A Novel Approach for Predicting the Tropical Storm Trajectories using Grid-based Recurrent Neural Networks

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A Novel Approach for Predicting the Tropical Storm Trajectories using Grid-based Recurrent Neural Networks

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Abstract

Tropical storms have wreaked havoc in the past on humanity and pose a great threat to disrupt the civilizations in future considering rapid global warming. Different statistical forecasting algorithms have slowly evolved over the past decades to mitigate this problem, but precise prediction still continues to be a difficult task. The present study proposes the novel approach for prediction of storm trajectory by implementing Grid-based recurrent neural networks model. LSTM and BiLSTM models are implemented and compared in this research as they perform better for sequence data inputs. The models are applied on HURDAT2 dataset by National Hurricane Center (NHC). Grid points are generated using latitude and longitude features and integrated with the neural networks. The research improves the previously applied LSTM model and also implements BiLSTM model which outperforms LSTM model with accuracy of 74%. With this model, the storm trajectory can be predicted well in advance which can save human lives and property damage. Storm prediction centers across the coastal regions will benefit from this analysis to provide reliable results for storm tracking.

Keywords — Tropical Storm Trajectory, Climatology, Recurrent Neural Networks, Long Short-Term Memory, Deep learning, BiLSTM

1 Introduction

Tropical cyclones are severe climatic events due to their ability for massive effects in the coastline regions. Uncertain storm formations leads to unusual and dynamic phenomenon of heavy winds affecting a low-pressure regions. (Giffard-Roisin *et al.*, 2020)(Mercer and Grimes, 2017). The ability to predict its progression is critical to save human lives and property. Considering the severity of the tropical cyclones, traditional models have failed to predict the complex atmospheric attributes which controls the storm trajectories accurately. Multiple countries experience billion dollar damages owing to severe weather incidents (Gagne *et al.*, 2017) which makes the problem of prediction of the tropical storm track essential. In other terms, predicting the storm trajectory has a vital role to play in various country's disaster control centers.

At present, deep learning has grown into a very significant prerequisite in various industries especially in the field of climatology where storm intensity, trajectories or other extreme weather events can be forecasted using various artificial neural network (ANN) models(Kurniawan, Usman and Fuadah, 2019).There are already numerous systems in place to assess the tracks of the storm but they are either sluggish or very costly(Cloud *et al.*, 2019)(Sahoo and Bhaskaran, 2019)(Salman, Grover and Shankar, 2018). In addition to these conventional methods, scientists have also developed machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM) to predict trajectories of storms but it still lacks the faster processing and accuracy. On the other hand, Artificial neural network models have proven to be effective in providing accurate results over time, and can address complicated non-linear data problems better than other approaches(Kurniawan, Usman and Fuadah, 2019). Recurrent Neural Networks (RNN) are one of the types of artificial neural which are being used widely in recent times to predict the complex systems. In RNN, weight modification enables the model to develop complex hierarchical sequential actions which leads to optimized modelling(Alemany *et al.*, 2019). As multiple researchers have successfully utilized RNN and demonstrated its advantages over other models, this work proposes Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) models which are expanded RNNs, for prediction of storm trajectory

Although there are various experiments on prediction of storm paths using recurrent neural networks, this is the novel approach where bidirectional long short-term memory (BiLSTM) and long short-term memory (LSTM) models are utilized using Grid-based architecture to build a fully connected network. Although LSTM model is discussed in the work by (Alemany *et al.*, 2019), the paper presents improved LSTM over the existing model. The new approach can model tropical storm trajectories more reliably compared with conventional methods of forecasting used by hurricane centers in USA. Storm track data[1] provided by National Hurricane Center (NHC) is utilized for this work. The data consists of key storm parameters like windspeed, pressure, intensity levels, latitude and longitude which ranges from 1851 to 2015. The training and testing set is derived from these parameters. The grid model is based on latitude and longitude parameters where multiple grid points are created to track the storm movement. Once the grid model is developed, the features of trained data are scaled and reshaped for recurrent neural network input. The final models are compared using mean squared error, r-sqaured value and mean absolute errors

The research focuses on answering the question *"How efficiently integration of grid model and recurrent neural networks would help in predicting storm trajectories in the region?"* by implementing LSTM models. Both the models are compared in order to determine which model is predicting the tropical storm track accurately. It weighs on below list of objectives:

- Perform a critical review of previous researches on storm tracking and examine the difficulties and drawbacks in predicting storm trajectories.
- Design and implement grid-based LSTM and BiLSTM models with superior performance
- Test and evaluate the models with multiple evaluation techniques

Rest of the document is organized in following sequence. The next section focuses on investigating literature work carried out on prediction of tropical storm or extreme weather events. Methodology of the research is explained in section 3 whereas the design is discussed in section 4. The methodology and design provide detailed information on data selection, data preprocessing, data mining methods. The design is implemented in section 5 where all the steps carried out for implementing BiLSTM and LSTM model is documented. Section 6 discusses the comparison of the models with experiment results and evaluation techniques. The final section deals with conclusion and future work for this work.

[1] https://www.kaggle.com/noaa/hurricane-database

2 Related Work

In the past, there have been multiple researches on analysing how the storm is impacting human lives and infrastructures. Many scholars have tried to predict the storm tracks and storm intensity using machine learning and deep learning models. However, machine learning models has few downsides like poor prediction skills and slower computational performance. On the other hand, the deep learning techniques have illustrated better performance and have proved cost effective. This section discusses the research carried out by various authors on storm data

2.1 Deep Learning Methods for Storm Trajectory Prediction

Multiple deep learning techniques are applied previously to estimate the storm tracks. Researchers (Kordmahalleh, Sefidmazgi and Homaifar, 2016) have used the sparse recurrent neural networks (RNN) to forecast the path of the hurricanes in Atlantic region. Before applying the model of pre-processing the data, authors have done the similarity analysis which provides the matching parameters. The dynamics of the neural networks are explained precisely. The network consists of multiple nodes including processing units, context and the recorded information. Furthermore, the research provides overview on crossover, mutation and fitness methods. With this research, the authors have demonstrated how the RNN can be used for one-step ahead or two-step ahead prediction. The sparse neural networks do not have any restrictions on number of neurons or other layers; hence this algorithm is flexible and easy to implement as compared to traditional mathematical models. The algorithm provides good accuracy with mean absolute error ranging between 0.1 to 1

In an another research work, (Alemany *et al.*, 2019) also suggested that RNN can help in predicting hurricane path for up to 120 hours. RNN model is integrated with grid-based model for this study. RNN can process the historical data and provide the weight matrix data efficiently. The paper also discusses the techniques like dropout, Long Short-Term Memory Cell (LSTM) which helps the data model in providing accurate results. The overall results explained by authors suggests that the grid based RNN approach could track the hurricanes with better accuracies, under the assumption that the hurricanes won't travel backwards. Yet, authors have suggested that Bayesian neural networks can provide better results than the applied method in the paper.

Additionally, researchers (Kim *et al.*, 2019) in the study titled 'Deep Hurricane-Tracker' have proposed the Convolutional Long Short-Term Memory (ConvLSTM) model to track the storms+-. It replaces the fully connected layers in LSTM with convolutional layers to provide better results for image or video-based data. Encoding and forecasting structures have been utilized to deploy ConvLSTM design. The input variables while performing the encoding consists of density maps. The forecasting layers then takes the hidden layers for analysing the tracking and estimate the density from all the hidden layers. The CNN models provide better results as the number of layers are increased. Study shows that CNN with 6 layers have performed better that traditional 2-layer architecture. The experiment has yielded the accurate results with up to 30km error for hurricane path. Since CNN utilizes graphical data in order to predict the problem, the algorithm requires advanced system with faster GPU to overcome the memory issues. However, it can be efficient than traditional mathematical models and can be beneficial if the data fed to the model is precise and well processed.

