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Predicting Oceanic Wind Speed and Direction using LSTM

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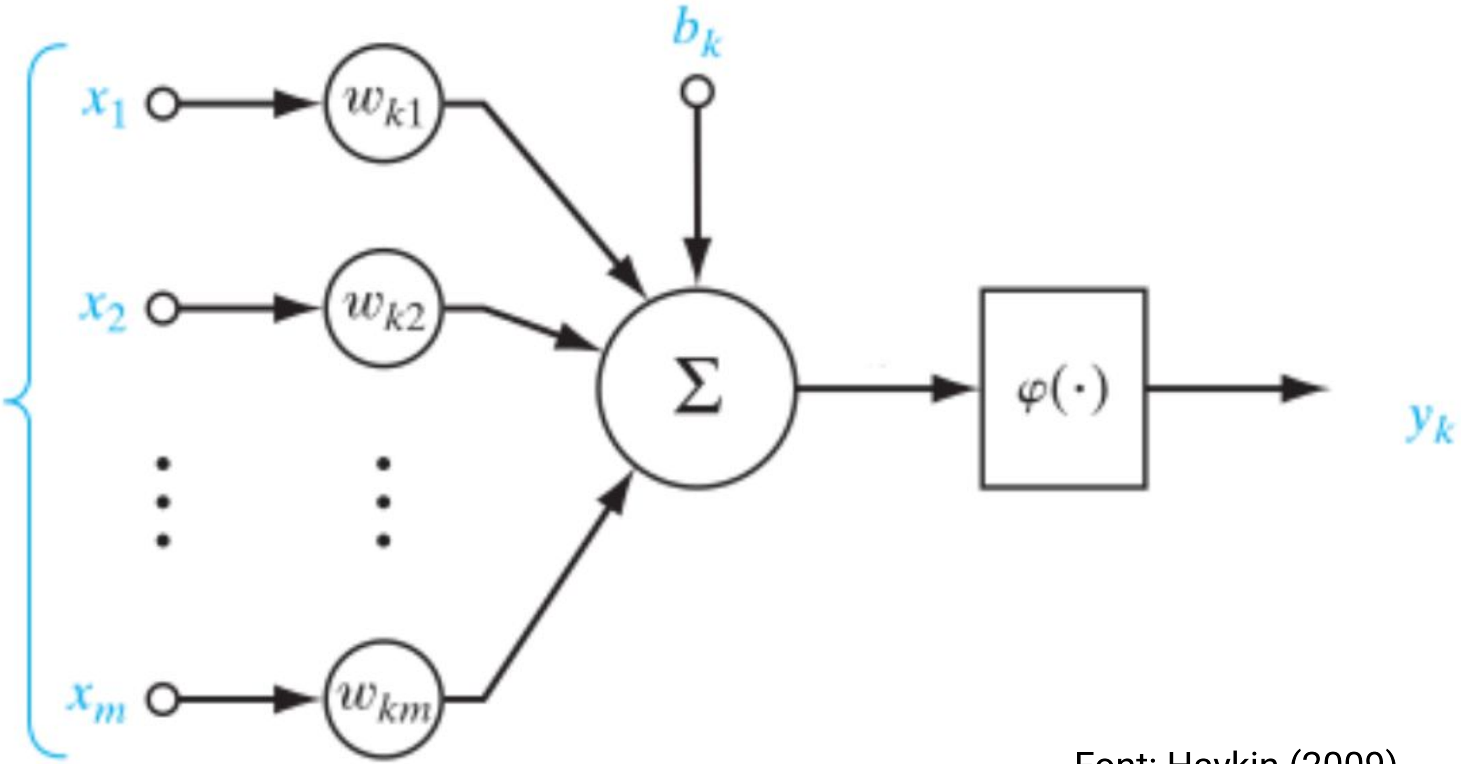
Motivation

- ➢ Cnidarian found along the entire Brazilian coast
- ➢ Floating pneumatophore: strong influence of **wind** on movement
- ➢ Tentacles with stinging cells
- ➢ Responsible for many incidents
- ➢ Limited monitoring
- ➢ Need for long-term **wind** prediction for forecasting

