Department of Computer Science

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Detecting Tropical Cyclones using Deep Learning Techniques

Daniel Galea | Bryan Lawrence | Julian Kunkel

Abstract

A Deep Learning model that is intended to detect the presence of tropical cyclones in weather data is being presented. Tropical cyclones are events which have massive effects, and so it is important to understand how their location, frequency and structure might change in future climate. Answering such questions requires the analysis of vast amounts of data, so there is value in being able to identify the presence or absence of tropical cyclones, so that appropriate analysis can be made, potentially even avoiding the need to save the data for further analysis. A data filtration method could be used for this purpose. The first step in building such a filtration method is to develop a suitable Deep Learning model. The model was trained on ERA-Interim reanalysis data from 1979 to 2017 and achieved an accuracy of 94.28% when used on the two subsequent years.

Data

The model being presented was trained on ERA-Interim data [1] from January 1979 until July 2017 and tested on data from July 2017 until August 2019. Each timestep from ERA-Interim was split into 16 overlapping regions that covered the 60ºN-60ºS band around the world. In total, there were 901888 cases in the training set, of which 45180 (5.01%) were positive, and 48704 cases in the testing set, of which 2401 (4.93%) were positive. A case was positively labelled if a TC centre, which was obtained from the IBTrACS dataset [2, 3], is inside the region. The input fields from the ERA-Interim dataset used as inputs to the model were the 10-metre wind speed, mean sea level pressure (MSLP) and vorticity at 850hPa, 700hPa and 600hPa and each had their resolution lessened by a factor of 9.

Deep Learning Model

The model presented takes in input which has been standardized. This input is passed through three blocks of layers. Each block uses a 2D convolution layer, followed a Batch Normalization layer, proceeded by a 2D MaxPooling layer and finishes off with a Dropout layer. Each layer uses the ELU activation function and the He Normal weight initialization method as well as a dropout rate of 0.3. The convolution layers each use a 2x2 kernel, a stride length of 1 and have 4, 8 and 16 filters respectively.

This convolutional base is flattened and attached to a fully-connected classifier made up of one hidden layer and an output layer. The hidden layer has 64 nodes and it also uses the ELU activation function and the He Normal weight initialization method. The output layer has one node which is activated with a sigmoid function.

Results

The model developed was tested on data spanning from July 2017 until August 2019 and obtained an accuracy of 94.28%. Out of 46303 negative cases, 44344 were correctly classified while 1575 out of 2401 positive cases were correctly classified.

		Predicted	
		Positive	Negative
Ground Truth	Positive	1575	826
	Negative	1959	44344

Model Performance across Regions

The model presented performs better on cases that originate in the Southern Hemisphere, with all of the regions achieving an accuracy of 94.55% or higher. On the other hand, half of the regions in the Northern Hemisphere obtained an accuracy of less than 90%, with the region bound by 135ºE-225ºE obtaining an accuracy of 79.83%.

Performance by Hurricane categories

The model was found to struggle with correctly classifying cases with weak TCs. To help quantify this, the cases which had a TC present were split by the maximum category of TC present in the case. Then, the metric of recall, was used to check how well each category was classified. An upward trend of recall with maximum category was found which shows that TCs of higher categories are being identified better than TCs of lower categories, which is as expected, as higher category TCs have features which are more easily identifiable.

Conclusions and Future Work

A Deep Learning model that is aimed at being capable of detecting the presence or absence of tropical cyclones in weather data has been presented. The model has an accuracy of 94.28% on test data compiled. Future work includes implementing the developed model into the UK Met Office's United Model and continuing to improve the Deep Learning model.

References

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3. "International Best Track Archive for Climate Stewardship (IBTrACS) Project, Version 4."