2.2 Recurrent Neural Networks for forecasting Strom intensity

There have been lot of research on storm surge prediction as well in the past. Many of the researchers have applied machine learning as well as deep learning techniques on the storm parameters and compared the models with traditional mathematical models. One such study of storm surge predictions is covered in the research work done by (Kim *et al.*, 2016) where recurrent neural networks (RNN) are used to predict the surge levels for different lag periods. Number of layers in RNN plays significant role in providing accurate predictions, however the study utilizes single layer of input, output and hidden layers along with Levenberg-Marquardt method. The present research works on limitations of this model by introducing robust LSTM along with multiple input layers. Similar technique is applied by authors (Pan, Xu and Shi, 2019) predicts the tropical cyclone intensity using multi-layered RNN and utilizes sequential data processing for various data operations. Authors have designed the algorithm with multiple assumptions, the key assumption being dependency of final predictions on historical data. With multiple layers of input, recurrent neural networks have shown better results than statistical models. However, in some of the scenarios, statistical model has outperformed RNN. The results clearly state that neural networks can be designed in better way as there are still few limitations with suggested methods.

Both the studies (Kim *et al.*, 2016)(Pan, Xu and Shi, 2019) used lag parameters in analysing storm intensities across coastal regions. The lag parameters are derived from time attributes of the storm, for example, the authors here explore how the intensity or surge levels can be predicted for the lag period in the range of 5 to 48 hours. The lag is generated using mathematical equation which depends on previous lag value and it provides a better way to look at the problem of the storm surge from broader perspective. Other parameters like sea-pressure, latitude, longitude, sea-temperature also plays vital role in this analysis. Building the model on lag parameters is one of the best ways for this problem as it can be easily compared with actual implemented mathematical models and even can be effective than the traditional models. Additionally, paper (Fente and Kumar Singh, 2018) uses Long-Short Term Memory (LSTM) model which for prediction of weather events. LSTM model is expansion of RNN model which increases the memory of RNN and enables retention of inputs for larger time span. Number of parameters like precipitation, humidity, pressure, temperature is used to feed the input layer of the LSTM. Final result of the thesis shows that LSTM provides better results than the conventional methods.

2.3 Convolutional Neural Networks for forecasting Strom intensity

Apart from RNN, researchers have also demonstrated other techniques like feed-forward recurrent neural networks (FNN) and convolutional neural networks (CNN) to forecast storms and different weather events. In paper (Sahoo and Bhaskaran, 2019), the Feed-forward neural network is implemented with two hidden layers and on more than 200 variables. In contrast with other works mentioned above, the study focuses on location parameters such as longitude and latitude in predicting the cyclone along with other attributes like speed of the wind, cyclone angle. Combinations of these parameters are used as inputs to the neural network model. Accuracy of the model is dependent upon number of neurons at each level. The exact number of neurons is difficult to obtain from one experiment. Therefore, multiple iterations are required to figure out it. Methods like trial and error can be the best way as it performs multiple iterations on training data and provides optimal results, the study suggests that 25-30 neurons in each layer can result in better accuracy for FNN. Authors were able to achieve the accuracy score of 99% and 92% for train and test data respectively. However, the accuracy score shows there is a possibility of overfitting of the data which usually is the case with neural networks. There are different ways with authors have utilizes the Feed-forward models. Authors (Cloud *et al.*, 2019) have processed the data using Hurricane research and forecasting (HWRF) model. The mathematical model provides the data attributes which can further be processed using deep learning. This model has multiple time-based observations of the storm and the variables which are selected for the final model are part of archived data. As mentioned earlier, number of neurons are critical for the model and research focuses on carrying out multiple iterations on the train data to find out best possible structure for model. Combination of up to 4000 neurons is tested to find out the optimal number and further validated for lag time of 3 hours. Authors have selected 1300 neurons with one output layer based on the experiment. This research dealt with the problem of overfitting by splitting the details by storm knowledge rather than the single findings. Techniques like amputation and normalization have been used for better outcome. Additionally, it uses cross-validation technique on the data which yields best results for FNN in this case. This shows that the ANN models can produce improved performance with advanced data processing techniques.

Convolutional Neural Networks (CNN) is another deep learning model which is widely used for research studies. (Chen *et al.*, 2019) in their research, demonstrated CNN architecture on satellite-based data to estimate the cyclone intensity. The method adopted in this article is designed for a 24-hour lag time taking into account multiple attributes as model parameters. It also clarified the data processing method for CNN where all the findings are evaluated and the errors measured for each observation. The thesis suggested the usage of pooling approaches as well as the dropout approach to reduce the difficulty of the computations. Similarly, paper (Giffard-Roisin *et al.*, 2020) have developed CNN algorithm for real-time storm forecasting. The model uses the latitude and longitude parameters to illustrate the difference in cyclone locations. As part of the feature selection technique several data sets representing displacement details, characteristics and spatial field knowledge are generated. In both the studies, (Chen *et al.*, 2019)(Giffard-Roisin *et al.*, 2020), CNN has resulted in efficient model with optimal performance. However, for CNN technique, the position encoding and object orientation is difficult to achieve. Hence, the final evaluation is dependant on whatever data input is provided for the model. CNN also requires large image data sets which can slow down the performance of CPU based machines. Researchers have also utilized CNN model for forecasting the change in weather. In one such article (Scher and Messori, 2018), scholars have presented CNN architecture for error-based forecasting as well as training data based forecasting. Often times, deep learning models can generate biased results and hence authors use data scaling for avoiding bias in the data. The model is evaluated using multiple methods such as Persistence and Local dimension, Nearest Neighbour and Clustering. Using these evaluation methods, article compares two approaches in which the training data-based estimation outperforms the error-based model. Deep learning models have consistently provided optimal performance for image-based data classification and studies mentioned above confirms it further.

2.4 Machine Learning Techniques

Machine learning algorithms have also been explored to address the problem of storm surge level predictions. Algorithms like Support Vector Machine (SVM), Random Forest (RF) have provided optimal performance in some of the studies(Mercer and Grimes, 2017)(Kurniawan, Usman and Fuadah, 2019). Before applying the algorithms, methods like feature selection, bootstrapping, have been incorporated by authors to achieve the normalized train and test data. Cross validation is applied in paper (Mercer and Grimes, 2017) to avoid the overfitting of the data whereas authors (Kurniawan, Usman and Fuadah, 2019) have explored multiple kernel-processes for classifying the data. In addition, paper also discusses the four specific steps which deals with putting the data into matrices and normalizing them for optimal performance of the model. Both articles have concluded that SVM algorithm provides better accuracy than other machine learning models based on multiple evaluations techniques.