Portuguese man-of-war (*Physalia physalis*)

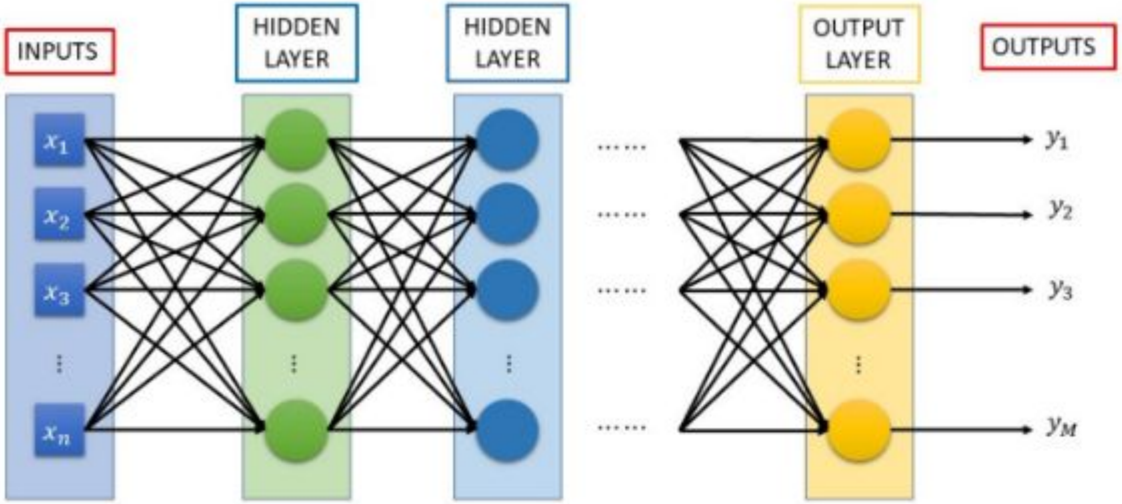
Font: Instagram

Perceptron



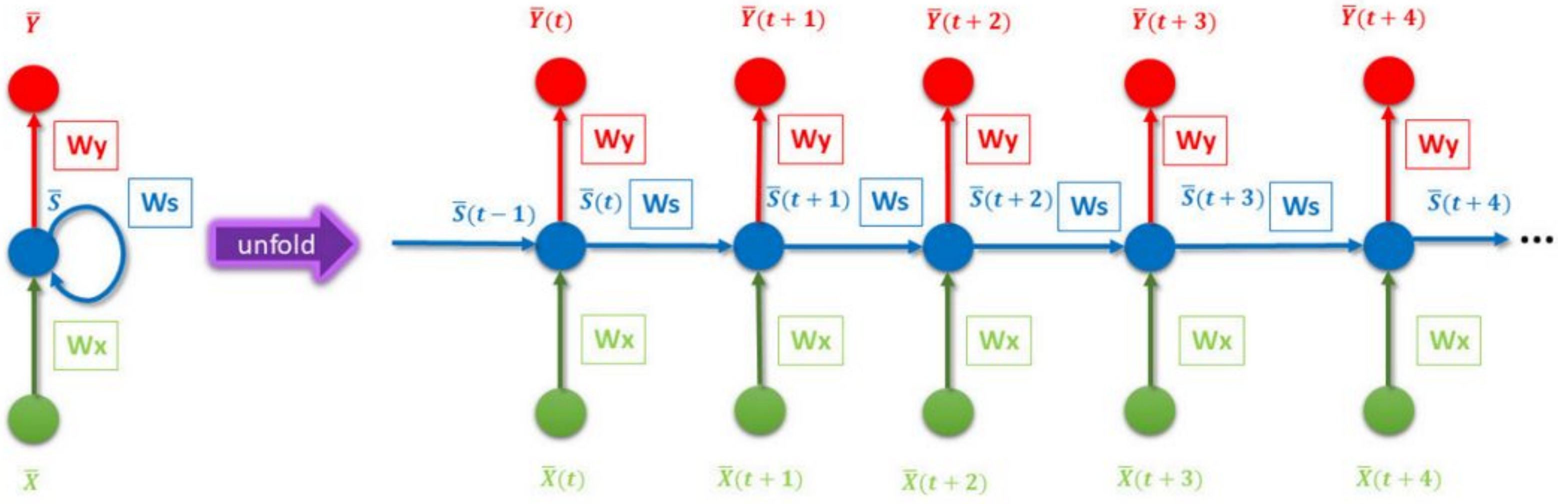
Font: Haykin (2009)

