Hurricane Trajectory Monitoring using Long-Short Term Memory (LSTM) Networks

1. Introduction

Hurricane is one of the most devastating natural hazards which is causing significant loss of property and human life. With prevalent climate change and variability scenarios, its frequency and severity are becoming severe. Identification of its inception, understanding of contributing and aggravating factors, monitoring its future trajectory is very relevant to reduce loss and damage associated with hurricanes by establishing early warning systems. With the advent of weather monitoring systems and the high-edge development of geosynchronous weather observation satellites, hurricanes can be sensed from space. Though this kind of sensing and monitoring can provide the current status of the event, there is still high demand to undertake short and mid-level temporal prediction and trajectory forecast. In this regard, some studies tried to predict future hurricane trajectories from historical time series data using deep learning approaches (Alemany, Beltran, Perez, & Ganzfried, 2019; Giffard-roisin et al., 2018). Similar to these works, this project is undertaken to demonstrate the potential of Long-Short Term Memory (LSTM) (Hochreiter & Schmidhuber, 1997) to predict future hurricane trajectories(locations) 6 hours ahead given the last 18 hours of historical data (3 observations with 6-hour interval).

2. Methods

2.1. Data and preprocessing

The provided data for this assignment is obtained from National Hurricane Center (https://www.nhc.noaa.gov/data/). Before directly ingesting the data into the model, firstly a large number of records with complete missing values of some hurricane attributes was excluded from further analysis. Following that, still there are almost 80 rows that have some missing values. As these values were not from consecutive observations, the missing values were filed by average values of the attributes only taken from specific hurricanes using unique hurricane ID. Then Latitude and Longitude values provided as string value with hemispherical information is converted to respective numeric value where Latitude and Longitude values with "**S**" and "**W**" tag were first converted from alphanumeric to numeric values by dropping the tags and further multiplied by -1 where it is converted to a negative float value. Then the values were also visually checked from a spatial trajectory plot (Figure 1)

Similarly, the date information which is provided with Year, Month, and Day of the Month (YYMMDD) format is converted to Day of the Year (DOY) format which is cyclic and can also serve as a surrogate for season (climatic) condition of the location. The time format is also converted to a valid 24-hour format by dividing the value by 100. The time-series data is also checked if there is acute autocorrelation of predictor variables. As can be seen from Figure 3, there are two variables (Minimum pressure and Minimum wind) that have a high negative correlation. Given the two variables are very important for hurricane monitoring, it is opted to keep both in further analysis.

