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Tropical Cyclone Classification using Deep Learning

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Abstract Tropical cyclones (TC) are among one of the deadliest natural disasters which affect millions of people living in coastal areas around the world. In early days limited tools were available to analyze the huge meteorogical data that were generated continuously over time. With the advent of computing power and artificial intelligence based techniques it is now possible to predict the origin, landfall and intensity of the tropical cyclone by collaborative efforts of the resources available in countries around the world. The real time data analysis plays a major role. From early simulation models built upon the hydrological and satellite data to current sophisticated data driven deep learning models are continuously evolving to serve the human civilization to combat cyclones by providing accurate early warning systems and making efficient disaster preparedness. This paper studies the deep learning based systems along with few early Mesoscale systems to predict TC and compared their relative performances.

Keywords-- Tropical Cyclone, Convolution Neural Network (CNN), Generative Adversarial Network (GAN), Cyclogenesis, Climate Change,

I. INTRODUCTION

Humanity stands at a crucial point in all of its combined history. For us to overcome the great filter as cited by Robin Hanson the hidden web leading to climate change needs to be solved [1]. Disaster as defined by United Nation in 1992 is the disruption of the functioning of society causing widespread human, material and environmental losses which exceed the ability of the affected society to cope using only its own resources.[2] Disaster may be categorized as natural or manmade. Natural disasters may be earth-based e.g. earthquake, tsunami, avalanches, volcanic eruption, landslide etc; water-based e.g. flood, cloud burst, GLOF (glacial lake outburst flood), drought etc.; wind-based e.g. cyclone, tornedo, hurricane etc. Manmade disaster includes war, riot, accidents, forest fire, nuclear contamination, deforestation, suicide-bombers etc.[3] It had been studied that the development of post industrial revolution (1750 AD) paid havoc to the environment. Now countries are taking oath about sustainable development in different earth summits.To sustain disasters disaster management (DM) should be practiced to reduce potential losses, assistance to victims should be prompt and appropriate along with rapid and durable recovery from disaster. Risk is measured as (hazard x vulnerability x exposure)/capacity of society. The disaster risk management includes risk reduction, preparedness, response and recovery strategies. Risk reduction measures includes community awareness, drill exercise, insurance, conflict resolution etc. [4] Tropical cyclones (TC) are disasters generated over warm oceans and move toward the land with extremely high velocity and water content causing tremendous damage over a wide region to human lives and infrastructures. [5] In general, it has a calm central eye region and dangerous eye wall region having extreme high velocity ring of winds drawing moisture from ocean. Some of the deadliest TCs that were originated over the Bay of Bengal(BoB) and Arabian Sea(AS) and hit the coastal states of Indian-subcontinent are Bhola (1970), Odisha cyclone (1999), Nisha (2008), Aila (2009), Hudud (2014), Titli (2018), Fani (2019), Amphan (2020), Tauktae (2021), Yaas (2021) etc. [6][7][8][9]The early warning systems of TC are being developed to reduce the catastrophic damage. Weather prediction models are used worldwide like National Center for Environmental Prediction (NCEP) and Global Forecast System (GFS) of USA, UK Meteorogical Office Model etc. for accurate prediction of TCs. Three dimensional mesoscale models like National Oceanic and Atmospheric Administration (NOAA) and National Centre for Atmospheric Administration (NCAR) of US were developed parallaly. [10] Accurate forecasting of the models depend on quality of data and accuracy of numerical representation of physical processes. Simulation studies for TC over North Indian Ocean (NIO) have been conducted by Indian Meteorogical Department (IMD) using mesoscale models. Different aspect of cyclone development need to be studied like cyclogenesis, track analysis and evolution to reduce damage. Wind-Field analysis and pattern matching

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are commonly used to track cyclone evolution. Cloud intensity patterns are widely used for TC classification. GIS and remote sensing data are very vital. [11][12] Machine learning models are effective in the study of cyclogenesis and intensity from wind speed analysis. Deep learning models like Convolutional Neural Network (CNN) models are now used by many researchers for TC classification [13][14][15]. In this work the role different deep learning models in cyclone prediction are studied. Section-II studies the relevant works, Section-III observes their relative performances and Section-IV draws a conclusion and gives a future research direction.

II. Related Work

In this section works are studied related to deep learning based modelling of tropical cyclones.

