

Time Series Forecasting

USING LSTM

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OVERVIEW

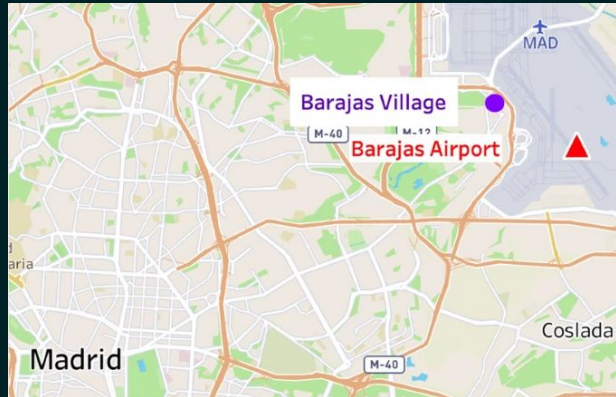
1. Introduction
2. State of the Art
3. Methodology
 - Data analysis
 - Models and optimizations
4. Experiments
5. Results
6. Discussion
7. Conclusions
8. References

INTRODUCTION

- Accurate daily weather prediction model using LSTM networks.
- Relevant for sectors like agriculture and urban planning.

STATE OF THE ART

Modelling time series with multiple seasonalities: an application to hourly NO pollution levels (by M. Avila, A. Alonso & D. Peña) [1]



Air quality station in Barajas, Madrid

STATE OF THE ART

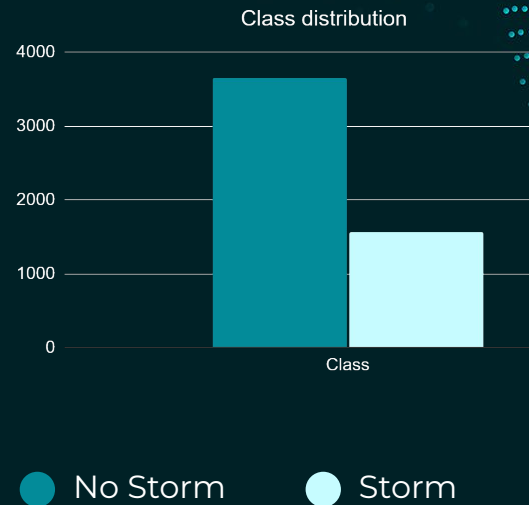
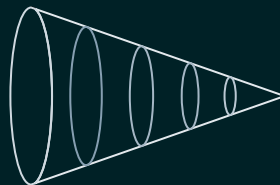
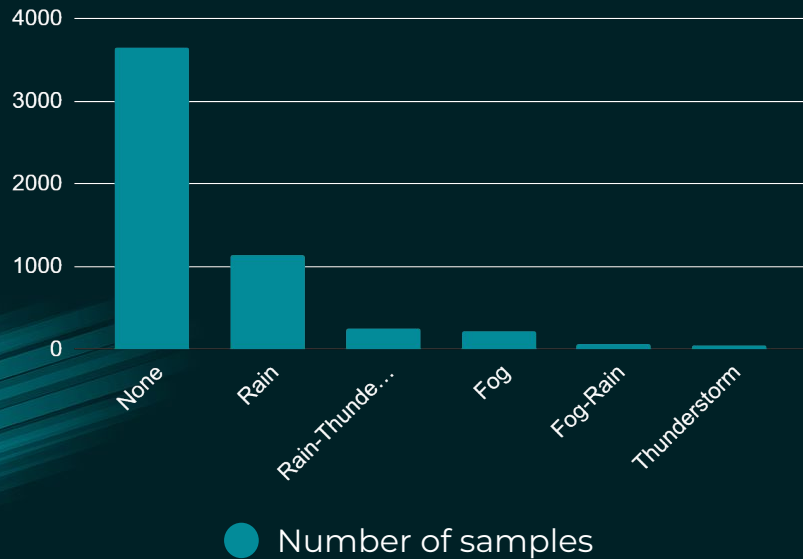
Spatio-temporal Stacked LSTM for temperature Prediction in Weather Forecasting (by Z. Karevan & J.A.K. Suykens) [2]