Similar to regression, many papers have also discussed classification techniques which classifies cyclones based on different intensity levels. Classifiers like Logistic Regression, Naïve Bayes, K-Nearest Neighbour (KNN), SVM, Decision tree, Random Forest(RF) along with ensemble techniques like AdaBoost have been explored to achieve maximum performance for the problem(Zhang *et al.*, 2019)(Gagne *et al.*, 2017)(Burke *et al.*, 2020)(Czernecki *et al.*, 2019). Authors (Zhang *et al.*, 2019) discusses these models in their thesis and compares all the classifiers to evaluate the best performing model. Evaluation techniques like confusion matrix, Kernel Density Estimation (KDE), F1 score are used to find out the best performing model. AdaBoost with feature selection has provided better results than other models in the research. However, other researchers (Gagne *et al.*, 2017)(Burke *et al.*, 2020)(Czernecki *et al.*, 2019) emphasizes on Random Forest model as their respective studies have demonstrated that RF achieves optimal performance. Model selection is crucial for predicting the accurate outcomes, but along with selecting the right model, understanding the data also is vital for the research. Authors utilizes some of the techniques like grouping, cross validation, random sampling and feature selection to collect information like correlation, skewness, quartile ranges which helps in forming the accurate training attributes for the final model(Gagne *et al.*, 2017). Researchers have also compared these methods for different climate events such as prediction of sand storms and storm endurance (Shaiba, Alaashoub and Alzahrani, 2018)(McGovern *et al.*, 2019).

2.5 Analysis of Damage caused by storms

Furthermore, in the past hurricanes or storms have wreaked havoc on human life and economies. Scientists have failed to provide accurate estimation due to inefficient models. However many authors have discussed aftermath of the storm and investigated the failure of storm based conventional models to avoid the damage in future.(Yang *et al.*, 2020)(Labib and Read, 2015). To build outage prediction model (OPM), authors (Yang *et al.*, 2020) grouped RF, Decision tree, BT and ENS techniques into OPM. The performance of the model is measured using matrix and MAPE values. On the other hand, methods Fault Tree Analysis(FTA), Reliability Block Diagram (RBD), Risk Priority Number (RPN) are combined to analyse the damage caused by hurricane Katrina(Labib and Read, 2015). These models have helped in identifying the optimal solution in the risk management domain. Article (Richman *et al.*, 2017) proposes Support Vector Regressor (SVR) algorithm to reduce the errors in estimation of the storm intensity. The data is arranged by ranking as per the year of the storm occurrence which later undergoes kernel testing and wrapper selection technique. The accuracy of SVR is measured using correlation score and Mean Absolute Errors (MAE). In another work carried out by (Barajas, Gobbert and Wang, 2019), the performance of existing storm prediction models is evaluated using CNN baseline model. The MPI architecture is specified to manage the load to the system. Data comparisons are done using various observations for augmented and pre-augmented data. GPU and CPU performance also are compared for the experiment. Authors have suggested the method which can be applied on neural network algorithms to understand the flaws in the models. This approach can help in addressing the data bias or overfitting issues, generally observed in artificial neural network models.

2.6 Conclusion

Related work in this field, demonstrates that while there have been many methods to forecast the storm trajectory, there is still a vast variety of innovative theories that can be applied in this area to expand work and produce more practical outcomes. Recurrent Neural Networks have performed better than other models, therefore this research has selected a novel approach of applying grid-based model on RNN models. The next section discusses the methodology for the proposed approach

3 Research Methodology

This research utilizes KDD methodology as it suits the best out of other data mining methods. Since KDD phases rely mostly on implementation rather than project management strategy, it is thus better fit for predicting or classifying the data(Ma *et al.*, 2015). From the below figure, the methodology is divided into five main stages. The methodology is modified considering the research requirements. The data is collected from Kaggle website and is processed further in the phases. The phases are explained below in detail:

Figure 1: KDD Methodology

Data Selection: The research focuses on the storm or hurricane events in Atlantic region and the dataset used for the same is HURDAT2 dataset. This dataset is available on Kaggle[2] website and is publicly available for research. The original source of the data is from National Hurricane Center (NHC)[3]. The dataset is in CSV file format and contains 49105 rows of data with 22 columns covering all the storms from 1851 till 2015. Each storm is defined by Storm ID along with its name. Other parameters include location of the storm (latitude and longitude), wind speed, pressure, intensity level of the storm, time and date of the storm and other wind and pressure related parameters.

Data Cleaning and Preprocessing: The data contains few columns which are not relevant for the study. Columns like Low Wind NE, Low Wind SE, Low Wind SW, Moderate Wind SE, High Wind NE, etc does not contribute in predicting the trajectory as the location parameters are already present in the data, hence these columns are removed. The remaining columns are renamed to make the data meaningful. Latitude and Longitude columns are in the string format ##.##N. These columns are changed to datatype Float for further calculations. The processed data is further transformed using multiple data operations.

Transformation: In this step, the data is transformed for further processing. The date and time columns do not provide clear understanding because of the way it is formatted. These columns are transformed into Day, Month, Year and Time columns. Also, the Storm_ID column is enumerated as integer to count number of records for each storm. Using SKLearn package, the data is vectorized from numerical information. The vectorized information is further inserted in the final models.

Data Mining: At this stage, the models are applied to the data for prediction of storm trajectory. The recurrent neural networks (RNN) is applied to the model. Bidirectional Long Short-Term Memory (BiLSTM) and LSTM which are an extension of recurrent neural networks is created. Both the models are compared using different evaluation techniques.

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[2] https://www.kaggle.com/noaa/hurricane-database
[3] https://www.nhc.noaa.gov/data/#hurdat

Interpretation/Evaluation: Bidirectional LSTM and LSTM models are evaluated using mean squared error (MSE) and Root mean square error (RMSE) values. Also, mean absolute error (MAE) and R-square is calculated for both the models.

4 Design Specification

Below figure represents the design for prediction of Storm trajectory with the LSTM and BiLSTM models. It has two key components, one in which the models are trained using training data and the other one is prediction of the models using test data. The grid-based model is utilized to train the model in order to improve the learning process for recurrent neural networks (RNN). The proposed architecture has potential to gather verified Storm data which consists of unstructured dynamics of climate events by modifying the weight matrices correctly.(Alemany *et al.*, 2019). The design also compares deep learning and machine learning techniques to find out which one is best suited to predict storm tracks accurately.

