Prediction of Cyclone and Its Classification Using Deep Learning Techniques

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***Abstract* - Climate is said to be the long-term average of prevailing weather conditions which are represented using a number of the meteorological variables that are commonly measured in the terms of temperature, humidity, air pressure, wind, and precipitation. Cyclones are the deadliest meteorological phenomenon results in flooding, storm surges, heavy rainfall, significant damages to fisheries, forestry etc. Tropical cyclones originate over ocean, powered by heat transfer from the ocean surface, and stops with cold water of land. The Indian sub-continent is the worst affected part in the world by the cyclone and such cyclones are much weaker in intensity and smaller in size, yet with highest death rate. Tropical cyclones are also known as typhoons, hurricanes etc. based on their origin. In Indian Ocean, they are called as tropical cyclones. The Dataset used in this work is North Indian Ocean Best track dataset and they are classified using the techniques of Convolutional Neural Network and Recurrent Neural Network.**

***Index Terms* - Tropical Cyclone, North Indian Ocean Best track dataset, Convolutional Neural Network and Recurrent Neural Network.**

INTRODUCTION

The Destructive meteorological phenomenon which results in flooding, storm surges, heavy rainfall, etc are termed as Cyclones. Tropical cyclones originate over ocean, powered by heat transfer from the ocean surface, and stops with cold water of land. The Indian sub-continent is the worst affected part in the world by the cyclone and such cyclones are much weaker in intensity and smaller in size, yet with highest death rate. Tropical cyclones are also known as typhoons, hurricanes etc. based on their origin. In Indian Ocean, they are called as tropical cyclones. The factors that influence the cyclone formation are sea surface temperature (SST), large Coriolis force, low level relative vorticity, weak vertical wind shear, mid troposphere relative humidity, convective instability, Maximum radial extent of 34, 50 and 64 kt wind in four quadrants, Radius of maximum wind, Eye diameter, Pressure and radius of the outer closed isobar. An increase in the upper bound on intensity from 60 to 70 meters per second would increase the frequency storms with winds greater than 50 meters per second by almost 70%, keeping the total frequency of all storms constant.

The tropical cyclone generates surface winds which exceed 17 ms−1 (33 knots); in extreme cases winds reach 90 ms−1 (175 knots). Tropical cyclone with its tremendous fury and destructive power has been a disastrous event for the people in coastal areas and ships on high seas throughout the history of human race. The greatest damage to life and property is from the storm surges associated with the cyclone, whereas the storm approaches the coast, sea level raises rapidly, and the sea enters land. Death toll in a single cyclone has reached very high figures, for example a cyclone in November 1970 which had landfall over Bangladesh coast killed nearly 300,000 people. In areas such as north Bay of Bengal, high storm surges occur due to the prevailing bathymetry. Eight of the ten deadliest tropical cyclones globally have occurred in the Bay of Bengal and the Arabian Sea with five impacting Bangladesh and three making landfall in India (WMO, 2010). In the recent years, during the 2005 Atlantic hurricane season, tropical cyclones Katrina, Rita and Wilma devastated the North American continent causing about 4000 deaths; these storms were accompanied by huge damage in the coastal areas.

A typical mature tropical cyclone has a low pressure central region called the 'core' region which in a severe cyclone develops an 'eye' of radius 5 to 30 km surrounded by a ring of cumulonimbus clouds of radial width 10-15 kms called the 'wall cloud' (figure 1.1). In the severest of cyclones, the atmospheric pressure inside the eye is about 10% lesser than that outside the cyclone at sea level. With the friction in the atmospheric boundary layer winds are forced to flow inward cyclonically (anti-clockwise in Northern Hemisphere and clockwise in Southern Hemisphere) spiralling up to the wall cloud in the lower levels of the atmosphere. At the wall cloud there is strong upward motion field which takes the warm moist air upward in cumulonimbus clouds. In the upper troposphere the mass flux from the central region of the cyclone is outward. The strongest radial inflow of the cyclone occurs in the layer between surface and 850 hPa, while the strongest outflow occurs between 300 and 100 hPa. The inflowing air creates spiral bands of cumulonimbus clouds from a radial distance of about 300 kms to the wall cloud. Maximum wind and rainfall in a tropical cyclone are in the wall cloud region. In the troposphere, the cyclonic winds can extend more than 1000 km from the center of the cyclone.

