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Deep Learning Regression and Classification of Tropical Cyclones based on HURSAT data

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Abstract

This study focuses on the application of Convolutional Neural Network (CNN) models for cyclone intensity estimation and classification. Cyclones are one of the most devastating natural disasters that cause significant loss of life and property damage. Accurate and timely estimation and classification of cyclones can help in effective disaster management and mitigation. In this study, a CNN Lenet architecture is used for classification and a proposed CNN model is used for intensity estimation of cyclone satellite images. The method involves pre-processing the data, training the models on the dataset, and evaluating the model's performance. The results demonstrate that the models achieve high accuracy in cyclone classification and low Root Mean Square Error (RMSE) in cyclone intensity estimation. This study provides insights into the potential of CNN architecture, which can be beneficial in enhancing disaster management strategies.

1 Introduction

The field of atmospheric science focuses on examining the Earth's atmosphere and understanding its intricate physical processes. Tropical Cyclones (TCs) are powerful warm cyclonic vortexes that originate from low-pressure systems over tropical oceans, propelled by intricate interactions between atmosphere and the sea [4]. The North Indian Ocean (NIO) basin typically comprises of 7% of the global TCs and most of the cyclone images are of Category 1 or below, nonetheless they cause massive havoc and destruction in the Arabian Sea and Bay of Bengal [1]. Recent trend analysis, considering both historical data and future forecasts, consistently indicate a rise in the average intensity of global TCs in the upcoming decades, even though there may be a decrease in the frequency of TC occurrences [5].

The emergence of Deep Learning (DL) and advancements in Computer Vision present an innovative and potent toolkit for addressing the challenging task of precisely determining the longitude and latitude of the cyclone center within a 2D input image [2],[7]. As cyclones predominantly form over expansive water bodies where weather stations are scarce, meteorologists frequently face the challenge of approximating the wind speed of cyclones [6]. This often involves relying on buoy observations, as well as utilizing microwave and infrared satellite imagery to derive these estimates. Various other methods have been used to estimate intensity of TC including [8] which studied TC Heat Potential (TCHP), a major ocean parameter for TC intensification.

The motivation behind selecting CNN models for cyclone intensity estimation and classification stems from the inherent challenges and limitations associated with existing methods in the field. Traditional methods for cyclone analysis often rely on manual interpretation of satellite imagery or approximate wind speed estimates based on limited data sources. The emergence of DL techniques, particularly CNNs, present an innovative solution to address these challenges.

The primary objectives of this study are two-fold. First is to develop and evaluate the application of CNN models for accurate cyclone intensity estimation in different basins. Second is to employ CNN Lenet architecture for the classification of cyclones based on the Saffir-Simpson scale. These objectives are driven by the pressing need for more effective disaster management and mitigation strategies in the face of increasing cyclone intensity. The study seeks to contribute valuable insights into the potential of CNN architecture to enhance current approaches in cyclone analysis and prediction.

2 Dataset

The HURSAT data project, managed by the National Centres for Environmental Information (NCEI), captures infrared satellite imagery of cyclones. This database stores cyclone satellite images in NetCDF file format. The centre of each cyclone was in the middle of each image. HURSAT-B1 data are derived from International Satellite Cloud Climatology Project (ISCCP) B1 data. The HURSAT-B1 v06 data spans 1978-2015 and provides coverage of global TCs at 8-km spatial resolution and 3-hourly temporal resolution. For this research, the data is taken from year 2001 to 2016. There were 14296, 6189, 195 images of North Atlantic, North Pacific and North Indian ocean respectively. The best track data is sourced from the HURDAT2 database, supplied by the National Hurricane Center (NHC). This database comprehensively documents all identified cyclones across various basins, including their wind speeds recorded at 6-hour intervals. The best track data of North Atlantic Ocean and North Pacific Ocean were taken from HURDAT2 database and the best track data of NIO is

Table 1. Saffir-Simpson Hurricane Wind Scale of cyclone

Category	Wind Speed
Tropical Depression	$\leq$ 34 knots
Tropical Storm	$\leq$ 63 knots
Category 1	$\leq$ 82 knots
Category 2	$\leq$ 95 knots
Category 3	$\leq$ 112 knots
Category 4	$\leq$ 136 knots
Category 5	$>$ 137 knots

taken from Indian Meteorological Department (IMD). Fig 1, Fig 2 and Fig 3 shows the image of TC in different basins at different intensities. The images are categorised into different categories based on Saffir-Simpson scale as shown in Table 1.

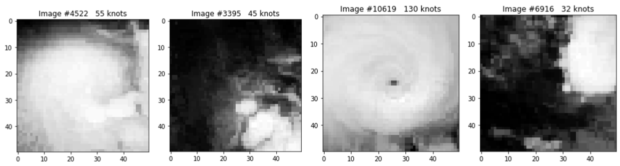

Figure 1. North Atlantic Ocean images with different intensity of cyclones.