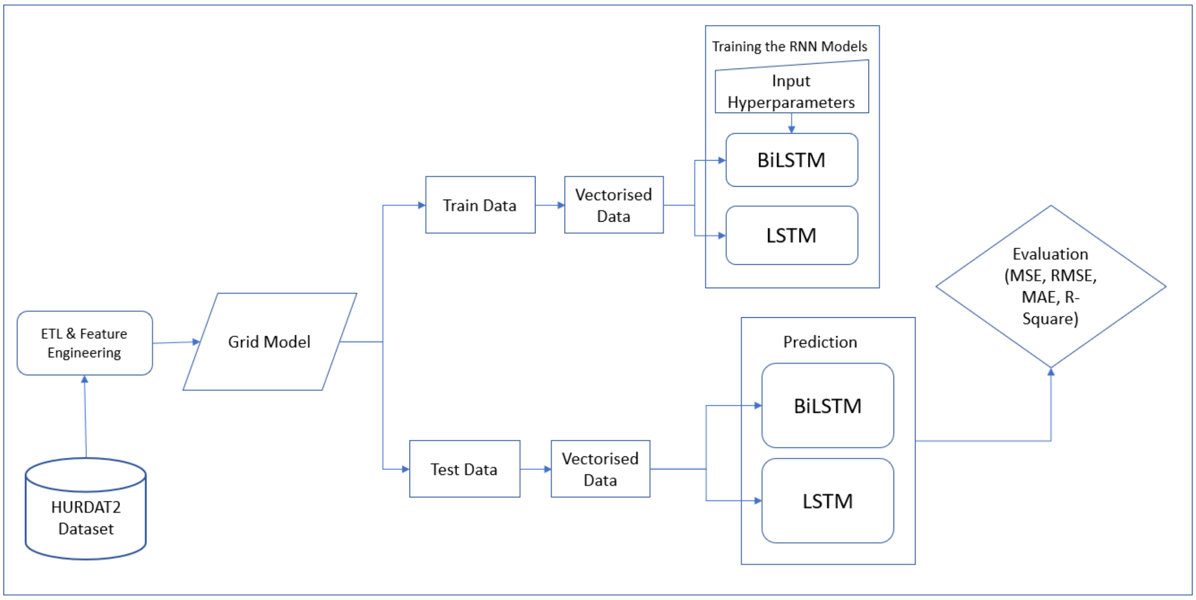

Figure 2 : Research Design

4.1 Grid-Based Architecture:

The LSTM model is trained using grid-based approach. Neural networks can be trained in predicting the track of the storm by utilizing grid points. Traditional models generally lack the precision and contains possible errors in predicting the trajectory. Any small error can lead to large amount of distances error in prediction. Grid based model overcomes this issue by controlling the loss in estimation(Alemany *et al.*, 2019). For this research, features latitude and longitude are utilized in a grid to provide the storm trajectories. It will help in reducing the errors and adapt the complexity of atmospheric data for recurrent neural networks.

4.2 Recurrent Neural Networks (RNN)

LSTM Model: Long Short-Term Memory (LSTM) is extension of Recurrent Neural Networks (RNN) which resolved the long-term memory issues. Recurrent neural networks are one of the types of Artificial Neural Networks that execute the same functions for increasing input data when the current input performance relies on the previous one. In contrast to feed-forward neural networks, RNN can use its inbuilt memory to interpret the input signals. RNNs are widely used in analysis of weather data, audio, video data due to the property of sequential modelling. LSTM is modified version of RNN which resolved the issue of vanishing gradient. It consists of different layers such as input, hidden and output layers which modifies the memory, assign the weights to the memory and finally providing output with the help of Sigmoid function(Fente and Kumar Singh, 2018)

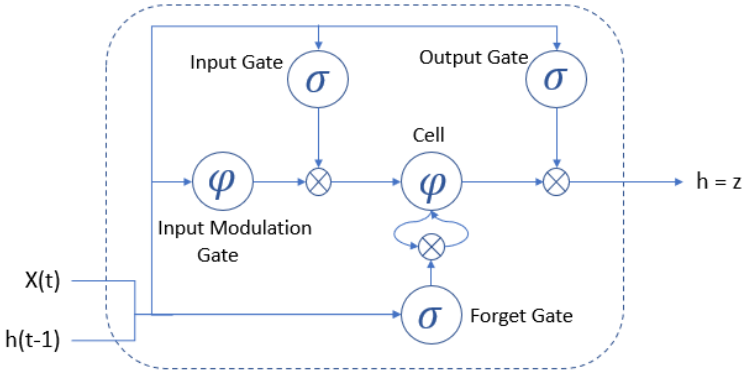

Figure 3 : LSTM Network

The above figure shows the three gates input, output and forget gate for the LSTM network. These gates control the knowledge flow from one cell to another. Cell remembers the information for random time intervals, the input layer regulates this information before processing, the forget gate decides how long the values must be stored in the cell and the output gate regulates the computation process based on the values upon activation of LSTM cell. The activation process utilizes logistics sigmoid functions. All three gates are linked in which few connections are recurrent. The training process determines weights of these connections between the gates(Fente and Kumar Singh, 2018)

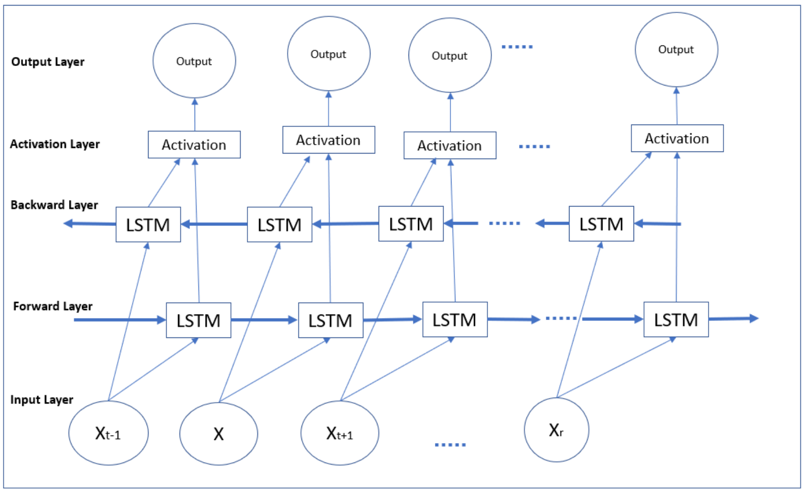

Figure 4: Bidirectional LSTM

Bidirectional LSTM: The bidirectional LSTMs are extended version of the LSTM algorithms where input data is processed with two different LSTM layers. The first LSTM layer is applied while inputting the data whereas the second LSTM layer is added to the inputs in backward order. These layers are called as forward and backward layers respectively. As the LSTM layer is applied two times, the overall performance of the model improves both in terms of learning process and the accuracy(Siami-Namini, Tavakoli and Namin, 2019).

5 Implementation

This section discusses the techniques which are applied for implementing RNN models. The dataset is explained along with Exploratory Data Analysis EDA for better understanding of the data. After performing feature extraction on the data, it is transformed with additional features in order to make the model more effective. Grid model is applied before splitting it to training and testing sets. Python programming language is used for implementing this work. The implemented models are compared on the basis of evaluation techniques to figure out the optimal model for predicting the storm trajectory.

5.1 Dataset

For developing the accurate model for tropical storm track forecasting, it is essential to consider the factors like wind speed, sea-pressure level, direction of the storm(Alemany *et al.*, 2019). Therefore, this work has chosen the HURDAT2 dataset from National Hurricane Center (NHC) which includes key features of all the storm generating at Atlantic Ocean from year 1851 to 2015. The data consists of 49105 records with 22 rows. It has details of 1030 storms with key parameters like Date, Time, Type of Storm, Intensity level of storm, Maximum wind speeds, Pressure, latitude and longitude. Each storm is separated by Storm ID and description which helps in analysing the data at storm level.

5.2 Data Cleaning

HURDAT2 data have few missing values as well as negative values which can impact the accuracy of the model. Hence, the data is cleaned using multiple data operations. The negative pressure values from the data are removed in order to improve the quality of the data. The columns like wind speed are divided into three different categories such as low, moderate and high wind in the original data. As it is generating repetitive information, these columns are dropped from the dataset. The columns are renamed to make the data understanding better. For calculating the distance, minimum two data points are Hence the storm which have only one entry is removed from the data. The columns latitude and longitude have the format ##.##N in the original dataset. This format does not support any calculation, hence it is changed to ##.## and converted to float64 for making it usable for calculations.

5.3 Feature Engineering

- Date Extraction: Date and Time columns in the data are transformed to sperate columns of Day, Month, Year and Time for better analysis.
- The Distance and direction columns are derived from latitude and longitude columns. Once the data is transformed, the original columns are dropped from the data.
- Handling Outliers: The data contains outliers with number of storm instances. The storm instances which are above 65 are removed from the data as it could result in poor model
- Feature Scaling: Before generating the training and testing sets, the data is scaled using MinMaxScalar function. Scaling will improve the quality of the data as it will bring all the data points in the range of 0 to 1
- Log Transform: The distance and direction columns are transformed using log transform function to improve the quality of the data
- Feature Selection: Manual feature selection is carried out to select the best features for the prediction. Features such as Wind Speed, Pressure, Grid Points, Distance and direction are selected as input parameters.