Wang et al. (2020) [14] stated a CNN-based tropical cyclone model that can extract spatial features from images taken from the Shanghai Typhoon Institute of the China Meteorological Administration (CMA), using automatic computation of features to improve detection or classification. Data augmentation method was used by adding Gaussian noise to every image with a mean value of 0 and variance of 0.0096. Two-dimensional AlexNet are commonly used to study translation-invariant features of the input data. Author used a shallow network where kernels fetch the information on each input TCs from the pixel neighborhood in the spatial Centre of the cube. ReLU activation function and ADAM optimizer were used along with normalized input data. The accuracy for the decision tree as well as TC-3DCNN were computed. For classification criteria between 5 to -5, the decision tree gives accuracy of 90.2% whereas TC-3DCNN showed 94.9% accuracy. For, criteria between 2.5 to -2.5 accuracies of 81.5% and 91.5% are observed for decision tree and TC-3DCNN respectively. Similarly, for criteria 0, it gives 77.4% and 83% accuracies for decision tree and TC-3DCNN respectively.

Liu et al. (2016) [15] presented the first climatic CNN model that was used in conjunction with Bayesian-based hyper-parameter optimization schemes on large meteorological datasets to find anomalies and predict extreme weather events. The accuracy achieved is in the range of 89-99%. Here, Tropical Cyclones, Atmospheric Rivers, and Weather Fronts have been considered events of extreme weather conditions. The Deep CNN model leverages AlexNet and has 4 learnable layers, including 2 convolutional layers and 2 fully connected layers. The model is constructed with NOEN, an open-source Python library. The datasets used for the experiment are CAM5.1 historical run, ERA-Interim reanalysis, 20-century reanalysis, and NCEP-NCAR reanalysis.

Kar and Banerjee (2021) [16] modeled cloud intensity machine learning based classification techniques for TC using feature extraction and pattern matching steps. Initially, the images are resized from 1024x1024 to 256x256 pixel and then find the region of interest (ROI) using Euclidean distance(ED) and Manhattan distance (MD) in which former was found to be more effective. Then a rotation-invariant image was formed by rotating the original image by 90, 180, and 270 degrees and all four images were combined. (COG). The feature extraction involved computation of Centre of gravity (COG), ED, normalized ED, variance, density, eccentricity, area of TC, zero-order moment of TC in ROI, and finally the entropy. For feature extraction from 600 images Weka data mining tool was used. The correctly classified instances of the above-mentioned models in 10-fold cross-validation with 66%, 75%, and 85% splits are as follows. For simple 10-fold cross-validation the Naïve Bayes, Support Vector Machine (SVM), Random Tree, Logistic Model Tree and Random Forest gives accuracies of 36.5%, 49.8%, 72.5%, 76.6%, and 84.1% respectively. For 66-34% training-testing split with 10-fold cross-validation accuracies reported were 39.8%, 40.1%, 67.4%, 70.5%, and 80.1% respectively. For 75-25% training-testing split with 10-fold cross-validation accuracies found were 36%, 46.6%, 66%, 67.3%, and 84.6% for the same models. Finally, if 85-15% split with 10-fold cross-validation accuracies reported were 33.3%, 45.5%, 71.1%, 75.5% and 84.6% respectively. Random forest had performed the best.

According to Vecchi and Soden (2007) [17] the correlation between tropical cyclones and global warming is widely debated. Authors used climate models and observational reconstructions to find a relationship between changes in sea surface temperature and tropical cyclone ‘potential intensity’—a measure that provides an upper bound on cyclone intensity and can also reflect the likelihood of cyclone development. Results indicate that although tropical Atlantic surface temperatures are at a record high, the Atlantic potential intensity probably peaked in the 1930s and 1950s, and recent values are near the historical average. The outcomes show that the response of tropical cyclone activity to natural climate variations, which usually involve localized changes in sea surface temperature, may be larger than the response to the more uniform patterns of greenhouse-gas-induced warming.

Emanuel (2005) [18] explained that the destructive potential of a cyclone is often underestimated and more effort is put into predicting the path or frequency of cyclones. A necessary Potential Destructiveness Index (PDI) is of more concern as studies show there is an upward trend of it which correlates to loss of coastal life and property. Prediction of 8-12% rise in PDI of a cyclone, considering factors like tropical ocean temperature, increase in storm lifetime does not match when data is reconstructed using Hadley Centre Sea Surface Temperature and averaged reanalysis data over the same tropical areas giving rise to a 40% increase in PDI. A sharp increase in PDI after the 1970s indicates global

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warming along with vertical wind shear, sub-surface temperatures, and many other missing variables to play a part in such an unprecedented increase

Matsuoka et al. (2018) [19] proposed A binary classification using CNN feeding on 2D Outgoing Longwave Radiation data classifying "developing tropical cyclones" from "non-developing depressions" and "precursors". Training data from 1979 to 1998 were equally divided into 50,000 negative (non-TCs) and positive (TCs and precursors) data each, generating ten deep CNNs by shuffling the data. Successfully predicting TCs in the western North Pacific from July to November with a detection probability of 79.9-89.1% also increases the False alarm ratio by 32.8-53.4%. Accuracy of 91.2%, 77.8%, and 74.8% for precursors was achieved for 2,5, and 7 days before their genesis suggesting the promise of a data-driven approach for analyzing tropical cyclogenesis.