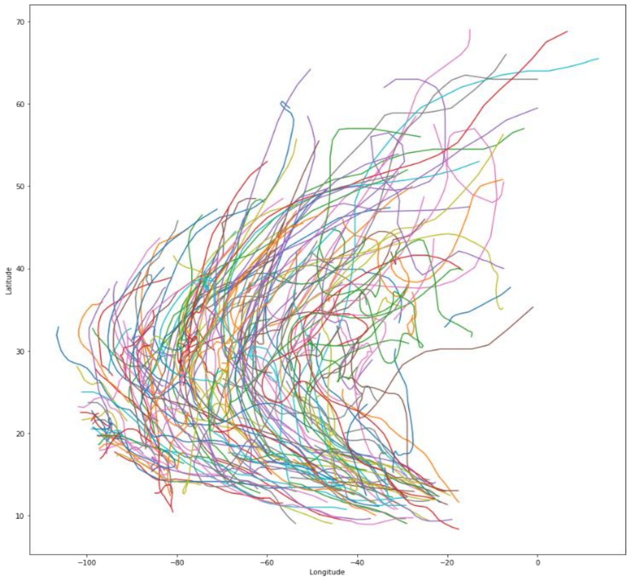

Figure 1: Hurricane trajectory spatial plots

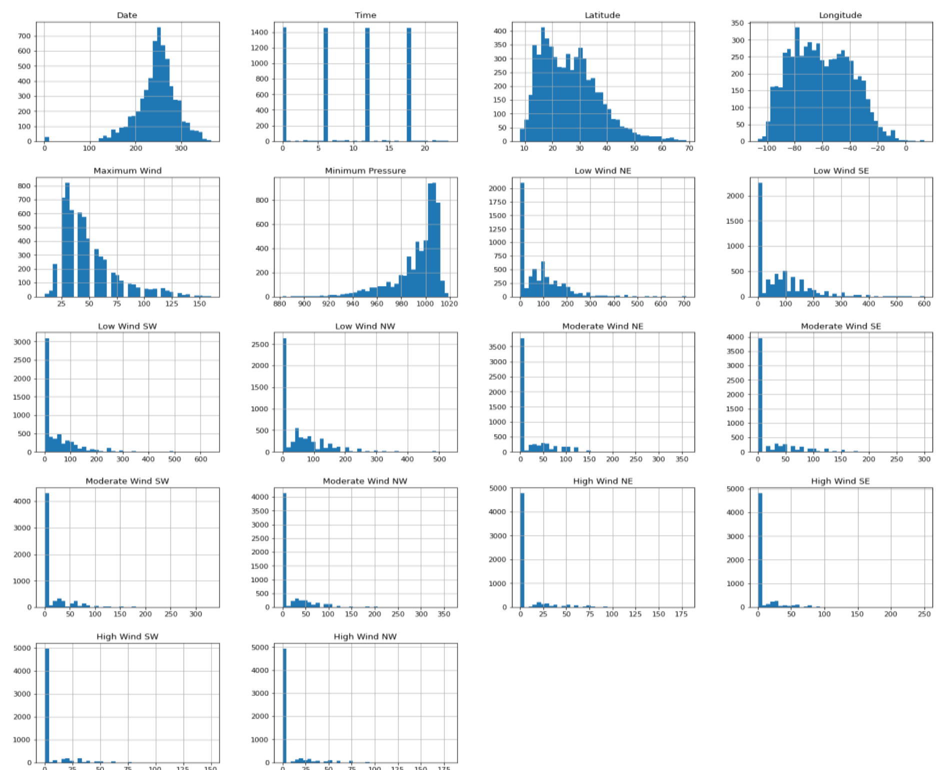

Figure 2: Histogram plots of all numeric attributes

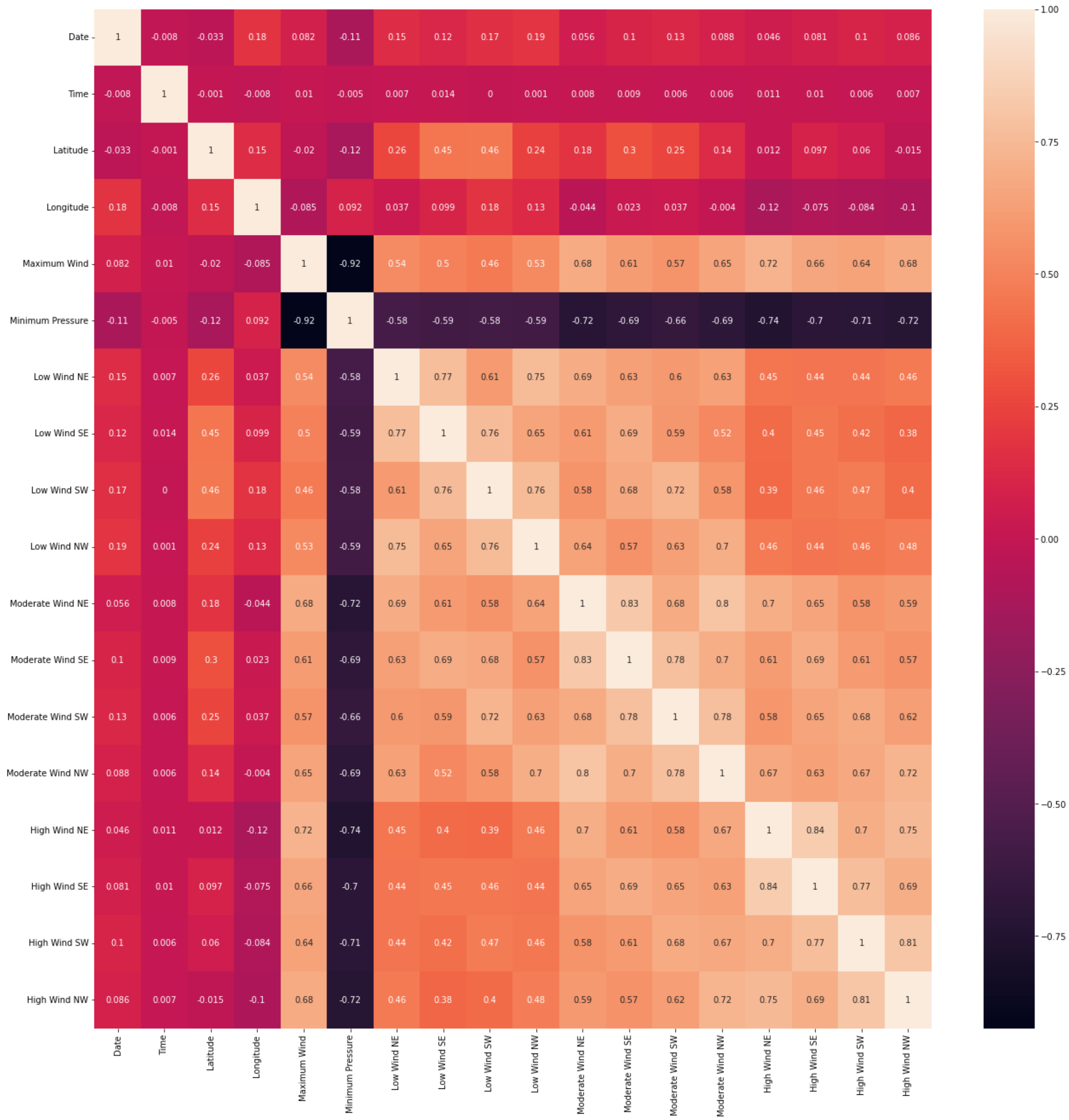

Figure 3: 2-D correlation matrix plot for all numeric attributes

The data is then partitioned into training and testing sets. After preprocessing and removing observations with missing values, the provided hurricane data is not large enough to model this complex phenomenon. Therefore, allocating a large amount of validation and test data will reduce the data used to train the model. As a strategy to overcome this problem, as the role of the validation set is to monitor the model training process and undertake some interventions on the flight, validation data is merged with the training set. It should be noted this strategy is not optimal in case the user has callback strategies depending on validation data like early stopping and learning rate modifications. For training 195 hurricane trajectories were used while testing purposes, randomly selected 3 hurricane trajectories were allocated.

Then time series observation of each unique hurricane is converted into a time series sequence order of [$\boldsymbol{B}$, $\boldsymbol{T}, \boldsymbol{A}$] where B is the number of batches (sequences with a specific time window, T is a time window used, and A is the number of predictor variables (attributes) in each time window. Here it should be noted that sometimes the connotation of T is a bit confusing and it does not always indicate the actual time gap between consecutive observations. For example, for this project, the main intention is to predict the next 6 hours of hurricane location given the last 18 hours of observation. Provided data is observed every 