5.4 Exploratory Data Analysis

Once the data is cleaned and transformed, it is analysed for better understanding.

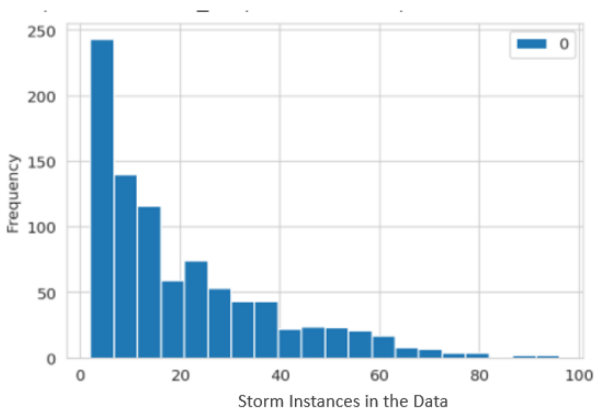

Fig 5 : Distribution of Storm instances

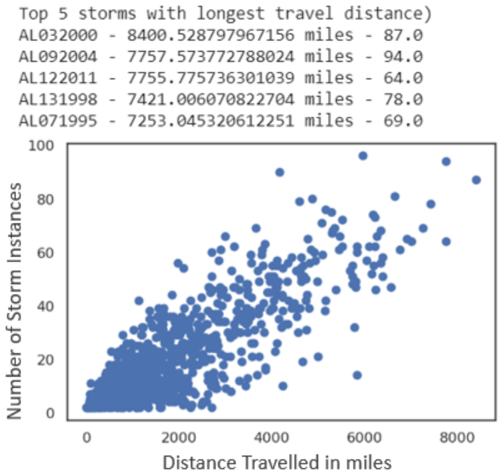

Fig 6 : Top 5 storms w.r.t. distance

As mentioned earlier, there are 1030 storms in the dataset where each storm has multiple records based on the it's trajectory. Figure 5 showcases the number of records of each storm in the data. As per the histogram, it can be seen that most of the storms have observations between 2 to 20. Figure 6 demonstrates the top 5 longest travelled storms with the list of storm IDs. As per the plot, the largest travelled storm is 'AL032000' (ALBERTO) with travel distance of 8400 miles. Also storms IVON and KATIA have travelled for 7757 and 7755 miles respectively. Figure 7 displays the trajectories for storms ALBERTO, IVON and KATIA. With this information, the research has found out the largest storms which can be alarming and can cause damage at coastel regions badly.

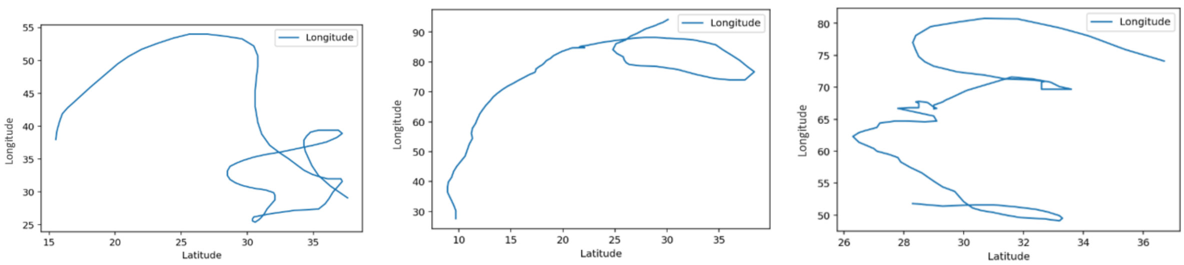

Fig 7 : Top 3 storm trajectories

As seen in figure 8, most of the storms have occurred in the month of July followed by June and August months. November and December have not seen any storms. This implies that tropical storms have high chances of occurrence in middle of the year. Additionally, figure have distributed the storms as per the categories mentioned in the dataset. For example, the category TS describes the tropical cyclones with intesity between 34-63 knots. Similarly, Category HU shows values of the storms which can convert into hurricanes with intestity more than 64 knots. It also shows that the data has maximum number of tropical cyclones followed by hurricanes

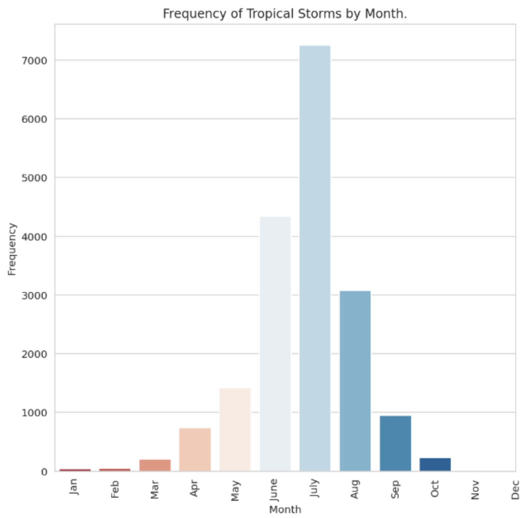

Fig 8 : Count of Storms by Month

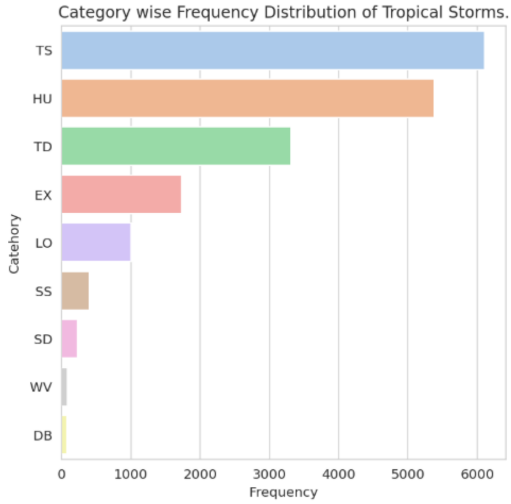

Fig 9 : Storms by Categories

Figure 9 and Figure 10 depicts the distribution of windspeed and pressure in the data respectively. With EDA, the model design can be focused on parameters like windspeed, distance, pressure. It also provides key insights on the intesity levels of the storm along with the months which in which storms can most probably occur.

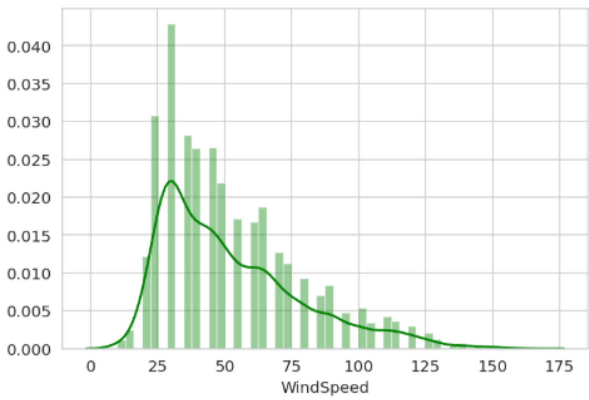

Fig 9: Windspeed distribution

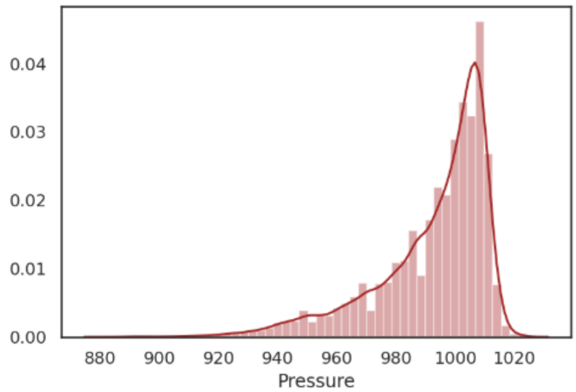

Fig 10: Pressure distribution

5.5 Model Hyperparameters

Hyperparameters are predefined values that are assigned efficiently by the developers prior to actually training the data. The hyperparameter values enabled differ considerably based on the algorithm being used, the volume and nature of the data being used and the complexity of the method. Hyperparameters are important in conveying the nonlinearity and uncertainty behind the estimation of storm tracks as they affect the decision-making system(Alemany *et al.*, 2019).