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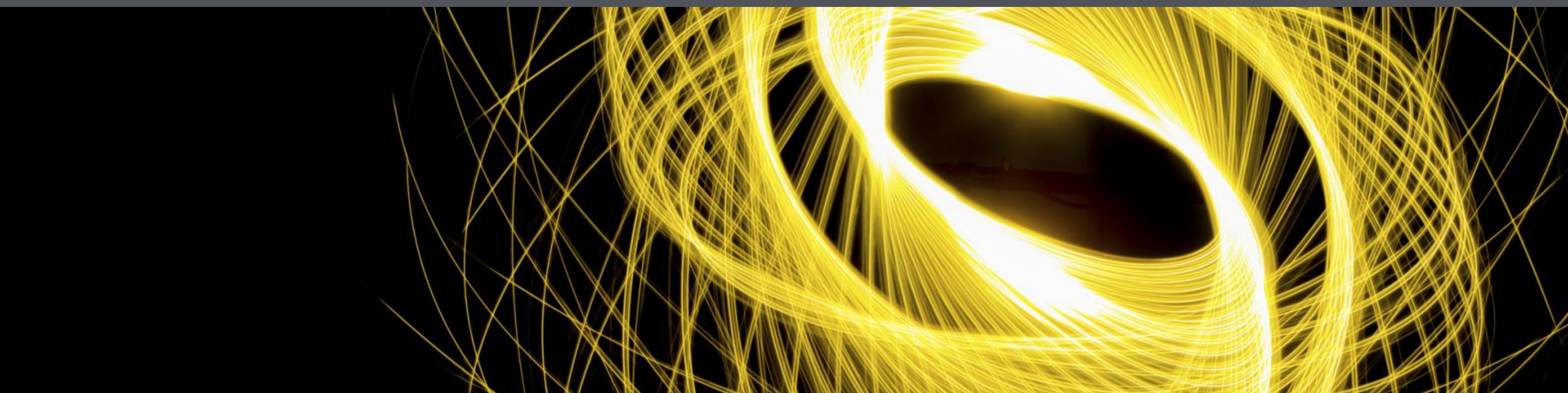

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Introduction and Aims

- Tropical Cyclones are events that leave devastating effects
- The effects of a changing climate on TCs are being investigated by long General Circulation Model (GCM) simulations
- Each simulation produces large amounts of data which can be inefficient to store and analyse
- The first step to reducing the amount of data is to create a filtration method, which is what is going to be presented.

Data

- ERA-Interim reanalyses dataset
- Each timestep split into 16 overlapping regions
- Training Set: January 1979 – June 2017 (910888 cases)
- Testing Set: July 2017 – August 2019 (48704 cases)
- Fields used: 10m wind speed; MSLP; Vorticity at 850hPa, 700hPa, 600hPa at a resolution of 2.1^{o} (a ninth of the original resolution)
- Labels obtained from the IBTrACS database

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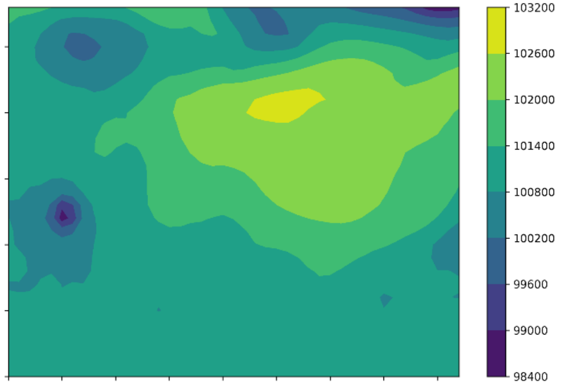
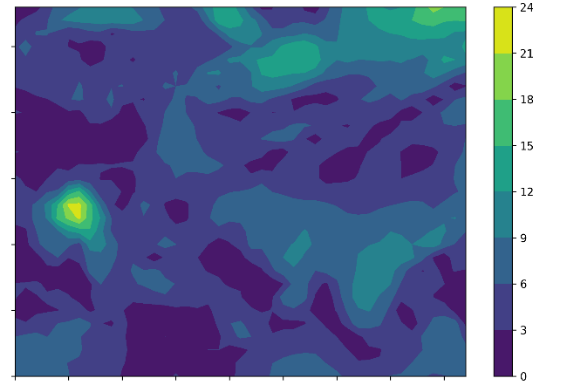
MSLP