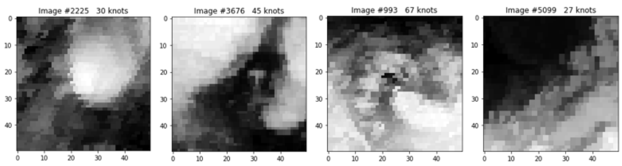

Figure 2. North Pacific Ocean images with different intensity of cyclones.

3 Methodology

TC images are downloaded from 2001 to 2016 into compressed zip files based on different basins, filtering only the images of cyclones for which the wind speed labels are present. The files are downloaded in NetCDF format which holds the satellite images. A CNN model is trained after data processing. Testing is done using k-fold testing. The most valuable information about a cyclone's intensity is near the centre. The satellite images undergo cropping to eliminate the outer regions of the cyclone captured in the image. After reading the satellite image from its NetCDF file and converting it into a NumPy array, the images are then cropped to a 50-by-50-pixel square. This data reduction is implemented to streamline the data augmentation and model training processes, optimizing computational efficiency. The corresponding labels are stored in NumPy files. To align satellite images with their respective wind speeds, a merging process is performed between HURSAT and HURDAT2 datasets. While each satellite image file provides information about the cyclone's name, data, and time, it lacks details on the cyclone's wind speed at that specific moment. To address this, the wind speed for each satellite image is retrieved by searching the cyclone's name, date, and time in the best track dataset. Subsequently, both the satellite image and its corresponding wind speed are simultaneously appended to a NumPy array, effectively labeling the satellite images with its associated wind speed.

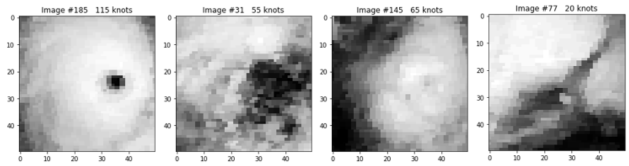

Figure 3. North Indian Ocean images with different intensity of cyclones.

For regression, a custom CNN model is proposed as shown in Table 2 and for classification, LeNet model is used as shown in Table 3. The activation function used for convolution layers is ReLU. The custom CNN model uses RMSProp as optimiser, MSE as loss-function, batch size of 64, 4 convolutional layers, image crop size of 50x50 and metrics as MAE. Data Augmentation of images is done using Keras. For 50-75 knots, 75-100 knots, greater than 100 knots, the number of generated images are 2, 6, 12 respectively. Prior to training the model, an examination of the data reveals a substantial disparity, with weak TCs greatly outnumbering strong TCs in the dataset. This is expected, given the higher frequency of tropical depressions and storms compared to cyclones. However, this imbalance in the dataset adversely affects the neural network's performance on cyclones. To address this, Keras' Image Data Generator is employed to augment existing cyclone data in the dataset. The incorporation of this augmented data during model training leads to a notable enhancement in performance, particularly in the accurate estimation of wind speeds for cyclones. The augmentation techniques used in this research are - Horizontal flip, Vertical flip, Rotation range: 360, Fill mode: Nearest.

4 Results

The Regression results are shown in Table 4 and Classification results are shown in Table 5. For Regression analysis, the number of k-folds taken were 5 for each basin. Fig 4, Fig 5 and Fig 6 shows the distribution of absolute error by category of North Atlantic Ocean, North Pacific Ocean and North Indian Ocean respectively. The legend shows the number of test samples inside each category. Tropical Depression is hardest to estimate because of noise and minimal characteristics in the images.

Individual evaluations for models associated with different regions (NA, NP, NI) reveal their specific strengths and weaknesses. Furthermore, combining these models showcases a promising trend in improving overall performance, as seen in reduced Mean Absolute Error (MAE) and Root

Table 2. Proposed Regression Model

Convolution	32(48, 48, 32)	(3, 3)
Max Pooling	(24, 24, 32)	(2, 2)
Dropout	0.2	
Convolution	64(22, 22, 64)	(3, 3)
Max Pooling	(11, 11, 64)	(2, 2)
Dropout	0.2	
Convolution	128(9, 9, 128)	(3, 3)
Max Pooling	(1, 1, 128)	(2, 2)
Dropout	0.2	
Convolution	128(2, 2, 128)	(3, 3)
Max Pooling	(1, 1, 128)	(2, 2)
Dropout	0.2	
Flatten		
Dropout	0.4	
Dense	512	
Dropout	0.2	
Dense	1	

Table 3. LeNet Model

Layer	Filters(Output shape)	Kernel size
Convolution	32(50, 50, 32)	(5, 5)
Max Pooling	(25, 25, 32)	(2, 2)
Convolution	64(21, 21, 64)	(5, 5)
Max Pooling	(10, 10, 64)	(2, 2)
Convolution	64(6, 6, 64)	(5, 5)
Flatten		
Dense	64	
Dropout	0.3	
Dense	5	

Mean Squared Error (RMSE) values. Notably, the combined model for NA and NP images demonstrates a reduction in both MAE and RMSE, suggesting a synergistic effect. The inclusion of the NI model in the combination slightly increases the errors but maintains a competitive performance. The consistent application of 5-fold cross-validation throughout the analysis enhances the reliability of the findings. The LeNet model for classification demonstrates notable accuracy in classifying cyclone images, with the highest accuracy observed when trained on NA images and tested on NI images in the 5-class scenario (64.23%). However, the model maintains competitive accuracy levels across different configurations.