5.6 Grid Model

As described in figure 2, the grid-based model is created for this research. Ideal number of grid points for recurrent neural networks is relational to the training data, which means that more the amount of training data, more are the grid points(Alemany *et al.*, 2019). For this research, 7627 grid points were created with 1x1 dimension converting the latitude and longitude variables. The region of each grid block is not constant in square miles, owing to the spherical shape of Earth. However, the majority of points are clustered around the Earth's equator due to which the size disparity for each grid block is insignificant (Alemany *et al.*, 2019).

5.7 Implementing the model

Before implementing the model, the data is divided into training and testing set using simple random sampling. The training set contains 80% of the data whereas remaining 20% is utilized for test data. After splitting the data to training, testing and validation sets, RNN models are applied on the training data and the test data is predicted. Keras library is used for implementing the RNN models. It has been widely used in scientific studies as well as at the enterprise level. It includes data, output, and hidden layers of time step based RNN model together with a learning rate value of 0.001. The learning rate depicts the amount of time at which RNN updates the neurons at each hidden layer which helps in reducing the error in the model. As the grid points are predicted using sequential modelling, LSTM model is chosen for this study as it works best for sequential space series data(Siami-Namini, Tavakoli and Namin, 2019). Furthermore, bidirectional LSTM is also applied and compared with LSTM model.

5.7.1 LSTM and BiLSTM Model

Both LSTM and BiLSTM model contains of three main layers, input, hidden and output layers. The key difference in both the models, is the usage of number of hidden layers. LSTM model consists of more hidden layers than BiLSTM, due to which the computational time for LSTM is comparatively more than BiLSTM. A data tuple is taken into the input layer. It contains a series of characteristics comprising wind speed, pressure, distance, direction and grid points. Hyperbolic tangent (tanh) activation function is chosen for optimal model movement in all directions, rather than Sigmoid or Relu. ‘Tanh’ function allows output values between -1 and 1 due to which the model have flexibility in both the directions. Output shape includes number of input variables, number of sequences or time step and size of the output(Alemany *et al.*, 2019). Hyperparameter of 15 sequences or time-steps is considered while building the model. Both the models are trained with 100 epochs and batch size of 512. The validation set for the model is 10% of the train set. Once the model is trained with these parameters, predict function is applied on the test data in order to predict the storm trajectory.

5.7.2 Dropout Regularization:

Dropout value is applied to the model in order to reduce the overfitting issue. Based on the value input, dropout parameter arbitrarily ignores the percentage of the input data(Alemany *et al.*, 2019). The dropout value in this study is set to 0.1 which means that 10% of the inputs are ignored while training the LSTM cell

5.7.3 Hidden Layer:

Apart from input and output layers, hidden layers play significant role in training the RNN model. Complexity of the model is determined by number of hidden layers present. As mentioned by authors(Alemany *et al.*, 2019), two or three hidden layers provide improved accuracy but more than this amount of hidden layers can trigger the problem of overfitting. For LSTM model, three hidden layers with dropout regularization have been utilized whereas for bidirectional LSTM only 1 hidden layer is utilized along with dropout regularization

5.7.4 Loss function:

Loss feature explains whether the applied model is built to be accurate or poor. More precisely, if the model's forecast is accurate the loss value would be zero. As the work focuses on designing the accurate model, the loss function will help in understanding the flaws in the model like overfitting or underfitting. This paper utilizes Mean Sqaured Error as loss function along with 'Adam' optimizer to compile the model(Siami-Namini, Tavakoli and Namin, 2019). The below loss curves explain the model loss for the training and testing set while training the model. The loss function is measured over each feature during an epoch. Loss curve plots the learning progress throughout the epochs. The loss curve shows that the BiLSTM has better learning progress and does not issue of overfitting or underfitting

Fig 11: Model loss for LSTM

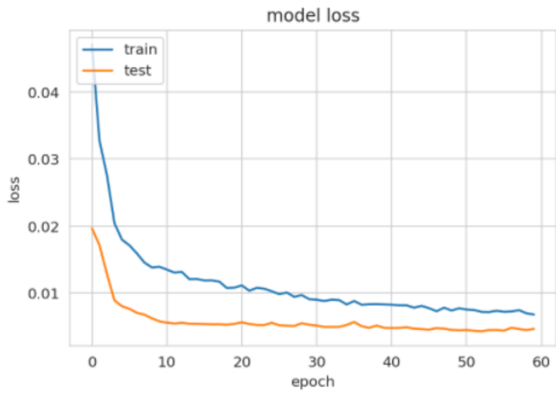

Fig 12: Model loss for BiLSTM

Both LSTM and BiLSTM models are evaluated using multiple evaluation techniques which are discussed in the next section.

6 Evaluation:

The recurrent neural network models were evaluated using test data. Multiple evaluation techniques are used to evaluate the model. Experiments carried out on both the LSTM models are discussed below.

6.1 Experiment on LSTM

The LSTM model is evaluated using multiple combinations of neurons, hidden layers, epochs and batch size. The model is tested with units ranging from 64 to 512, where the optimal performance was observed for 64 units. Two hidden layers are used to improve the computational performance of the model. Further assessment of the model is carried out by testing the number of epochs between 50 to 100. Ideal size of 60 epochs is selected for the model based on the testing. The model is also validated using different optimizers like Adam, AdaDelta, SGD. Also, activation functions like relu, sigmoid and tanh are tested for the model. The final model is evaluated using two hidden layers, 'tanh' activation function, 'Adam' optimizer, 60 epochs and 512 batch inputs. The loss curve is depicted in figure 11 which shows the training performance. The final model resulted in R-sqaured value of 66% with computational time of only 60 seconds for given set of training. Along with R-squared value, the model is also evaluated using MAE, MSE and RMSE scores which are mentioned in table 1. As the LSTM model uses only unidirectional approach in predicting the outcome, results observed are still not satisfactory, hence BiLSTM is applied in the next experiment which manages the inputs in two directions; forward to backward and vice versa. This experiment is explained in next section

6.2 Experiment on BiLSTM

Bidirectional LSTM is an extension of LSTM model with both forward and backward layers. It has been observed from previous work that BiLSTM model provides better performance than the unidirectional LSTM model(Siami-Namini, Tavakoli and Namin, 2019). Therefore, the BiLSTM model is selected for the research. The similar experiments are carried out on BiLSTM as that of LSTM model. The model is tested for different test cases such as varying the number of epochs, testing the model using multiple activation functions, utilizing multiple optimizers and selecting different number of hidden layers. Based on the rigorous testing process, the final model is chosen with single hidden layer along with dropout regularizations, tanh activation function, 60 epochs and 'Adam' optimizer. BiLSTM resulted in 74% R-squared value which is an improvement over LSTM model. The computational time is similar to LSTM. All the evaluation parameters for BiLSTM are discussed in table 1.