Neural Networks



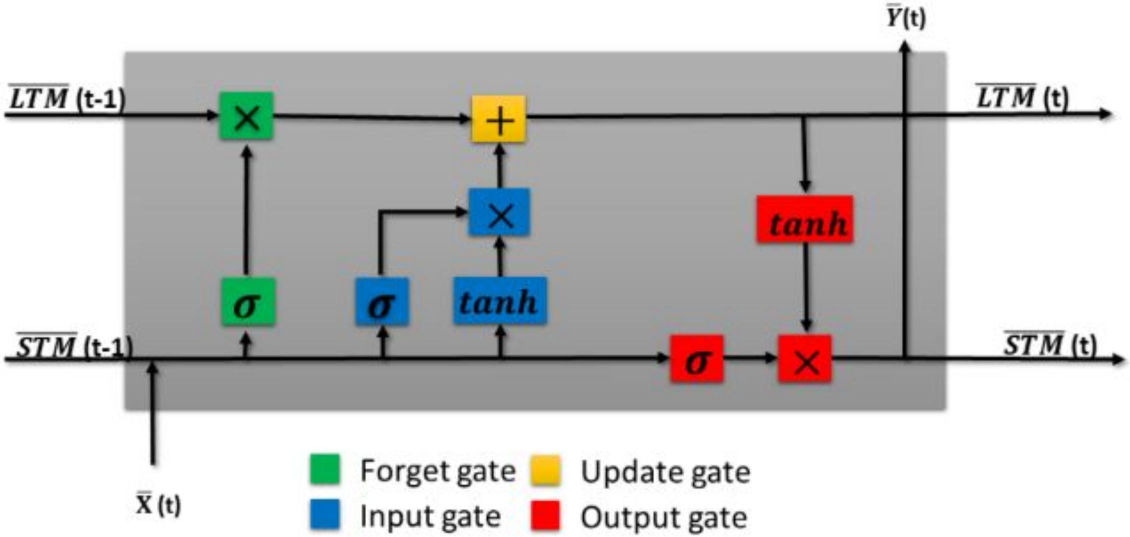
Font: Markovic et al. (2023)

Recurrent Neural Networks (RNNs)



Font: Markovic et al. (2023)

Long-Short Term Memory (LSTM)



Font: Markovic et al. (2023)

Studied Papers

Relation of studies on Portuguese man-of-war trajectories:

Work	Onshore	Predicition	Neural Networks	Open-sea
[Macías et al. 2021]	X	X		
[Headlam et al. 2020]		X		X
[Ferrer and Pastor 2017]	X			X
Proposed work	X	X	X	X