smaller in radial size (typically 800 kms) compared to those in the Atlantic and Pacific Oceans

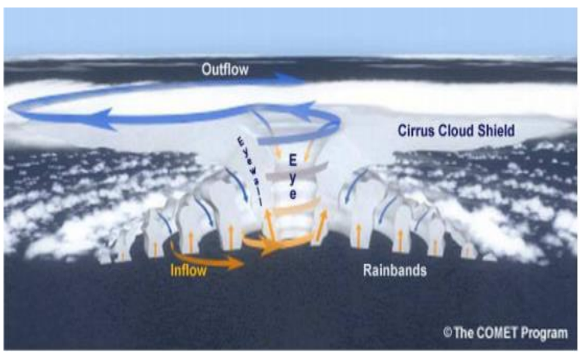


Figure 1.1 Vertical cross-section of a typical tropical cyclone

The outflow layer (300 to 100 hPa) consists of a small cyclonic central region of radius 200 to 300 kms surrounded by a large anticyclonic vortex. The central region of the tropical cyclone has a warm core with the eye having the highest temperature. The measured temperature anomaly in the eye region compared to the mean tropical atmosphere is about 10◦C in the lower troposphere and 15◦ to 18◦C in the upper troposphere in very severe cyclones. Tropical cyclones are classified into different categories according to the maximum sustained surface wind speed attained in the core region (wall cloud) or the minimum pressure reached in the eye of the cyclone (pressure drop of the cyclone). The generic name tropical cyclone is used when the observed maximum sustained wind speed is 17 ms^{-1} (34 knots) or more. For measuring the maximum sustained wind speed, different averaging time periods are used around the world. The World Meteorological Organization (WMO) convention is to measure 10-minute average surface wind speed, but the United States is following a 1-minute averaging. For the North Indian Ocean Cyclones India Meteorological Department uses a 3-minute averaging.

RELATED WORK

A CNN-based binary classification (Daisuke Matsuoka, 2018) that categorizes 2D cloud data ie. outgoing longwave radiation (OLR) into tropical cyclones, their precursors, and non-developing depressions. The Adam optimizer (Kingma and Ba 2015) is used in the CNN to update the network parameter thereby minimizing the loss function (binary cross entropy). CNN with Batch normalization (Ioffe and Szegedy, 2015) results in minimizing the initial-value dependence of the parameters. Additionally, TC tracking algorithm detects the tropical cyclones and pre-cursors from dataset captured for six-hours including horizontal components of wind, temperature, and sea level pressure (SLP). In the initiative, grid points at which the SLP was 0.5 hPa but the mean of its surrounding area (eight-neighbor grids) were selected as candidate TC centers. Tropical Cyclones need to satisfy the following criterion: (i) the wind speed at 10 m must be greater than 17.5 m/s, (ii) the relative vorticity at 850 hPa should be greater than 1.0×10^{-3} s^{-1} , (iii) the sum of temperature deviations at 300, 500, and 700 hPa must be greater than 2 K, (iv) the wind speed at 850 hPa should be greater than that at 300 hPa, (v) the duration of each detected storm has to be greater than 36 h, and (vi) the tropical cyclone will be formed within a limited range of latitudes (30° S–30° N).After identifying the grid points, these points were connected with nearest neighbors in regular basis, and tracks of "precursors", "TCs," and "extratropical cyclones" were obtained sequentially. The "non-developing depressions" ("non-TCs") are then identified a slow pressure clouds that do not satisfy criteria (i)–(vi).This CNN model has successfully detected tropical cyclones and their precursors of the western North Pacific with a probability of detection