Map of weather stations in Belgium and Netherlands

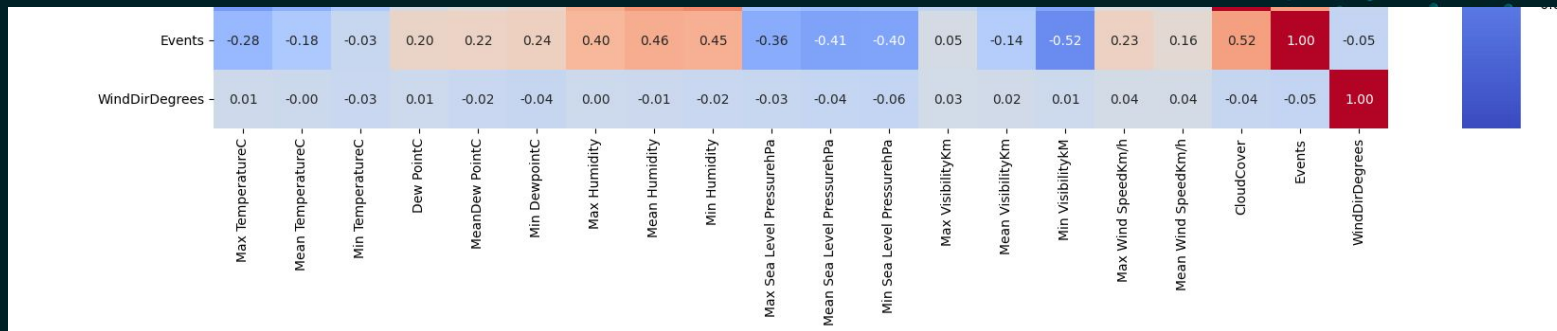
DATA ANALYSIS

Cleaning events label:

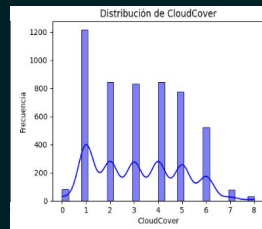
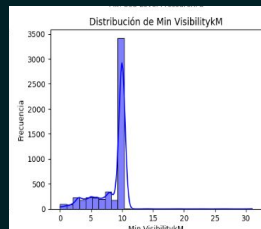
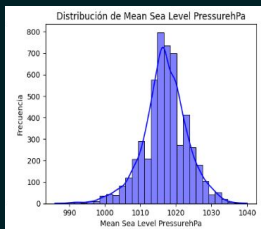
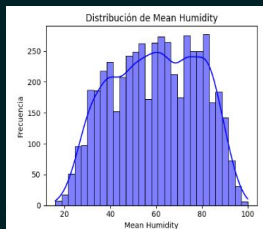
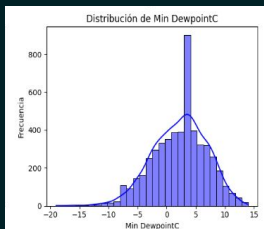
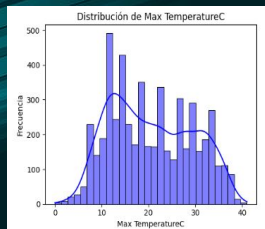


DATA ANALYSIS

Deciding the features:



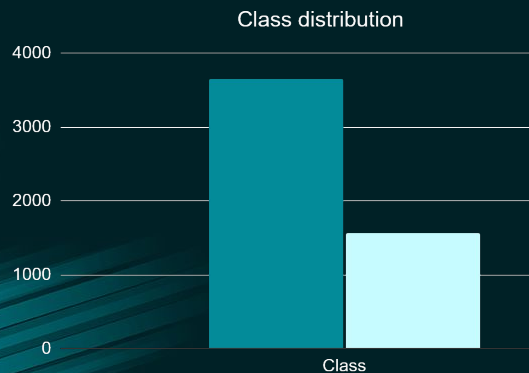
Part of correlation matrix



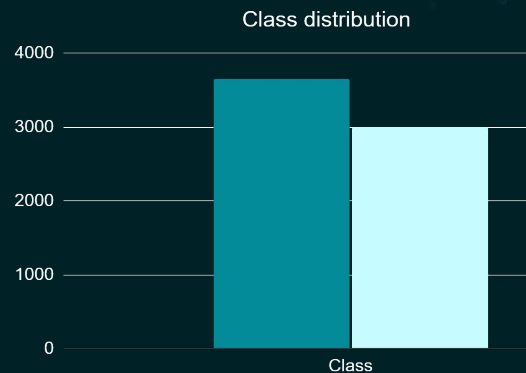
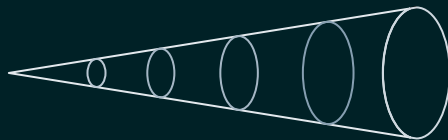
Distribution of features that have high correlation with Events

DATA ANALYSIS

Data augmentation:



● No Storm ● Storm



● No Storm ● Storm

MODELS AND OPTIMIZATION



Architecture

We implemented a LSTM architecture



Training procedures

Supervised training using Adam optimizer with backpropagation over multiple epochs