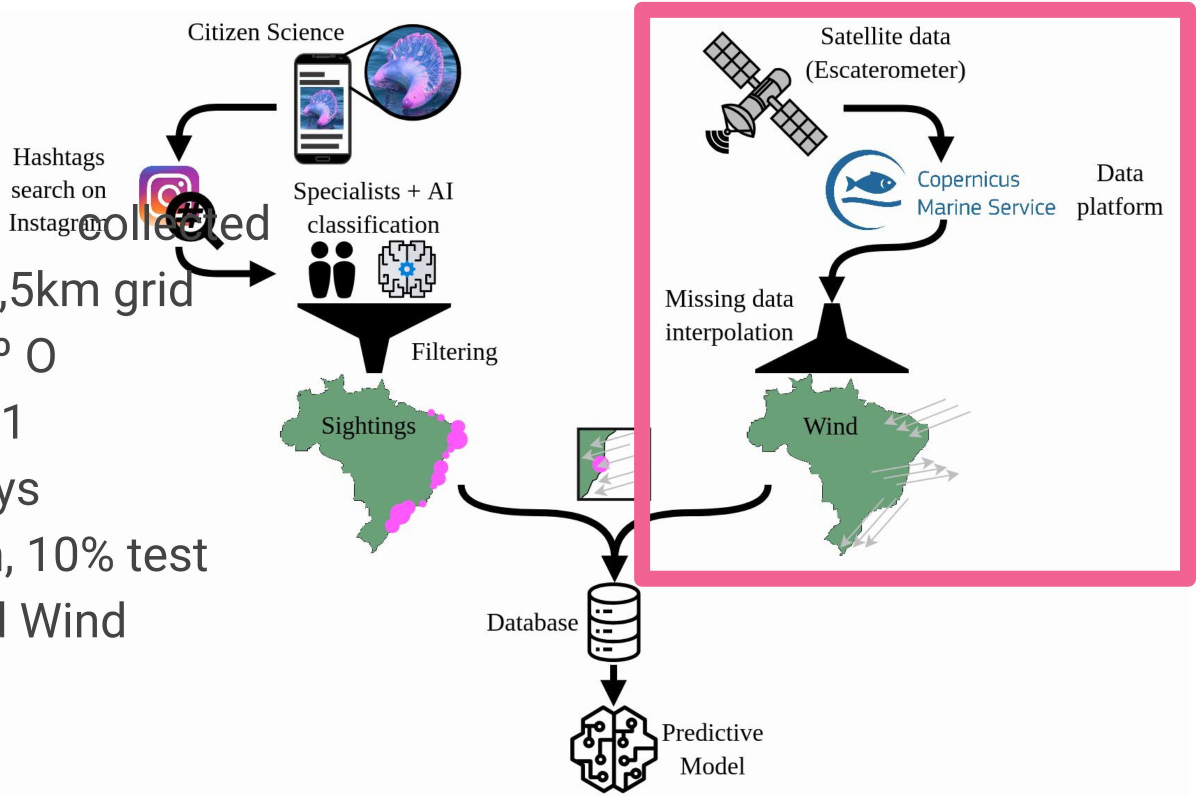
Studied papers

Relation of wind prediction works using neural networks:

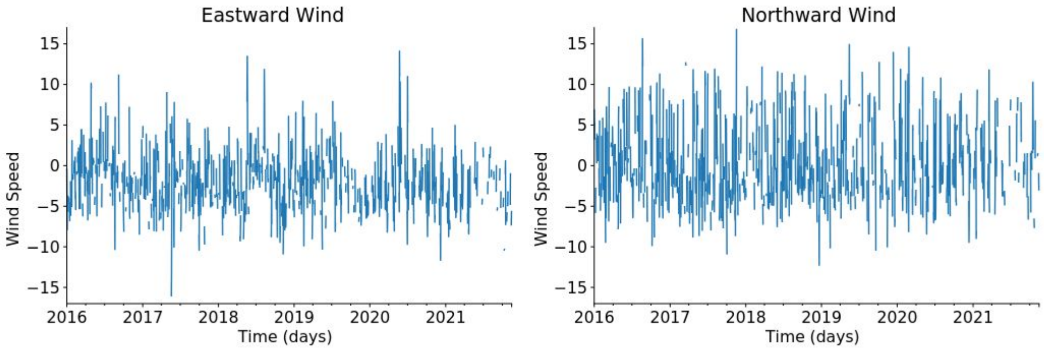
Work	Neural Network	Term	Variables	Offshore
[Huang et al. 2023]	((En)Ev)LSTM	Short	Speed	No
[Shahid et al. 2021]	(G)LSTM	Short	Power	No
[Chen et al. 2021]	CNN-LSTM	Short	Speed	No
[Hu et al. 2022]	SVM	Short	Speed	No
[Guo et al. 2012]	FNN	Long	Speed	No
[Lin et al. 2020]	Own	-	Power	Yes
This work	LSTM	Long	Direction/Speed	Yes