(POD) of 79.9–89.1% and a false alarm ratio (FAR) of 32.8–53.4%.The fused network model (Sophie Giffard-Raoisin, 2020) is created using Deep learning techniques for tropical cyclone track forecasting and this model is trained in such a way that it estimates the longitude and latitude displacement of tropical cyclones and their depressions. The benefit of this model of fused network can also be used for complementary prediction. The tracking problem is framed as the computation of the displacement vector, Ed, between current and future locations. This model is proposed to use the reanalysis data with cropped images (25 × 25◦) centered on the storm location. Thus, the computation time is reduced and easily identifies tropical cyclones coming from a large number of basins from both hemispheres. This model also includes past temporal information with reanalysis maps [1]. The fusion convolutional neural network considers reanalysis images with the features set of wind fields and pressure. This fused model used dataset that is composed of more than 3,000 tropical and extra-tropical storm tracks extracted from the NOAA database, IBTrACS (International Best Track Archive for Climate Stewardship). This fusion model is divided into three major steps: a Wind CNN, a Pressure CNN and a Past tracks with meta NN. The Wind CNN and Pressure CNN use longitude, latitude, stacked height and time in 2Dformat.The Past tracks with meta NN considers 0D features and even they are also stacked over time. The Haversine formula is used in this model to find the distances between two points from their longitudes and latitudes. This model used Adam optimizer in training with 200 epochs [2].

A CNN model that uses both 2D and 3D Neural Network model (Juhyun Lee et al, 2019) to detect the tropical cyclone intensity and analyses the relationship of geostationary satellite images. This model used the International Best Track Archives for Climate Stewardship (IBTrACS) dataset with parameters such as the location of the tropical cyclone center (degrees), maximum sustained wind speed (kts), minimum sea level pressure (hPa) and tropical cyclone radius for the Southern Hemisphere (SH), the Northern Indian Ocean (NIO) and the Western North Pacific (WNP) regions. This model predicts approximately 70% of the tropical cyclones have an intensity fewer than 63 kts and 12% with intensity of 96 kts. The 2D-CNN model yields better performance when compared to 3D – CNN because of increased parameters. The 2D-CNN-based approach resulted good performance with an RMSE of 8.32 kts, and3D-CNN yielded an RMSE of 11.34 kts [3].

A deep convolutional neural network architecture (Ritesh et al, 2018) has been designed for categorizing hurricanes based on intensity using graphics processing unit. This model used Saffir-Simpson Hurricane Wind Scale (SSHWS) with intensity categorization for tropical storm and tropical depression astropical cyclone. The critical features considered are curvature, bend, eye, color intensity, pattern, etc to estimate the intensity of tropical cyclone. This model used infrared (IR) hurricane images and data for hurricanes. The dataset is again reformed by collecting information from different resources with varying sampling rate, then apply interpolation and finally augment images by transformations. This model produced 80.66% accuracy. The performance of this model also depends upon the number of convolutional layers (5), pooling layers, fully connected layers (3), and the number of filters (kernels) used in each layer. And adjustments to the learning rate, the size of filters, stride, padding, etc. also improved the accuracy [4].

A CNN based model (Buo-Fu Chen et. al, 2019) that utilized the Gridded Satellite data set and the passive-microwave rain rate analyzed best track tropical cyclone intensities were proposed. This model represents tropical cyclone intensities as single values and updates the weights in many iterations and optimizes(minimizes) the loss function. It uses backward learning. This model used AlexNet (Krizhevsky et al. 2012) as the training set is smaller. The stopping criteria is set to 200 epochs for estimating tropical cyclone intensity [5]. A Recurrent Neural Network model (Sheila Alemany, 2019) has been proposed to track the hurricane at 6-hour intervals and can predict approximately 120 hours of hurricane path. This model reduced truncation errors by using latitude, longitude, wind speed, and pressure as spatio-temporal feature vectors from dataset provided by the dataset from the National Hurricane Center and the NOAA database. This model predicted the direction and angle of trajectory of tropical storm/hurricane. Testing process is performed against a normal distribution and hence the feature vectors out of this distribution is rejected. The feature values are normalized with invariant mean and variances. This RNN model learns from normalized data and hence, converges faster with greater accuracy. The learning process considers physical location and hence optimal prediction of hurricane trajectories are possible. The high accuracy in prediction is because of direction and distance travelled in the grid. This model results in 0.01 mean-squared error and 0.11 root-mean-squared error [6].