6 hours that the window is 3. As hurricane trajectory location is considered as a sequence to sequence prediction problem, for a specific hurricane with observations $t_0, t_1, t_2, \ldots t_n$, when all features from $t_0\colon T_{0+w}$ are used as features while an observation at a time t_{0+w+1} can be used as a label where w is equal to T. An exemplary visual description (Figure 4) is provided for sequence preparation with a time window equal to 4. After preparation and conversion of long time series into segments, training set with feature dimension of **[5056, 3, 18]** and labels with a size of **[5056, 2]** is obtained.

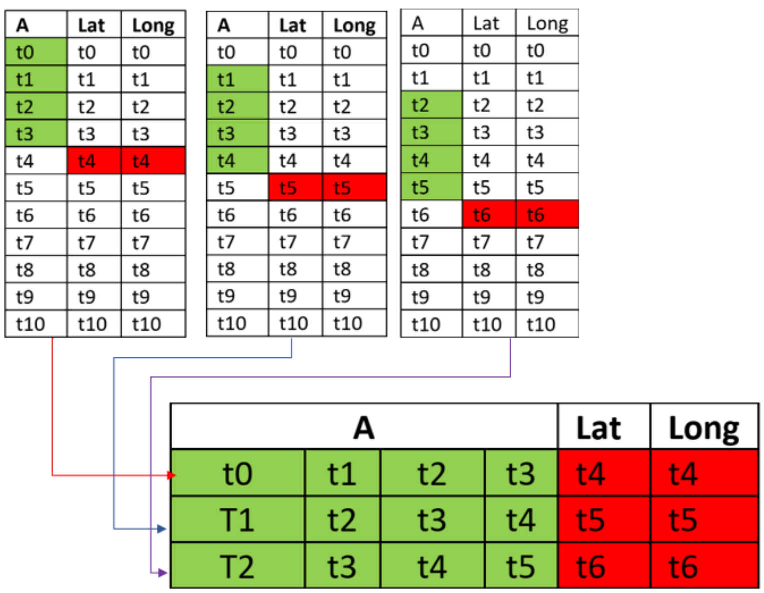

Figure 4: Input data arrangement strategy for LSTM model (time window 4 is taken as an example)

2.2. Model and training strategy

LSTM model with 8 layers is designed (Table 1). The final dense layer has two units, as the prediction is for both Latitude and Longitude values simultaneously. Batch normalization and dropout layers are used to reduce the overfitting of the model during the training phase. The overall model optimization is done using Root Mean Squared Propagation (MSprop) optimizer (Mukkamala & Hein, 2017), with a learning rate of 0.0001 and momentum of 0.9 together with a Mean Square Error as loss function. The model is converging well after 400 epochs. The model has a total of 8,152,194 parameters of which 8,148,194 are trainable and 4,000 are not trainable. Prediction outputs from the model are quantitatively evaluated using Mean Absolute

Error (MAE) and qualitatively by comparing trajectory paths in a 2-D spatial plot. The overall data processing was done using python 3.9 with TensorFlow and Keras version 2.5 with a windows server computer equipped with NVIDIA GPU A100 graphic card.