Database

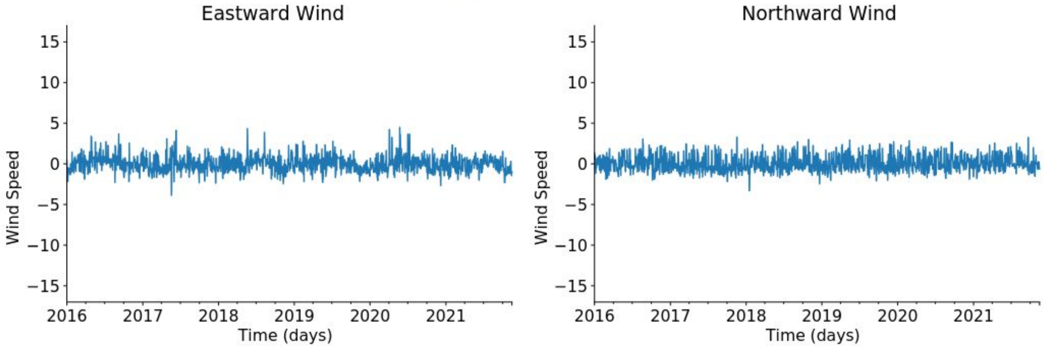
- ➢ Daily wind data collected by satellite, 12,5km grid
- ➢ 26,1875º S and 47.4375º O
- ➢ 01/01/2016 - 15/11/2021
- ➢ 1326 values for 2145 days
- ➢ 70% train, 20% validation, 10% test
- ➢ Eastward and Northward Wind



Preprocessing



(a) Raw data.

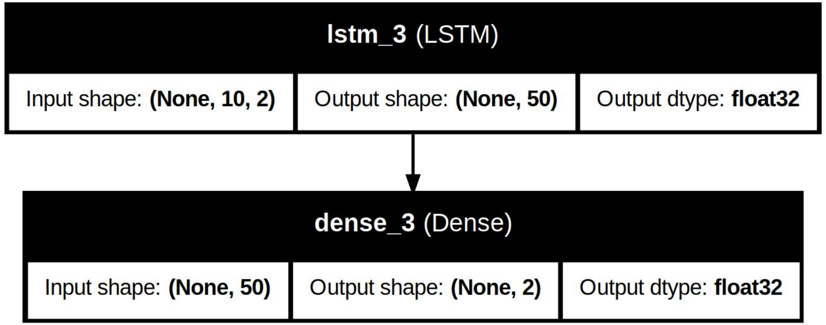


(b) Normalized and interpolated data.

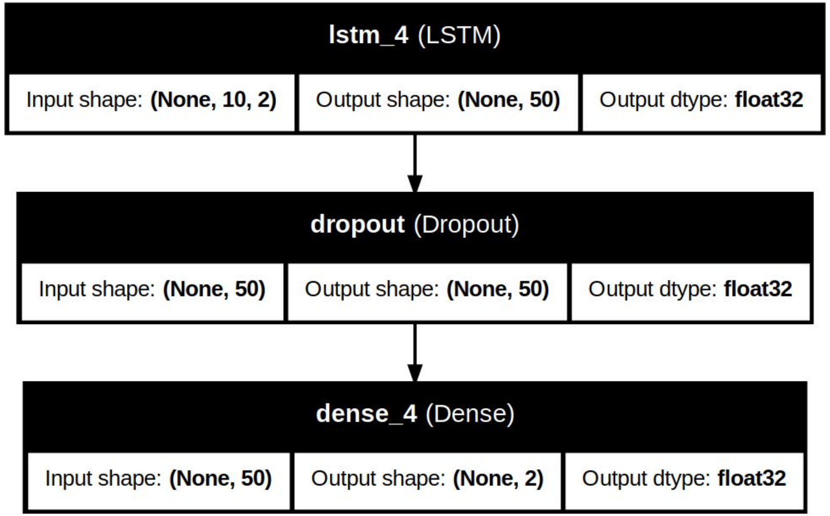
LSTM Architectures

Layer schematization of each used architecture:

Architecture 1



Architecture 2



LSTM Models

- ➢ LSTM: Architecture 1
- ➢ LSTM-RD: Architecture 1 with Recurrent Dropout at 25% rate
- ➢ LSTM-RDD: Architecture 2 with Dropout at 50% rate
- ➢ Batches of size 32, sequence length 10 and sampling rate 1
- ➢ Loss function: Mean Squared Error (MSE)
- ➢ Early stopping with patience 10 based on validation loss
- ➢ Maximum of 100 epochs
- ➢ Tests executed 10 times for each model

