectively captured the non-Euclidean nature of road networks. Results showed improved accuracy over baseline ML models. However, its static graph structure limited adaptability to dynamic traffic changes.

Hu et al. [9] introduced the Spatial-Temporal Prediction Model Network (SPTMN) for traffic forecasting. By leveraging a Temporal Convolution Network (2DTCN) and GCN, the model captured both global spatial relationships and temporal dependencies. It demonstrated high stability and adaptability to sudden traffic speed changes. Bao et al. [10] developed a Deep Belief Network (DBN) for prediction in adverse weather. Integrated with Support Vector

Regression, the model accurately mapped complex traffic relationships, maintaining a prediction error below 9%. However, its computational demands were high. Pan et al. [11] introduced the FD-Markov-LSTM method, combining a fundamental diagram (FD), Markov chain, and LSTM for traffic state estimation (TSE) and prediction in congested and uncongested conditions. The method lacked real-world validation for nonrecurring delays and was unsuitable for long-term forecasting.

Current road transport forecasting models face significant limitations. They rely heavily on large, high-quality datasets, which are challenging to collect due to the uneven distribution of traffic sensors and the high costs associated with processing such data [7]. Most models are restricted to single arterial roads, making scalability to larger networks difficult. Furthermore, these systems struggle with computational expenses [5], especially when managing diverse traffic scenarios and simulating dynamic traffic patterns. While information fusion has enhanced spatial relationship modeling, it remains limited by insufficient datasets and difficulties in handling long-series traffic data. Additionally, static graph structures hinder the models' ability to adapt to dynamic traffic changes, underscoring the need for scalable, data-efficient, and adaptive approaches to improve forecasting accuracy [8].

3.MATERIALS AND METHODS

The data are selected from the surrounding areas of the two beaches that were chosen to customize the model to forecast the traffic flow for Portugal's coastal beaches. The datasets from an ITS network created in the Portuguese city were used for this purpose, making use of field-installed roadside infrastructure sensors. TSE models were trained using ML methods, especially LSTM, AR-LSTM, and a CNN, to predict the traffic flow on Portugal's two distinct coastline beaches such as Barra and Costa Nova.

The relevance of the provided data to support the induction of the prediction models was then assessed. The datasets are from two distinct sources. Figure 2 (a) and (b) visualize the radar and meteorological station locations. The locations of the radars are shown in Figure 2 (a). The first one takes place before crossing the bridge, the middle one takes place in the interconnected segment between Costa Nova and Barra and the last one takes place near the southern edge of the Costa Nova. The two meteorological stations gathering environmental information are shown in Figure 2 (b). For every hour of the day, each record corresponds to one observation every ten minutes. Two main objectives in the processing of the meteorological data: correcting the stations' missing measurements, and converting the values of wind direction from degrees to cardinals.

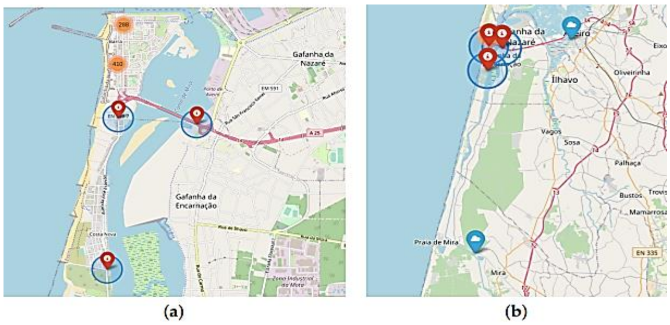


Fig - 2: PASMO radar and meteorological station locations (a) radar and (b) meteorological stations and radars

Figure 3 depicts the process for handling the traffic flow prediction on Portugal beaches. Parking and radars are the two datasets taken from telemetry dataset, which contains the recordings from radars and parking sensors. After that data preprocessing is done to obtain the radar and meteorological data for the mining process. The pre-processed data are combined into a single dataset for the mining task. The data mining approaches processed the data in the model training phase across the CNN and LSTM.

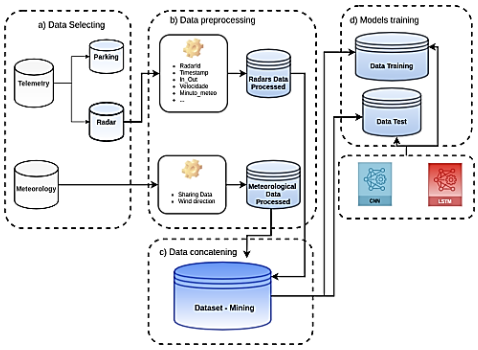


Fig - 3: Data preparation and model training method

3.1 Dataset

Over 170 million recordings (170,158,409) from parking sensors and radars make up the original Telemetry collection, which consider the years 2019, 2020, and 2021. Only radar data were chosen for this study and the features of the original data are illustrated in Table 1. In this study, the Portuguese Institute of Sea and Atmosphere supplied the weather dataset [12].