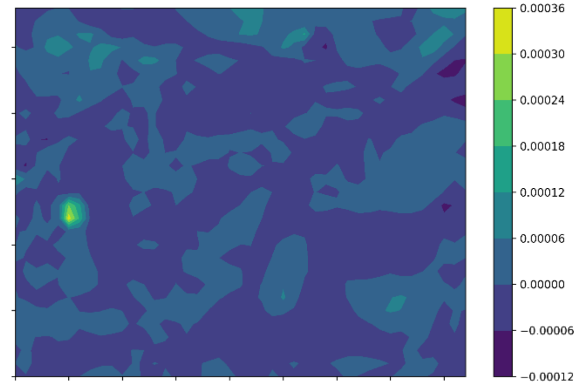


10m wind speed

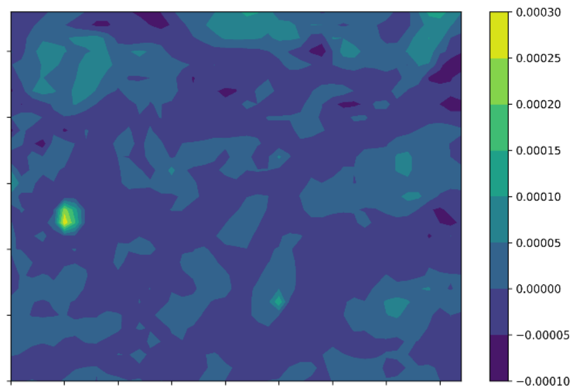


Vorticity at 850 hPa

Vorticity at 700 hPa



Vorticity at 600 hPa



Deep Learning Model

- The model presented was optimized to the use case of classifying whether an input of weather data has a TC present
- The optimizations tested included using:
  - different weight initialization methods and activation functions
  - early stopping to avoid overfitting
  - various methods of data augmentation
  - a tuned architecture (number of nodes and layers)
  - tuned values for the batch size and the dropout rate

Layer (type)	Layer (specification)
Input	
Conv2D	He Normal Weight Initialization; ELU; Stride = 1
BatchNormalization	
MaxPooling 2D	Stride = 1
Dropout	Dropout = 0.3
Conv2D	He Normal Weight Initialization; ELU; Stride = 1
BatchNormalization	
MaxPooling 2D	Stride = 1
Dropout	Dropout = 0.3
Conv2D	He Normal Weight Initialization; ELU; Stride = 1
BatchNormalization	
MaxPooling 2D	Stride = 1
Dropout	Dropout = 0.3
Flatten	
Dense	He Normal Weight Initialization; ELU; 64 nodes
Dense	He Normal Weight Initialization; Sigmoid; 1 node

Results

- An accuracy of 94.28% was obtained when testing on data from July 2017 until August 2019
- 1575 out of 2401 (65.6%) of positive cases were correctly classified

		Identified	
		TC Present	TC Not Present
Ground Truth	TC Present	1575	826
	TC Not Present	1959	44344

Results: TC Category

- The cases which had a TC present were split by the maximum category of TC, as given by IBTrACS according to the Saffir-Simpson scale, present in the case
- The metric of recall, was used to check how well each category was classified
- Recall can be defined as the percentage of positive cases correctly classified

Results: TC Category

Category	Recall
1	53.41%
2	65.15%
3	73.66%
4	75.18%
5	88.89%

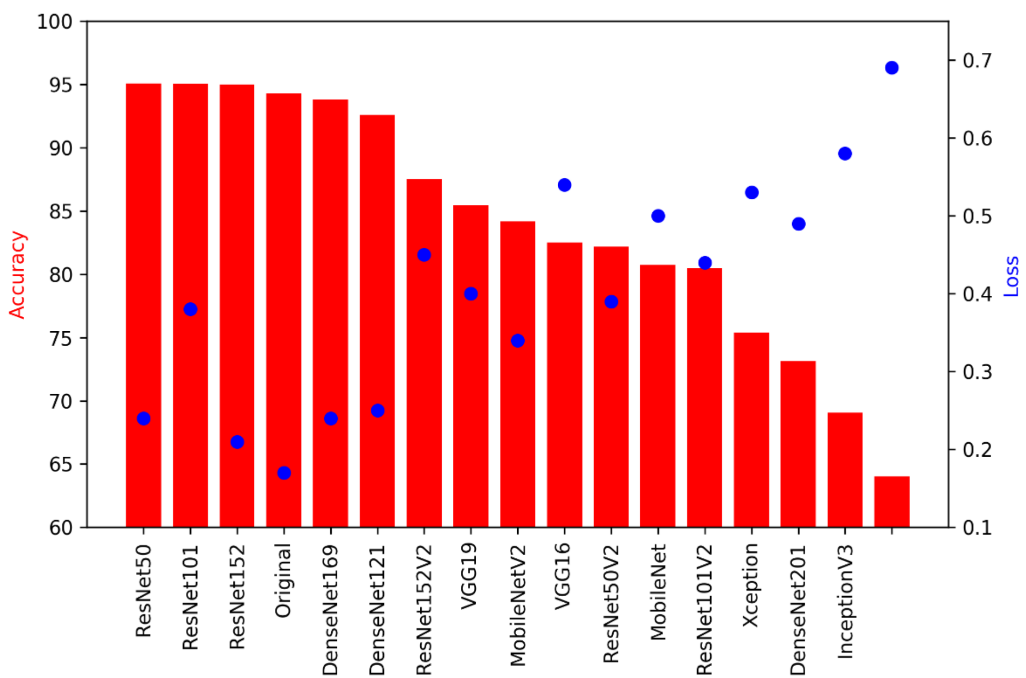
- This upward trend of recall with maximum category shows that TCs of higher categories are being identified better they have features which are more easily identifiable