A model referred to as deep learning-based Model with Recurrent neural network (Bin Pan, 2019) used the Western North Pacific TC database for tropical cyclone intensity prediction. This model predicts the next intensity data of tropical cyclone at four time point using location and intensity data. The relationship between latitude, longitude and intensity is represented as a single vector. This model is executed in desktop machines and predicts the tropical cyclone intensities [7]. A model based on Granger causality and Gated Recurrent unit (Pingping Dong, 2019) uses the meteorological factors to predict tracks of the tropical cyclones. This model works in three layers. The first layer performs the preprocessing on the input dataset. The second layer does the feature extraction based on the Granger causality analysis. This analysis performs the forecasting of time-series data and removes the data that are irrelevant to the target. The third layer deals with the non-equalized tropical cyclones dataset. The GRU model used two gates (i) Long Short-Term Memory, (ii) Reset gate. The reset gate determines how current state inherits the previous state. This model is tested with the Western North Pacific Ocean Best Track Data provided by Joint-Typhoon Warning Center [8].

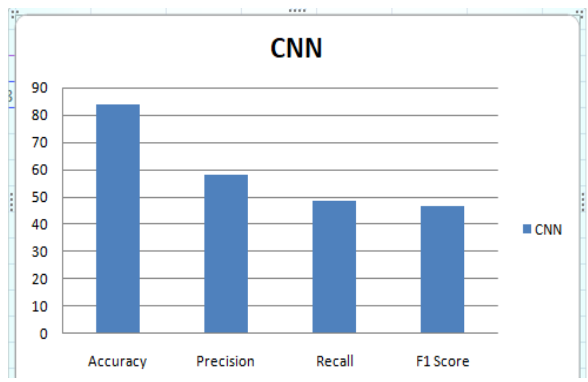
DATA AND METHODS

North Indian Ocean Best Track dataset

The Tropical cyclone formations are classified into seven basins. These seven basins include the north Atlantic Ocean, the eastern and western parts of the northern Pacific Ocean, the southwestern Pacific, the southwestern and southeastern Indian Oceans, and the northern Indian Ocean. The Northern Indian Ocean covers both the Bay of Bengal and the Arabian Sea Basins. This dataset contains BASIN, CY, YYYYMMDDHH, TECHNUM, TECH, TAU, LatN/S, LonE/W, VMAX, MSLP, TY, RAD, WINDCODE, RAD1, RAD2, RAD3, RAD4, RADP, RRP, MRD, GUSTS, EYE, SUBREGN, MAXSEAS, INITIALS, DIR, SPEED, STORMNAME, DEPTH, SEAS, SEASCODE, SEAS1, SEAS2, SEAS3, SEAS4 all together 27 features. It contains data with row value of 1380.

CONVOLUTIONAL NEURAL NETWORK (CNN)

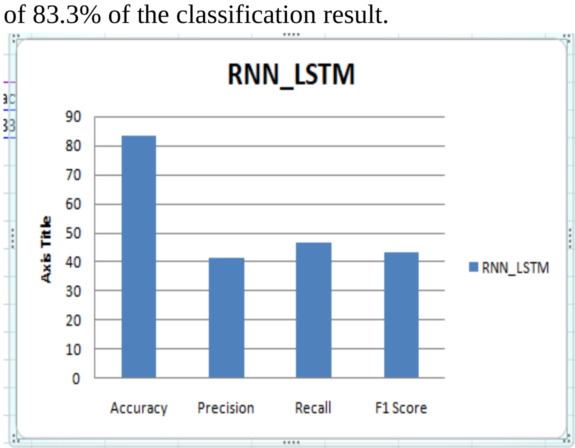
A Convolutional Neural Network is a class of deep neural networks, most generally applied to analyzing visual imagery. The name “convolutional neural network” indicates that the network employs a statistical operation called convolution. Convolution is a specific kind of linear operation. Convolutional networks are just neural networks that use convolution in place of common matrix multiplication in at least one of their layers. They are also called as space invariant artificial neural networks (SIANN) or shift invariant, based on their shared-weights manner and translation invariance characteristics. In this work, the dataset (North Indian Ocean Tropical Cyclone data) is subjected to proceed the Convolutional neural network process. At first, the dataset is classified for the training and testing phase in which 70% of the data is subjected for training phase and remaining 30% is for testing phase. The training phase is carried out with 965 data values and these are tested with 414 other data values.