6.3 Comparison between the models

Below table depicts all the values of different evaluation methods for LSTM and BiLSTM models.

Table 1: Result comparison between LSTM and BiLSTM models

	LSTM	**BiLSTM**
Mean Absolute Error (MAE)	0.0568	0.0404
Mean Squared Error (MSE)	0.0076	0.0057
Root Mean Squared Error (RMSE)	0.0871	0.0755
Median Absolute Error	0.0453	0.0261
Explain Variance Score	0.7615	0.7694
R2 score	0.6599	0.7446

Both the models have performed efficiently but BiLSTM has performed marginally better than LSTM. The mean absolute error value shows that the expected value for error to occur on average while predicting the storm trajectory is 6% for LSTM and 4% for BiLSTM. The MSE values also shows that BiLSTM is predicted the storm tracks close to the regression line in comparison of LSTM. Similarly, RMSE value depicts the spread of residuals while forecasting storm trajectories, it is 8% for LSTM model and 7% for BiLSTM. Median absolute error is similar to MAE, and calculates the expected error value from median instead of mean position. The values in median absolute error are better in BiLSTM while comparing with LSTM models. Both the models have explained 76% of variance in data. Finally, BiLSTM model outperforms LSTM model as it depicts how close the predicted values are to the actual values with score of 74%.

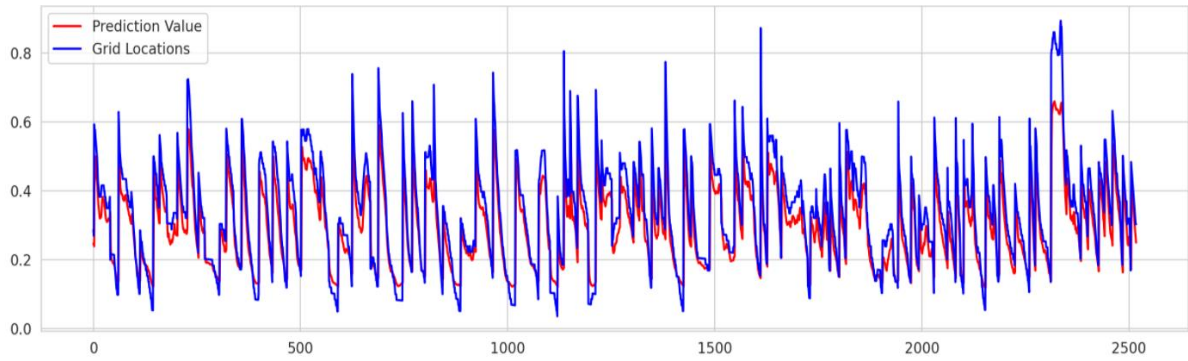

Fig 13: Predicted vs Actual Grid Values for LSTM

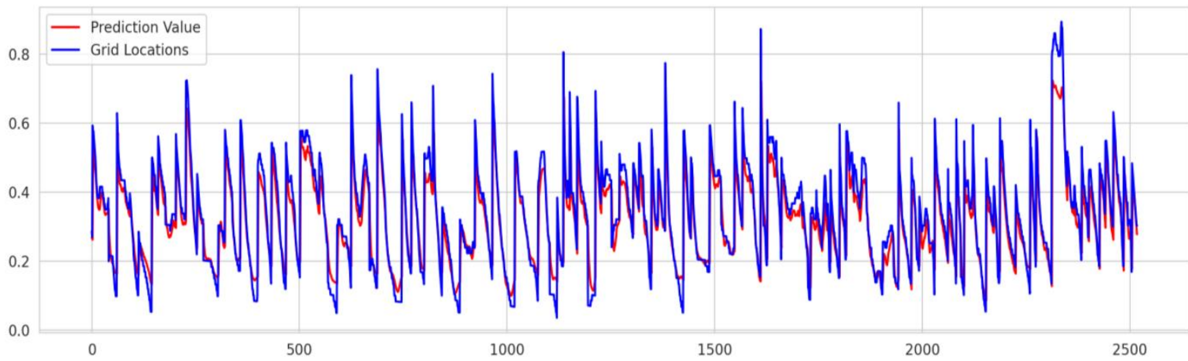

Fig 14: Predicted vs Actual Grid Values for BiLSTM

Figure 13 and 14 depicts the results graphically and compares the actual grid locations and the predicted grid locations of the storm. BiLSTM model shows that the grid value predictions are very close to the actual values.

6.4 Discussion

This paper has suggested two different grid-based recurrent neural network models to predict the storm progressions. The existing grid-based model presented in (Alemany *et al.*, 2019) is improved significantly in terms of computational speed and accuracy. Along with LSTM, a new and more accurate BiLSTM model is also applied on the storm data from National Hurricane Center (NHC). The results show that both the models have performed efficiently in predicting the track of the storms based on grid points and different features like wind speed, pressure, direction, distance of the storm. LSTM model has achieved 66% of R-squared value whereas BiLSTM has performed better with 74%. The learning curve also demonstrates that there is no issue of overfitting and underfitting for both the models. Previously, authors (Alemany *et al.*, 2019) have also implemented Grid-based LSTM and RNN for estimating hurricane tracks with mean square error (MSE) of 0.1 which is higher in comparison to the implemented models, also the downside for that model is the higher computational time. The previous model is not tuned for better computational performance. In contrast, LSTM model suggested in this paper is optimized and shows faster computational speed. BiLSTM has shown better results than LSTM model for grid-based forecasting. Implementing BiLSTM to tropical storm data makes this study novel approach as authors have not discussed this model for trajectory prediction previously. In another approach presented by (Dong and Pi, 2013), data mining based prediction algorithm (HTPDM) is used to predict the hurricane trajectory. The model resulted in 65% of accuracy. Apart from grid-based approach, scientists have also used sparse RNN approach (Kordmahalleh, Sefidmazgi and Homaifar, 2016) for estimating the storm tracks with MAE scores in the range of 0.1 to 1. Some researchers have also utilized ConvLSTM models(Kim *et al.*, 2019) which resulted in providing better accuracy than other RNN approaches. However, both the models suggested in this paper could have been more stable.

7 Conclusion and Future Work

The paper tried to answer the research question *"How efficiently integration of grid model and recurrent neural networks would help in predicting storm trajectories in the region"* by implanting Grid-based recurrent neural network models. The grid model is developed based on the latitude and longitude of the storms. A novel approach of implementing a bidirectional LSTM is discussed along with unidirectional LSTM model. Both the models are compared based on multiple evaluation techniques. LSTM model is able to predict the storm trajectory with 66% r-sqaured value where as BiLSTM performs better than LSTM with 74% r-squared value. By implementing the RNN models, research has achieved the objective of suggesting the efficient model for the climatological problems. This research can benefit disaster management centers across the coastal regions by prediction the trajectory well in advance. It can replace the existing computational systems for better prediction. This will help in saving the human lives and infrastructure damage. The most challenging part of the research is to develop the logic for grid points and utilizing the grid model in sequential time series data. The research has limitations in terms of data handling and stability. Even though the model has performed efficient, being unsupervised model, it can generate issues of overfitting or underfitting for larger datasets. It may also result in unstable accuracies if not tuned correctly for the larger datasets.

7.1 Future Work

The research will focus on collecting data from multiple sources with few more features like sea temperature, damage levels, etc. to predict the trajectory of the storm. Along with predicting the storm trajectory, study will further try to predict intensity levels of the storm by applying BiLSTM model on grid-based data. Additionally, research will focus on designing a simulator for tracking the storms based on the proposed models.