Meng et al. (2022) [20] described a method for predicting TC by directly forecasting the Passive Microwave Rainfall (PMR) estimation from satellite infrared (IR) images of TC. There are many related studies to convert IR signals into surface precipitation rates by statistical and machine learning techniques such as the Persian algorithm- which used artificial neural network (ANN) techniques to establish the relationship between cloud-top bright temperature and surface precipitation rate. Deep learning technique – which uses a slacked noise reduction self-encoder based ANN to give an estimation of IR images and water vapour precipitation. Here TCR generative adversarial networks (GAN) technique is used to estimate the prediction of IR to PMR which is essentially an image-to-image translation. The generator predicts the PMR image with asymmetric structure and then uses the discriminator to determine whether the PMR image is similar to the IR image, or not. Well-known metrics Peak Signal-to-Noise Ratio (PSNR), Root Mean Square Error (RMSE), Pearson Correlation Coefficient (CC), and Structure Similarity Index Measure (SSIM) were used measure the performance of TCR-GAN. Grid-Sat and CMORPH dataset were used for experiment. It was compared to the advanced models Cycle-GAN, Pix2Pix and Res-Pix2Pix. All the models are trained with 100 epochs using the Adam optimizer. For Cycle-GAN the PSNR, RMSE, CC, and SSIM were 9.781, 7.433, 0.096, and 0.397 respectively. For Pix2Pix the values are 14.080, 6.861, 0.596, and 0.530. With Res-pix2Pix the values are 14.376, 6.848, 0.623, and 0542. Finally, for TCR-GAN the values are 14.480, 6.705, 0.637, and 0.550 making it best models among these four.

Srinivas et al. (2013) [21] proposed a mesoscale model Advanced Research Weather (ARW) which amalgamated compressible non-hydrostatic equations and terrain conditions. The outer part of two-way interactive nested domains, covers a larger area of 27km and the inner part has a 9km resolution with the minimum grid. The terrain data is collected from the US Geological Survey Topography. To predict TCs planetary boundary layer (PBL), surface fluxes, cumulus convection (CC), and cloud microphysics (CMP) for conversion schemes, vertical fluxes as updraft and downdraft outside the cloud as per the Grell scheme were used. The KF scheme follows a Lagrangian method with moist updraft and downdraft. Other schemes like CMP and WSM3 use the prognostic equation for these purposes. Here, for all the cyclones CSLP is much errorless as compared to the KF scheme. The time variation of MSW shows the higher winds with KF and GDE schemes. Updraft, downdraft, and shallow convection are related to increasing the performance of KF. LIN microphysics is preferred with the combination of KF to reduce the track errors and achieve the same intensity as WSM6 and better than WSM3.

Lian and Dong (2020)[22] had experimentally fused a data preprocessing layer, an AE (Auto Encoder) layer, and a GRU (Gated Recurrent Unit) layer with a customized batch process to train a model on Western North Pacific (WNP) Ocean Best Track Data from 1945-2017 provided by the Joint Typhoon Warning Center (JTWC). The dataset was randomly split into 9:1 ratio for training and testing respectively, within which the training set was further split into 7:3 ratio for testing and validation resulting in 54,981 tropical cyclone records for training, and 6108 records for testing. It outperformed the Numerical Weather Prediction (NWP) model by about 15%, 42%, and 56% in 24, 48, and 72 hour forecasts, and 27%, 13%, 17%, and 17% better than RNN, AE-RNN, GRU, and LSTM, respectively, in 24 hour forecasts.

Chen et al.[23] used semi supervised model with SVM, Back Propagation Neural Network (BPNN) and CNNs including LeNet, GoogLeNet, and ResNet etc. using feature extraction, semi-supervised CNN and training set update. 2 years data of FY-4 meteorological satellite collected, preprocessed using cropping, augmentation. Data used were 5243 sets of MSIs/cyclone with 14 bands with resolution of 4000 m. PCA features were extracted and fed to the proposed semi-supervised CNN with many unlabeled samples. First CNN maps the features and generate feature-label pair, followed by second CNN fine-tuned by feature-label pair of CNN1 and remaining samples are added to CNN2 to predict the Labels. SGD used for optimization, Histogram distance and Euclidean distance were combined and he training set is updated. With only 5% of labeled samples the accuracy for SVM, BPNN, MLR, k-NN, CNN and proposed method were 67.13%, 69.48%, 63.49%, 50.08%, 64.62%, and 77.05% respectively. Experimental results reported for 10%,15%,20%,25% and 30% labelled sample the accuracy 88.92%,94.68%,94.56%,95.59% and 96.69% respectively which is superior with respect other models mentioned earlier.