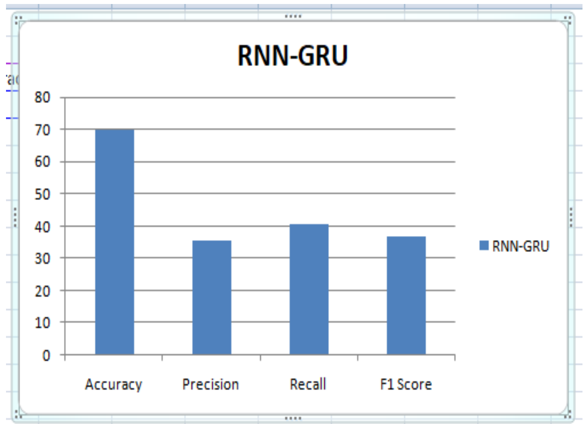
A convolutional neural network contains an input and an output layer along with multiple hidden layers. The hidden layers of a CNN consist of a series of convolutional layers that undergoes a process with a multiplication or other dot product. The activation function is generally called as a RELU layer, and contains additional convolutions such as pooling, fully connected and normalization layers, referred to as hidden layers. In hidden layers, their inputs and outputs are veiled by the activation function and final convolution. This process results with the accuracy of 83.8% of classification result.

RECURRENT NEURAL NETWORK (RNN)

The Recurrent Neural Network (RNN) is a neural network in which the nodes together are connected to form a directed graph along with temporal sequence. This allows the neural network to exhibit temporal dynamic behavior. RNNs can use their memory to process variable length sequences of inputs which is derived from feedforward neural networks. The term “recurrent neural network” is used to refer to two broad classifications of networks with a similar related structure. They are classified as finite impulse and the other is infinite impulse. Both finite impulse and infinite impulse recurrent networks can have any number of additional stored states, and the storage can be directly under the control by the neural network. The storage can be replaced either by a network or graph, if that incorporates time delays or has feedback loops. Therefore, these controlled states are referred to as gated state or gated memory and are part of long short-term memory networks (LSTMs) and gated recurrent units. This is also called Feedback Neural Network. Both long short-term memory networks (LSTMs) and gated recurrent units (GRU) are implemented in this case for the better classification result. The Long Short-Term Memory (LSTM) is processed similarly like convolutional neural network with 70% of training data and remaining 30% data values for the testing phase with the data values classified as 965 and 414 data values. These are processed using categorical cross entropy loss and with adam optimizer. This resulted with the accuracy of 83.3% of the classification result.

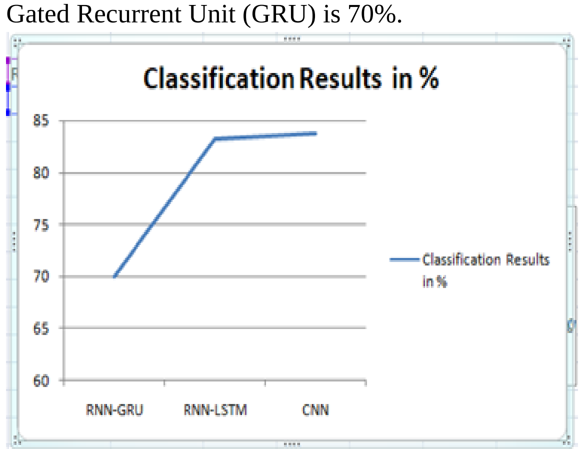


The Gated Recurrent Unit (GRU) is performed because of its best purpose of using the better output of the previous state is taken for the further processing. The data values are classified like 70% for training and remaining 30% of data for testing phase. After processing, it results with the accuracy value of 70 % of the classification result.



RESULT AND CONCLUSION

In this paper, an approach was developed to identify the best classification used for the best track dataset. The Deep Learning techniques involved in this work is Convolutional Neural Network and Recurrent Neural network. The best classification result is given by Convolutional Neural Network in this with 1380 data values. The Classification percentage for Convolutional Neural network is 83.8%, Recurrent Neural Network using Long Short-Term Memory (LSTM) is 83.3%, Recurrent Neural Network using Gated Recurrent Unit (GRU) is 70%.



The Classification result varies each and every time because of the less amount of data values.

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