8 Acknowledgement

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References

Alemany, S. *et al.* (2019) 'Predicting Hurricane Trajectories Using a Recurrent Neural Network', *Proceedings of the AAAI Conference on Artificial Intelligence*, 33, pp. 468–475. doi: 10.1609/aaai.v33i01.3301468.

Barajas, C. A., Gobbert, M. K. and Wang, J. (2019) 'Performance Benchmarking of Data Augmentation and Deep Learning for Tornado Prediction', *Proceedings - 2019 IEEE International Conference on Big Data, Big Data 2019*. IEEE, pp. 3607–3615. doi: 10.1109/BigData47090.2019.9006531.

Burke, A. *et al.* (2020) 'Calibration of Machine Learning–Based Probabilistic Hail Predictions for Operational Forecasting', *Weather and Forecasting*, 35(1), pp. 149–168. doi: 10.1175/waf-d-19-0105.1.

Chen, B. F. *et al.* (2019) 'Estimating tropical cyclone intensity by satellite imagery utilizing convolutional neural networks', *Weather and Forecasting*, 34(2), pp. 447–465. doi: 10.1175/WAF-D-18-0136.1.

Cloud, K. A. *et al.* (2019) 'A feed forward neural network based on model output statistics for short-term hurricane intensity prediction', *Weather and Forecasting*, 34(4), pp. 985–997. doi: 10.1175/WAF-D-18-0173.1.

Czernecki, B. *et al.* (2019) 'Application of machine learning to large hail prediction - The importance of radar reflectivity, lightning occurrence and convective parameters derived from ERA5', *Atmospheric Research*. Elsevier Ltd, 227, pp. 249–262. doi: 10.1016/j.atmosres.2019.05.010.

Dong, X. and Pi, D. C. (2013) 'Novel method for hurricane trajectory prediction based on data mining', *Natural Hazards and Earth System Sciences*, 13(12), pp. 3211–3220. doi: 10.5194/nhess-13-3211-2013.

Fente, D. N. and Kumar Singh, D. (2018) 'Weather Forecasting Using Artificial Neural Network', *Proceedings of the International Conference on Inventive Communication and Computational Technologies, ICICCT 2018*. IEEE, (Icicct), pp. 1757–1761. doi: 10.1109/ICICCT.2018.8473167.

Gagne, D. J. *et al.* (2017) 'Storm-based probabilistic hail forecasting with machine learning applied to convection-allowing ensembles', *Weather and Forecasting*, 32(5), pp. 1819–1840. doi: 10.1175/WAF-D-17-0010.1.

Giffard-Roisin, S. *et al.* (2020) 'Tropical Cyclone Track Forecasting Using Fused Deep Learning From Aligned Reanalysis Data', *Frontiers in Big Data*, 3(January), pp. 1–13. doi: 10.3389/fdata.2020.00001.

Kim, S. *et al.* (2016) 'A real-time forecast model using artificial neural network for after-runner storm surges on the Tottori coast, Japan', *Ocean Engineering*. Elsevier, 122, pp. 44–53. doi: 10.1016/j.oceaneng.2016.06.017.

Kim, S. *et al.* (2019) 'Deep-hurricane-tracker: Tracking and forecasting extreme climate events', *Proceedings - 2019 IEEE Winter Conference on Applications of Computer Vision, WACV 2019*. IEEE, pp. 1761–1769. doi: 10.1109/WACV.2019.00192.

Kordmahalleh, M. M., Sefidmazgi, M. G. and Homaifar, A. (2016) 'A sparse recurrent neural network for trajectory prediction of atlantic hurricanes', *GECCO 2016 - Proceedings of the 2016 Genetic and Evolutionary Computation Conference*, pp. 957–964. doi: 10.1145/2908812.2908834.

Kurniawan, A. A., Usman, K. and Fuadah, R. Y. N. (2019) 'Classification of tropical cyclone intensity on satellite infrared imagery using SVM method', *Proceedings - 2019 IEEE Asia Pacific Conference on Wireless and Mobile, APWiMob 2019*, pp. 69–73. doi: 10.1109/APWiMob48441.2019.8964184.

Labib, A. and Read, M. (2015) 'A hybrid model for learning from failures: The Hurricane Katrina disaster', *Expert Systems with Applications*. Elsevier Ltd, 42(21), pp. 7869–7881. doi: 10.1016/j.eswa.2015.06.020.

Ma, Y. *et al.* (2015) 'A data mining model of knowledge discovery based on the deep learning', *Proceedings of the 2015 10th IEEE Conference on Industrial Electronics and Applications, ICIEA 2015*, pp. 1212–1216. doi: 10.1109/ICIEA.2015.7334292.

McGovern, A. M. Y. *et al.* (2019) 'Quasi-operational testing of real-time storm-longevity prediction via machine learning', *Weather and Forecasting*, 34(5), pp. 1437–1451. doi: 10.1175/WAF-D-18-0141.1.

Mercer, A. and Grimes, A. (2017) 'Atlantic Tropical Cyclone Rapid Intensification Probabilistic Forecasts from an Ensemble of Machine Learning Methods', in *Procedia Computer Science*. Elsevier B.V., pp. 333–340. doi: 10.1016/j.procs.2017.09.036.

Pan, B., Xu, X. and Shi, Z. (2019) 'Tropical cyclone intensity prediction based on recurrent neural networks', *Electronics Letters*, 55(7), pp. 413–415. doi: 10.1049/el.2018.8178.

Richman, M. B. *et al.* (2017) 'Reducing Tropical Cyclone Prediction Errors Using Machine Learning Approaches', in *Procedia Computer Science*. Elsevier B.V., pp. 314–323. doi: 10.1016/j.procs.2017.09.048.

Sahoo, B. and Bhaskaran, P. K. (2019) 'Prediction of storm surge and coastal inundation using Artificial Neural

Network – A case study for 1999 Odisha Super Cyclone', *Weather and Climate Extremes*. Elsevier B.V., 23(September 2018), p. 100196. doi: 10.1016/j.wace.2019.100196.

Salman, H., Grover, J. and Shankar, T. (2018) 'Hierarchical Reinforcement Learning for Sequencing Behaviors', 2733, pp. 2709–2733. doi: 10.1162/NECO.

Scher, S. and Messori, G. (2018) 'Predicting weather forecast uncertainty with machine learning', *Quarterly Journal of the Royal Meteorological Society*, 144(717), pp. 2830–2841. doi: 10.1002/qj.3410.

Shaiba, H. A., Alaashoub, N. S. and Alzahrani, A. A. (2018) 'Applying Machine Learning Methods for Predicting Sand Storms', *1st International Conference on Computer Applications and Information Security, ICCAIS 2018*. IEEE, pp. 1–5. doi: 10.1109/CAIS.2018.8441998.

Siami-Namini, S., Tavakoli, N. and Namin, A. S. (2019) 'The Performance of LSTM and BiLSTM in Forecasting Time Series', *Proceedings - 2019 IEEE International Conference on Big Data, Big Data 2019*. IEEE, pp. 3285–3292. doi: 10.1109/BigData47090.2019.9005997.

Yang, F. *et al.* (2020) 'Quantifying uncertainty in machine learning-based power outage prediction model training: A tool for sustainable storm restoration', *Sustainability (Switzerland)*, 12(4). doi: 10.3390/su12041525.

Zhang, T. *et al.* (2019) 'Prediction of tropical cyclone genesis from mesoscale convective systems using machine learning', *Weather and Forecasting*, 34(4), pp. 1035–1049. doi: 10.1175/WAF-D-18-0201.1.