Table – 1: Original data attributes

Attribute	Content
time stamp	Record time stamp
id	Object ID
radar_id	Radar identification
radar_lon	Longitude radar coordinate
radar-lat	Latitude radar coordinate
yspeed	Speed component: Y-axis
xspeed	Speed component: X-axis

3.2 Data preprocessing

The meteorological data is produced at a frequency of 10 minutes, while the radar data is created at a frequency of 100 milliseconds. Other derived radars data such as day, month, year, hour, and minute attributes, were generated prior to modifying the granularity. The speed measure is generated by the $xspeed$ and $yspeed$ features. Positive values for speed indicate an object moving away, whereas negative values indicate the speed of an object similar to the radar. For each radar, the quantity and speed at the level of radar are determined using the speed and moving object's direction.

In order to generate a single set, the two datasets must be combined, as depicted in Figure 3. The following characteristics were taken into account as indexes while concatenating: year, month, day, hour, and minute. As a result, every record in the final dataset is made up of attributes that represent the radar and weather measurements as well as index columns.

The aim of this study is to make an approach that can predict traffic flow in both regions taking into account the weather and speed of the vehicle. The traffic flow is represented by two measures such as TF_Barra and TF_Costa expressed in Equation (1) to (4).

$$TF\_Barra = (AR_1 + DR_2) - (AR_2 + DR_1) \quad (1)$$

$$TF\_Costa = (AR_2 + AR_3) - (AR_2 + DR_3) \quad (2)$$

where AR_i is the number of the objects approximating the radar i and DR_i is the number of detaching objects.

$$AR_i = \sum_{i=1}^{3} \sum_{j=0}^{50} count\_A_{i,j} \quad (3)$$

$$DR_i = \sum_{i=1}^{3} \sum_{j=0}^{50} count\_D_{i,j} \quad (4)$$

Where i= radar identification, j= interval minute ranges from 1 to 50, $count\_A_{i,j}$= value of the attribute where in_out =1, $count\_D_{i,j}$= value of the attribute where in_out = 0.

If TF value is positive, then it represents the traffic flow increase in that region, and if it is negative, then region has less traffic flow.

3.3 Model development

Training, validation, and testing sets were created from the final dataset that was pre-processed in the earlier stages and are divided in the ratio 70:20:10 respectively. The dataset includes contextual information including weekday, temperature, solar radiation, wind direction and speed. Figure 4 represents the splitting of entire dataset into subsets, time in x-axis and traffic flow values in y-axis.

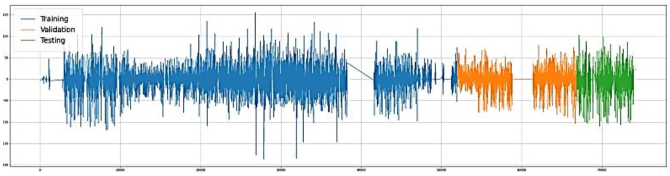
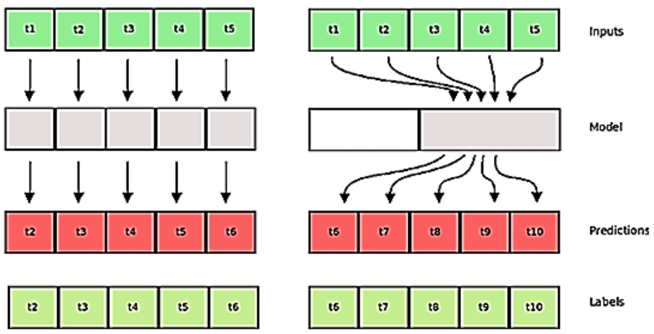


Fig - 4: Division of subsets into training, validation, and testing

For predicting the traffic flow, three DL regression techniques such as term memory LSTM, AR LSTM, and CNN, and MAE was utilized as an evaluation metric. The optimal configuration, which was determined by an optimisation phase utilising the hyperparameter options, was taken into account when building each model. Six distinct time intervals were taken into consideration for each method: (1,1), (2,2), (3,3), (4,4), (5,5), and (6,6). In (1,1), there was one historical record (ten minutes) and one forecasted traffic flow (ten minutes). As a result, this study uses a multi-step model to estimate traffic flow between 10 and 60-minutes. Single and multi-models are illustrated in Figure 5

A layer with 64 filter maps, a ReLU function, and a kernel size equal to the time interval value were used to build the CNN model. The number of nodes was calculated by multiplying the number of features with the time interval value. The format was finally altered by the final layer to show the expected traffic flow statistics.