Results: Model Generalization

- The Deep Learning model performs better on Southern Hemisphere cases, with the worst performing region obtaining a 94.55% accuracy
- The worst performing Northern Hemisphere region is the region bounded by 135ºE and 225ºE with an accuracy of 79.83%

Results: Standard Models

- The model developed was compared with some standard models. It did not obtain the best accuracy, but did get the best loss

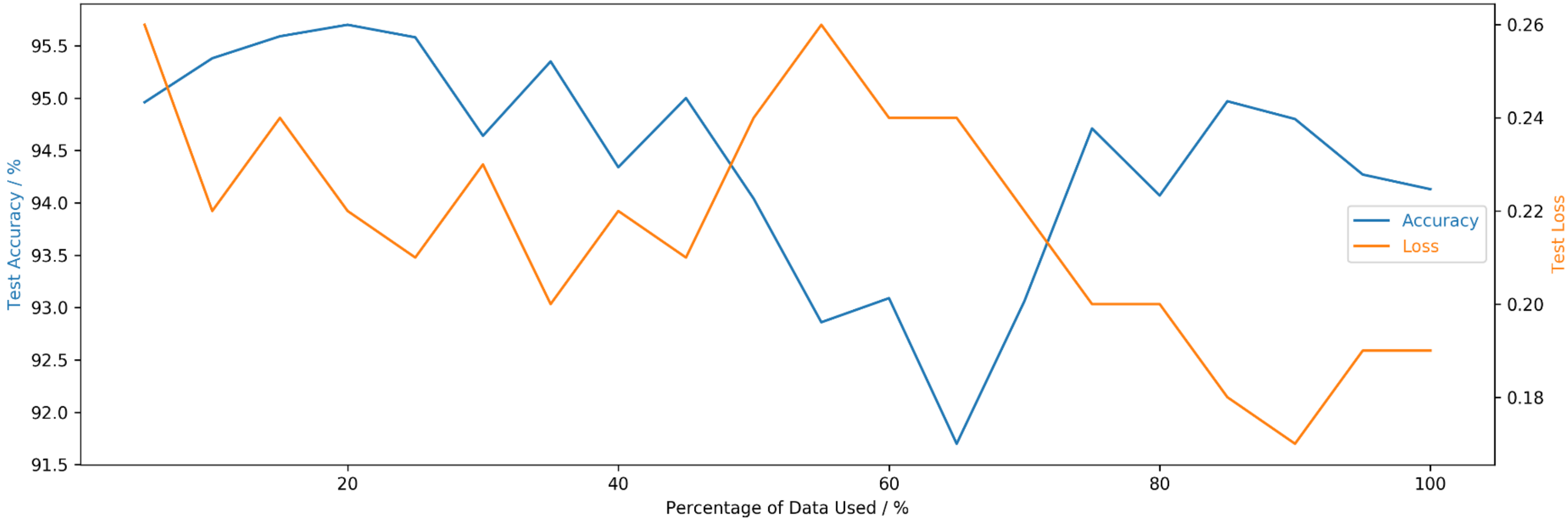


Results: Effect of non-TC storms

- It was thought that storms on non-TC strength could hinder the model's performance
- The model was retrained on the same dataset but cases with storms of non-TC strength, which are negative cases were excluded
- When this model was tested on the test dataset, it obtained an accuracy of 92.80%, showing that the inclusion of such storms are important to the model's performance

Results: Size of Dataset

- The effect of the size of the training dataset was queried
- The graph below shows how test accuracy and loss varied with varying sizes of training data.
- Not a lot of variability is seen, so this effect is minimal



Conclusions and Future Work

- A Deep Learning model aimed at detecting the presence or absence of a Tropical Cyclone in weather data has been presented
- It achieved a 94.28% accuracy on a test set spanning from July 2017 until August 2019
- The next step is to implement this model into the UK Met Office's Unified Model (MetUM) for it to act as a data filtration method that can work during the MetUM's execution, rather than after

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