Loss functions

We used the binary cross entropy function



Hyperparameters

Hyperparameters include input size, hidden size and number of layers

EXPERIMENTS

- Cross Entropy vs Binary Cross Entropy
- Giving importance to recall
- Other metrics: loss, accuracy, precision, auc-roc

		Predicted	
		0	1
Actual	0	TN	FP
	1	FN	TP

Example of confusion matrix

$$Precision = \frac{TP}{TP + FP}$$
$$Recall = \frac{TP}{TP + FN}$$

Computation of precision and recall

RESULTS

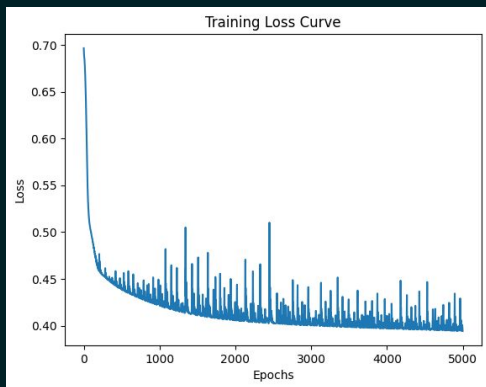
Hidden size	Number of layers	Test loss	Test accuracy	Test recall
32	1	0.4275	80.39%	77.33%
64	1	0.4033	81.74%	80.33%
128	1	0.4008	81.22%	75.67%
32	2	0.4208	81.67%	79.67%
64	2	0.4019	82.12%	79.33%
128	2	0.3953	81.44%	81.83%

Test results of the model with different hyperparameters

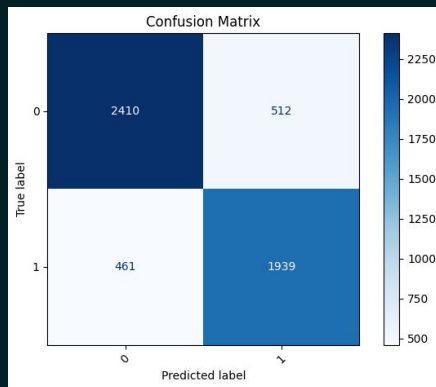
RESULTS

Training results of LSTM with HS = 128 & L = 2:

Loss	Accuracy	Precision	Recall	AUC-ROC
0.3949	81.72%	79.11%	80.79%	90.04%



Training Loss Curve



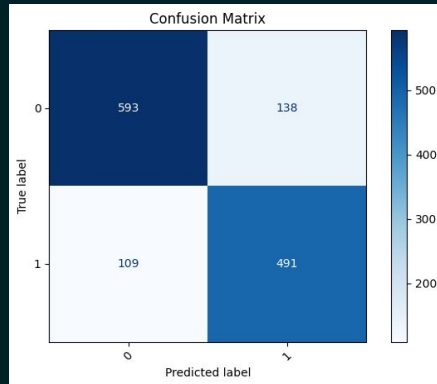
Training Confusion matrix

Loss, accuracy, precision, recall and AUC-ROC of training set

RESULTS

Testing results of LSTM with HS = 128 & L = 2:

Loss	Accuracy	Precision	Recall	AUC-ROC
0.3953	81.44%	78.06%	81.83%	90.11%



Testing Confusion matrix

Loss, accuracy, precision, recall and AUC-ROC of testing set

DISCUSSION

- Increasing hidden size (32 \rightarrow 64) improved accuracy, recall, and reduced loss
- More layers (1 \rightarrow 2) led to better recall and lower loss in most cases
- Best model: 2 layers, 128 hidden units
- Limitations:
 - Larger models didn't always outperform simpler ones
 - Limited size of the dataset

CONCLUSION

- Main findings:
 - LSTM work for time series forecasting
 - Higher complexity usually leads to better performance
 - Importance of cleaning and prepare data
- Challenge: Balancing complexity vs. generalization
- Possible improvements:
 - Try different activation functions (tanh, ReLU, ...)
 - Test on more and better datasets to validate generalization

REFERENCES

- [1] Avila, Matias & Alonso, Andres & Peña, Daniel. (2023). Modelling multiple seasonalities with ARIMA: Forecasting Madrid NO2 hourly pollution levels. <https://doi.org/10.1007/s00477-025-02958-6>
- [2] Karevan, Z., & Suykens, J. A. K. (2018). Spatio-temporal stacked LSTM for temperature prediction in weather forecasting. arXiv. <https://doi.org/10.48550/arXiv.1811.06341>

THANKS!

Do you have any questions?

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