(a) (b)

Fig - 5: (a) Single step (b) multistep

Time-series datasets have been analysed using the LSTM method, which suggests to calculate the prediction for the subsequent time gap after accumulating the internal state throughout the time interval. 32 neurons made up the first layer of the LSTM model used in this study. In the sequence, there was a dense layer that had the same setup as the CNN. To display the anticipated traffic flow values, the last layer transforms the format. In AR-LSTM approach, the prediction was decomposed into individual time steps. The method uses each model output to feedback into itself.

4.RESULTS AND DISCUSSION

An Intel(R) Xeon(R) CPU E5-2620 v4, a CPU frequency of 2100 MHz, and a RAM having a capacity of 16GB running Ubuntu 20.04.4 (LTS), was used to test the data related to both beaches. The tests were conducted in a server of an operating system, remotely scheduled via SSH. Additionally, equivalent intervals were utilized, ranging from a single ten-minute block to six 10-minute blocks and predicted the next 10-minutes during a 10-minute break and the next twenty minutes during a twenty-minute break, until reached sixty minutes.

CNN, LSTM, and AR-LSTM were the techniques employed and the tests were run ten times for each interval, evaluate the execution time and MAE. Each of these parameters' mean and standard deviation were determined. The CNN technique test results for both beaches are displayed in Table 2.

For Barra Beach, the test with a ten-minute input and output gives the best performance with the lowest MAE and execution time. For Costa Nova Beach, the lowest MAE is also achieved with a ten-minute input and output, but the best execution time is observed with a sixty-minute input and output.

Table - 2: CNN results

Beach	Input	Output	MEA/ Mean	Std	Time/ Mean	Std
Barra	1	1	6.79	0.41	56.42	16.38
	2	2	6.81	0.41	63.42	14.86
	3	3	7.28	0.58	55.81	26.43
	4	4	7.31	0.55	60.14	17.59
	5	5	8.05	0.59	63.27	18.97
	6	6	8.47	0.53	66.22	29.52
Costa Nova	1	1	6.74	0.23	59.40	16.87
	2	2	6.88	0.47	66.62	22.93
	3	3	6.96	0.45	70.03	18.63
	4	4	7.53	0.53	55.54	19.20
	5	5	7.73	0.32	62.59	18.89
	6	6	8.79	0.36	54.19	12.88

Table 3 represents the outcomes of the test obtained with the LSTM model to both beaches. Although tests with identical input and output equivalent to 60-minutes have a reduced standard deviation, the method obtained the lowest MAE for thirty-minute periods using the LSTM approach for Barra traffic. Ten-minute intervals yielded the lowest average execution time. The best outcomes for MAE and execution time were obtained using Costa Nova testing at ten-minute intervals. With execution times varies from 15 to 32 minutes, LSTM experiments enabled to acquire MAE values between 13% and 15%. The interval increases maintain MAE values within the same range even when execution times increase, consider the increase as pointless.

Table - 3: LSTM results

Beach	Input	Output	MEA/ Mean	Std	Mean/time	Std
Barra	1	1	14.91	1.41	920.80	108.14
	2	2	13.84	2.39	1038.09	125.18
	3	3	13.71	1.94	1190.37	142.13
	4	4	13.83	1.61	1370.07	180.46
	5	5	13.94	3.35	1661.48	267.81
	6	6	14.73	1.17	1872.14	264.06
Costa Nova	1	1	13.49	1.88	991.62	101.98
	2	2	14.29	1.73	1080.23	132.31
	3	3	14.29	1.92	1188.94	203.84
	4	4	14.47	2.07	1399.33	143.40
	5	5	14.92	1.16	1744.69	168.46
	6	6	14.97	1.23	1641.91	268.67

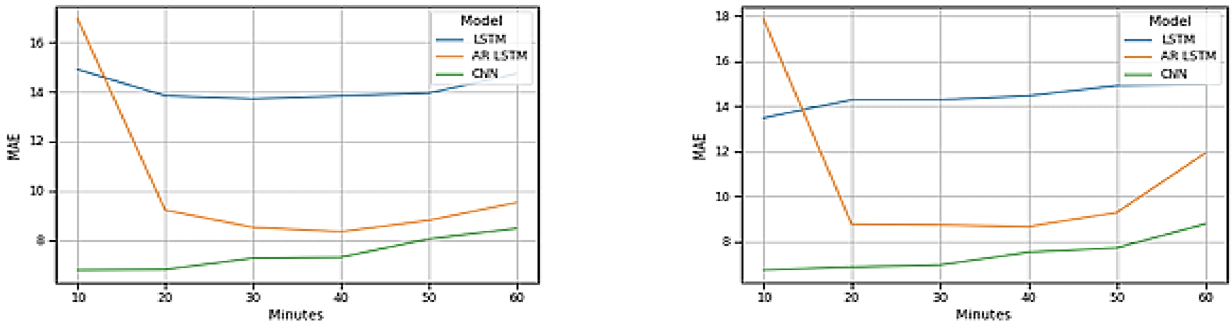
Table 4 represents the results of AR LSTM approach on both beaches. In the case of Barra beach, the tests with input and output times of 30 and 40 minutes had the minimum MAE. The tests with the smallest standard deviation have input and output times of forty minutes. In the case of Costa Nova beach, when input and output are equal to 30 minutes had the best MAE average result. It is noteworthy that the periods with the greatest results for average execution time and MAE average are the same for both beaches.