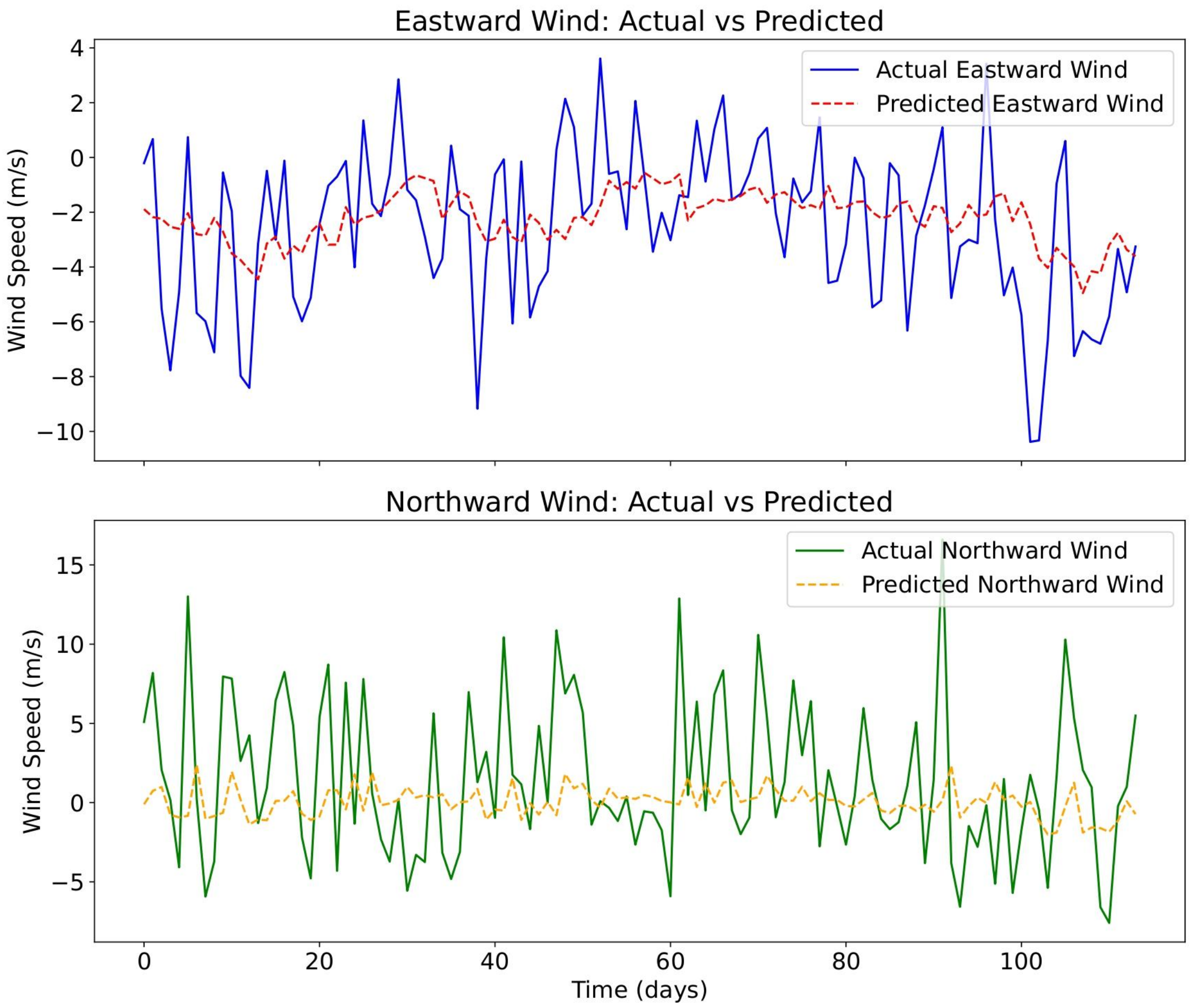
Results

Comparison between the average results of each model and data instance.
Average +- standard deviation:

Model	Data	Epoch	Loss	MAE
LSTM	Raw	13.7	16.87 ± 0.33	3.13 ± 0.03
	Preprocessed	23.4	9.19 ± 0.12	2.33 ± 0.01
LSTM-RD	Raw	20.5	17.03 ± 0.41	3.14 ± 0.03
	Preprocessed	43.2	9.25 ± 0.07	2.30 ± 0.03
LSTM-RDD	Raw	31.7	16.70 ± 0.16	3.11 ± 0.02
	Preprocessed	61.6	9.35 ± 0.10	2.33 ± 0.02

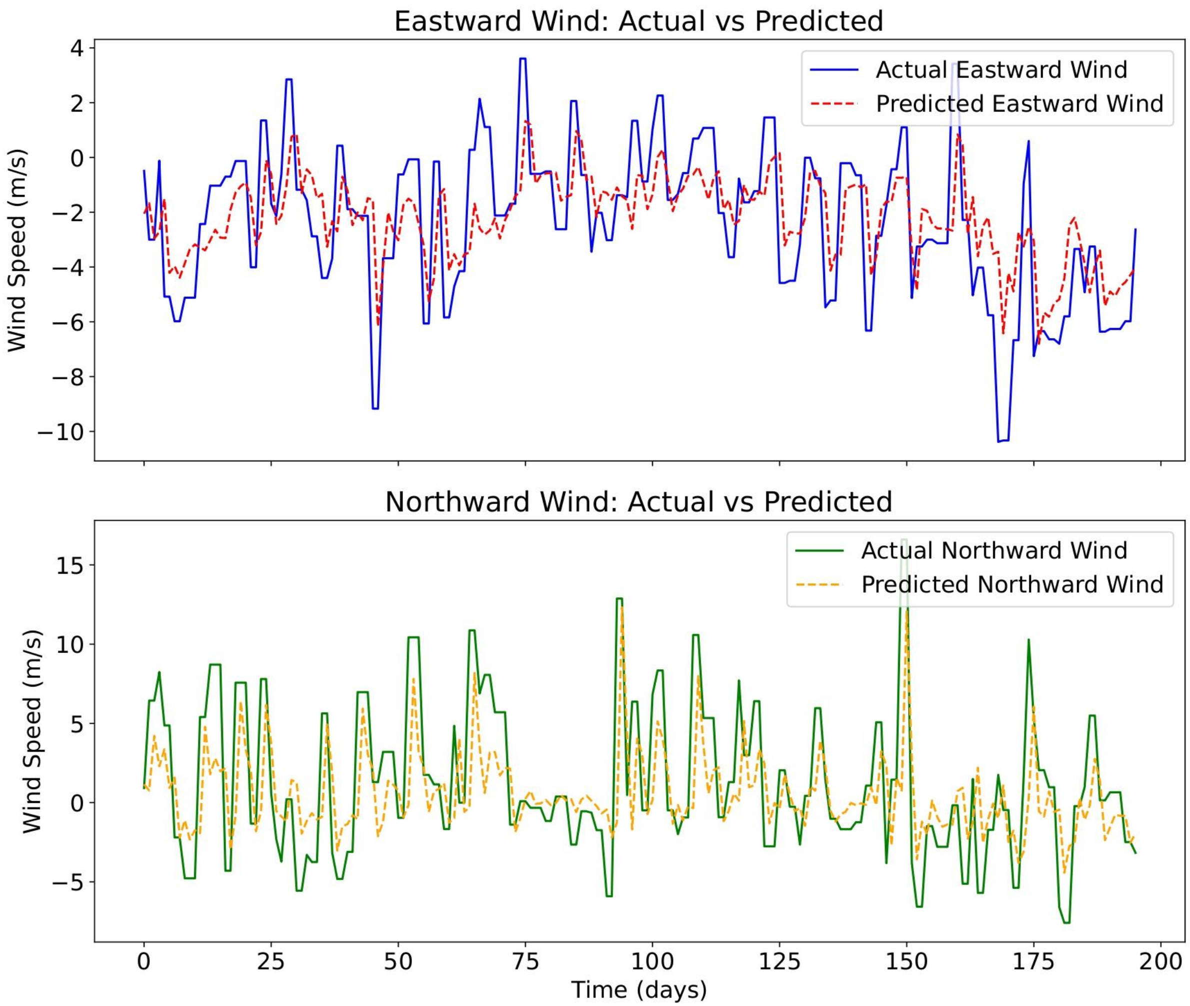
Results

Comparison graph between actual and predicted values from the best execution of LSTM-RDD with raw data:



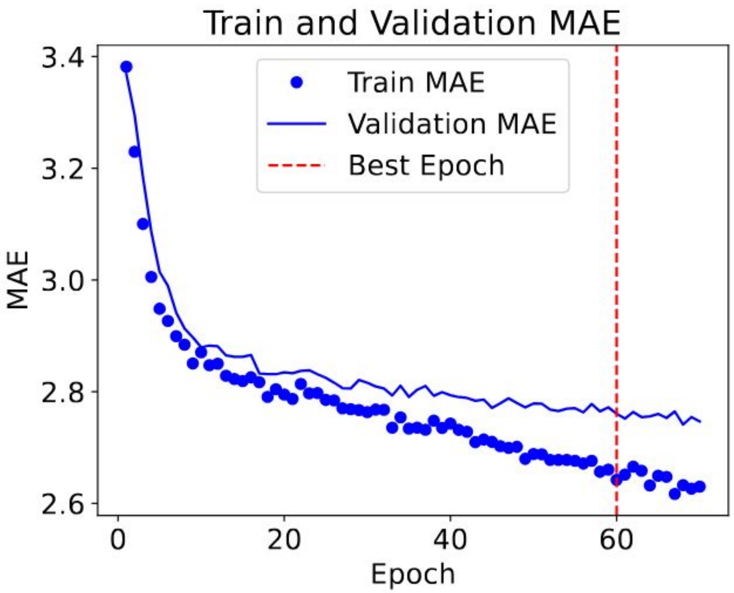
Results

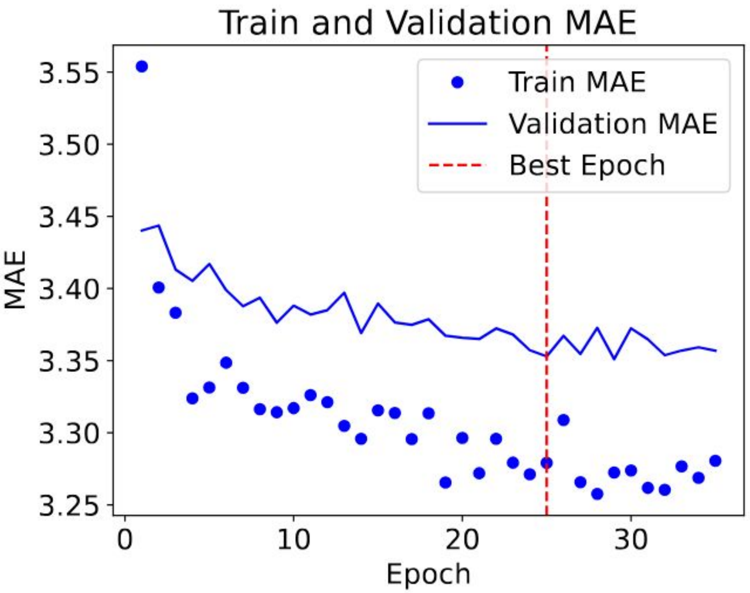
Comparison graph between actual and predicted values from de best execution of LSTM-RD with preprocessed data:



Results

Graphs of training and validation MAE from the LSTM-RD with preprocessed data, and from LSTM-RDD with raw data:





Conclusions and Final Considerations

- There are neural network techniques capable of predicting wind speed and direction with the presented scope
- A model to get future wind data is proposed for integration into the Portuguese man-of-war prediction system
- The importance of preprocessing techniques was observed
- Hyperparameters and architectural configurations were explored
- This work is expected to contribute to the use of neural networks for wind prediction, as well as for related problems such as the movement of the Portuguese man-of-war

Thank you!

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Questions?

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https://github.com/RESMA-PPGINF-UFPR-CAPES-PRINT

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Figuras:

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