Table 1: Description of model design

Layer ID	Layer name	Number of units	Number of parameters
1	Bidirectional LSTM	500	2076000
2	Batch normalization	-	4000
3	Bidirectional LSTM	500	6004000
4	Batch normalization	-	4000
5	Dropout(rate=0.2)	-	0
6	Dense	64	64064
7	Dropout (rate=0.2)	-	0
8	Dense	2	130

3. Results and discussion

As indicated in Table 2, for three randomly selected unique hurricane trajectories, the model has achieved a good Mean Absolute Error which ranges from 1.0 to 1.8 which varies based on hurricane types. These results are indicative of the possibility of predicting the probable hurricane locations within the coming 6 hours given the previous 18 hours of historical observation with a spatial accuracy of almost 110 kilometers range[1]. The results are also in good agreement with results reported in (Giffard-roisin et al., 2018) extended study that has compared many models. In contrast to this, compared to the findings of (Alemany et al., 2019), the model has underperformed with big margins.

Table 2: Accuracy performance of the LSTM model for randomly selected hurricane trajectories

Hurricane name	Hurricane Unique ID	MAE
IRENE	AL092005	1.05
EMILY	AL052005	1.88
IKE	AL092008	1.84

As indicated on spatial plots (Figure 5) the model has the skill of predicting hurricane trajectories almost resembling the shape of observed historical hurricane trajectories. Except at some segments, the trajectories are almost the same.

[1] *This is mainly in equator but in northern high latitudes it will be even lower than this value*

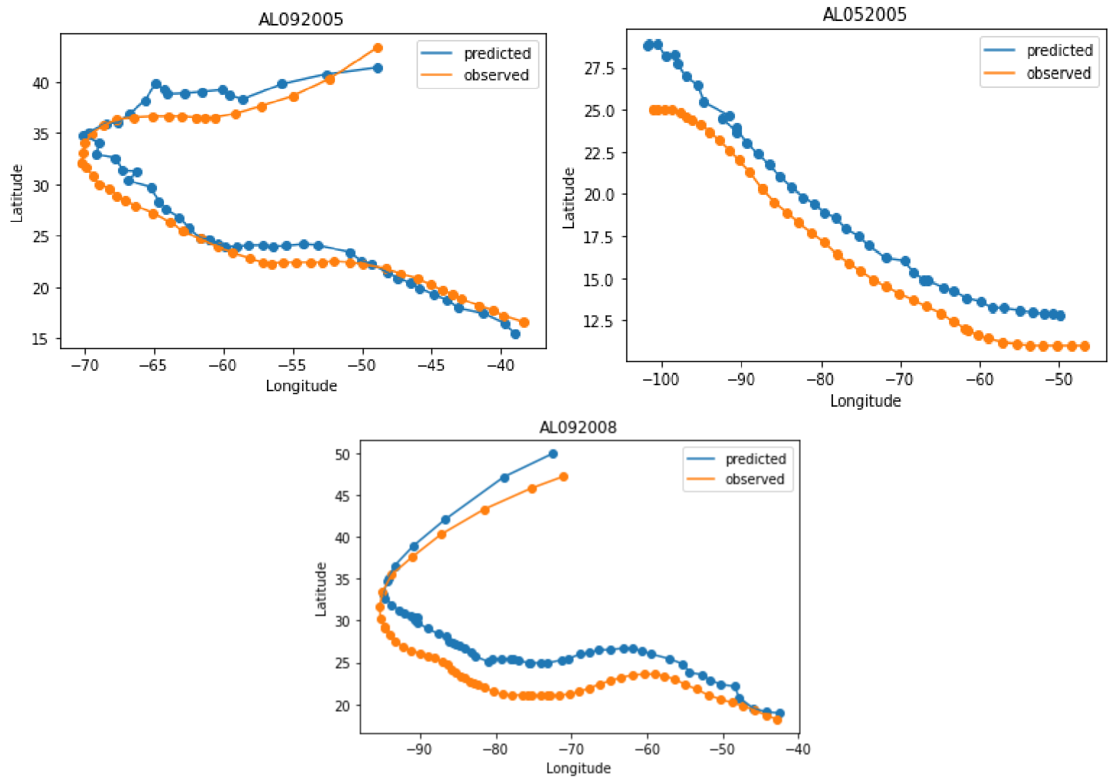

Figure 5: Predicted and observed hurricane trajectories

4. Conclusions and further remark

The tested LSTM model has provided reasonable prediction results for hurricane trajectory monitoring. With this general finding, the following remarks were made. The model could be even further improved if the attribute "**Status**" would be included after cautious conversion to numeric severity status of the hurricane. The performance of the model should also be tested with dense observations from other observatories.

References

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