Table - 4: Results of AR LSTM

Beach	Input	Output	MEA/Mean	Std	Mean/time	Std
Barra	1	1	16.97	4.67	902.99	48.63
	2	2	9.21	1.42	649.23	146.02
	3	3	8.52	0.57	811.02	121.65
	4	4	8.34	0.35	1006.01	96.47
	5	5	8.80	0.90	1320.48	218.51
	6	6	9.51	1.60	1413.75	370.97
Costa Nova	1	1	17.89	6.14	898.62	65.68
	2	2	8.76	0.63	730.98	154.28
	3	3	8.74	1.20	891.32	129.97
	4	4	8.66	0.95	1014.53	105.89
	5	5	9.29	1.02	1254.10	265.74
	6	6	11.92	2.67	1386.19	294.42

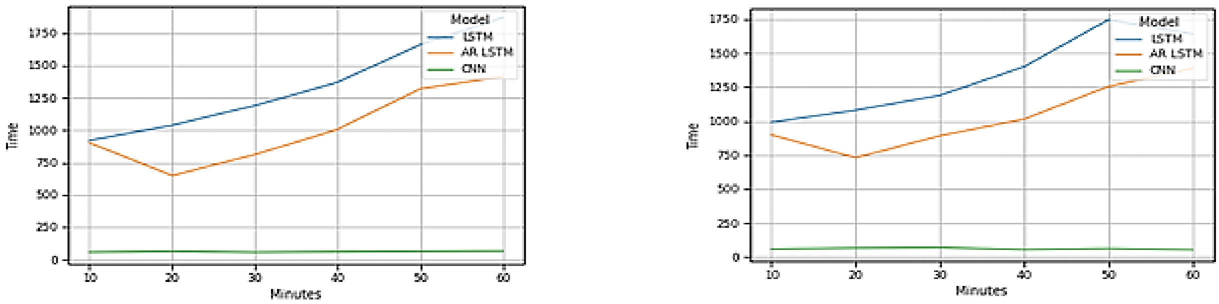
Based on meteorology and the data produced by the IPMA and PASMO project, a TSE was constructed to forecast the access traffic to both the beaches. Several approaches were attempted during the learning process to see which produced the best outcomes in terms of complexity and error. In order to maximize the total learning outcomes, several forecasting and learning periods were also employed.

Tests of traffic prediction utilizing CNN, LSTM, and AR-LSTM techniques showed the best execution times and interval lengths for accuracy (MAE). While Costa Nova had the best MAE with 10-minute intervals but faster execution with 60-minute intervals, Barra traffic exhibited the best MAE and execution time for CNN. Figure 6 depicts the MAE evolution of Costa Nova and Barra beaches and Figure 7 visualize the execution time of Costa Nova and Barra beaches.



(a) (b)

Fig - 6: MAE evolution of Barra (a) and Costa Nova (b) prevision



(a) (b)

Fig – 7: Execution time evolution of Barra (a) and Costa Nova (b) prevision

The graphs in Figures 7a and 7b illustrate the benefits of using a CNN approach for traffic forecasting by analyzing data on a global scale.

5. CONCLUSION

Road traffic forecasting is the process of predicting traffic conditions using vehicle flow, historical data, weather and different models to progress the traffic flow and management. Using weather data to increase forecast accuracy, this study demonstrates the promise of DL method for road traffic forecasting. With the lowest MAE and fastest execution times, CNN surpassed the other three methods such as LSTM, AR-LSTM, and CNN, during learning and predicting intervals of ten minutes. These intervals are appropriate for real-time applications since they obtained a balance between computational efficiency and precision. The results highlight how important it is to select the best time windows for various methods. CNN's accuracy and speed performance highlight how well-suited it is for dynamic traffic conditions when timely updates are essential. In conclusion, a robust framework for real-time traffic forecasting is provided by DL techniques, especially CNN. With minimal computing effort, they can be used to support smart city projects and regulate traffic flow.

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