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III. COMPARISON OF TECHNIQUES

In this section we discuss the methods based on their model architecture, dataset used for the experiments, features used to model input, pre-trained models used, the different training parameters used and finally their performances metrics. The details are given in Table-1.

Table-1: Comparative study of the methods on classification of tropical cyclone

	Architecture	Dataset used	Feature extraction	Pre-trained model used	Training parameter	Accuracy and other measures
[14]	3D-CNN	European Center for Medium-Range Weather Forecasts (ECMWF)	Weighted combination of every input.	Regression, TC-3DCNN	Epochs 50, Adam Optimizer	83.0% when intensity Δ>0
[15]	AlexNet with 2 CNN layers, Max pooling later and NOEN library	CAN 5.1 Historical Run, ERA-INT RIM Reanalysis, 20 Century Reanalysis, NCEP-NCAR Reanalysis	NA	AlexNet with custom layers	VBOT, UBOT, T200, TMQ, V850, U850 Atmospheric river - TNQ, LAND SEA MASK	89-99% accuracy
[16]	Cloud intensity classification techniques	Meteosat-8 and Meteosat-7 data of the US naval Research Laboratory.	COG, Euclidean Distance (ED) Mean ED Find variance, density, DC, entropy	Naive Bayes, SVM, Random Tree, Logistic Model Tree, Random Forest	NA	86.66%
[17]	Climate models and observational reconstructions	Reanalysis data from ERA-5	NA	NA	NA	Local sea surface temperature change has more impact on TC
[18]	Numerical Simulation	Daily averaged Reanalysis data and Hadley Center SST data	Sea Surface Temperature, wind shear, subsurface temperature	Numerical model	NA	40% increase in place of expected 10% PDI
[19]	2D deep CNN (4 convolutional layers, 3 pooling layers, and 3 fully connected layers)	30 years data produced by NICAM with 14 km horizontal resolution	Deep convective circulation	NA	Adam optimizer, Batch Normalization 100000 data Epoch: 19-46	91% (2 days prior), 77.8% (5 days prior),74.8% (7 days prior)
[20]	TCR-GAN, (PMR to IR mapping)	4579 pairs of images from Tropical Cyclone IR to Rainfall Prediction (TCIRRP)	Random cropping, Horizontal mirroring	UNet, Pix2Pix, Res-Pix2Pix	100 epochs, Adam optimizer, momentum beta1=0.5	PSNR=14.480, RMSE=6.705, CC=0.637, AND SSIM=0.550
[21]	ARW version 3.2 Mesoscale model	From IMD reports and Tropical Rainfall Measuring Mission (TRMM) satellite rainfall datasets	NA	NA	NA	About 67% of the cyclones are simulated with mean errors.
[22]	AutoEncoder with GRU	Western North Pacific (WNP) Ocean Best Track Data from 1945-2017	ANN generated	NA	LR=0.001, batch=64,loss=MSE	27%,13%, 17%, and 17% better than RNN, AE-RNN, GRU, and LSTM
[23]	Semi supervised deep network	FY-4 meteorological satellite data	Cropping, Data augmentation	LeNet, ResNet, GoogleNet	SGD optimizer	77.05 - 95.59% for 5-30% split

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IV. CONCLUSION

This paper gives an overall idea about the tropical cyclone as a disaster and the efforts made by human civilization to combat it scientifically in a structured way using the vast amount of ocean surface temperature, cloud data generated by satellites, coastal systems, hydrological data along with analysis models based on simulation, statistical and mathematical tools to predict the genesis and intensity of tropical cyclones. Here the focus was mainly on deep learning based models which proved to be superior with respect to other traditional models in terms of the performance metrics as can be seen from Table-1. The problem of training with huge volume data is a legitimate challenge which is becoming simpler nowadays with the advanced hardware's like GPU, parallel computing and others. With the increase of the accuracy of the model more and more human lives can be saved nowadays by shifting them well ahead of time. The material loss also can be minimized by taking precautionary measures in long term and short term basis A few long term measures may be localizing the frequently affected zones, mangrove plantation in coastal areas, vital dams construction, community shelter building, relief camp construction etc.

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AUTHOR CONTRIBUTIONS

Every author have contributed to the work equally and constantly researching on the context by critically studying relevant works and implementation of the models used so far.

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DECLARATION OF CONFLICT OF INTEREST

All authors hereby declare that they don't have any conflicting financial interests or personal relationships that have appeared here to influence this work.

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