These results highlight the Proposed model and LeNet model's potential in contributing to disaster management efforts by accurately classifying cyclones, aligning with the overarching goal of the study to leverage DL techniques for improving cyclone-related disaster management strategies.

5 Conclusion and Future Prospective

This study seeks to fill the gap in existing research by harnessing the potential of CNN architecture, offering

Table 4. Regression Testing Results

Basin	MAE(knots)	RMSE(knots)
NA	9.7	12.38 knots
NP	12.74	16.16
NI	12.34	15.61
NA & NP combined	11.58	14.74
NI, NA & NP combined	11.77	14.8

Table 5. Classification using LeNet model

Train	Test	Classes	Test Accuracy
NA images	NI images	5	64.23%
NP images	NI images	5	58.96%
NA images	NI images	7	57.8%
NP images	NI images	7	57.8%
NA and NP images	NI images	5	59.43%
NA and NP images	NI images	7	53.6%

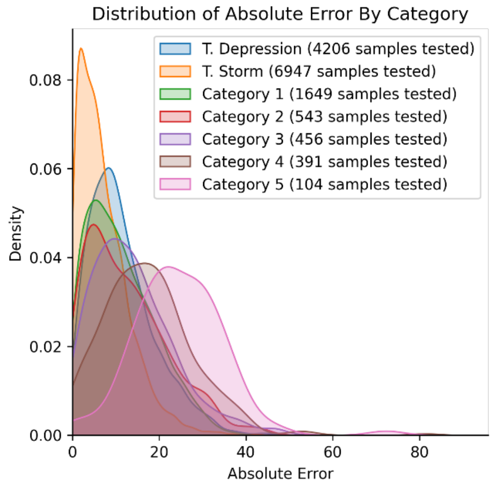

Figure 4. North Atlantic Ocean Absolute Error Distribution

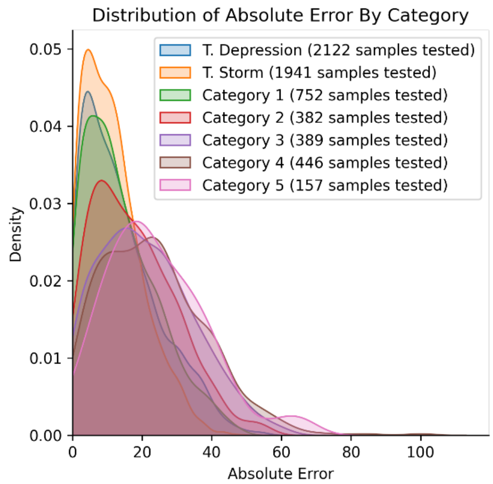

Figure 5. North Pacific Ocean Absolute Error Distribution

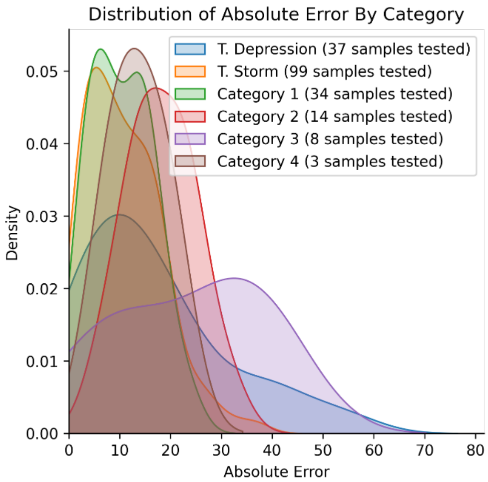

Figure 6. North Indian Ocean Absolute Error Distribution

a promising avenue for enhancing disaster management strategies and minimizing the devastating impact of cyclones on lives and property. DL techniques have demonstrated remarkable efficacy in addressing challenging issues across a diverse range of applications in Atmospheric Science and Climate Physics. These often involve data-driven problems related to optimization, classification, and prediction, among others. In instances of severe cyclones and adverse weather conditions, identifying regions where TCs exist and determining their intensity can be challenging. In such contexts, the objective of constructing a DL-based model is to enable the estimation and classification of cyclones based on imagery. This capability can significantly assist weather scientists in detecting points of rapid intensification.

The study lacks training data in a wide variety of classes. Efforts can be made to expand the dataset to include a wider range of cyclone images, especially the higher intensity cyclone images, and to cover a longer period of time. The work can be added for visualization and can also be used to predict the cyclone direction, increasing the accuracy by training over wide variety of cyclone data.

6 Acknowledgements

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References

[1] Anthony Wimmers, Christopher Velden and Joshua H. Cossuth, “Using Deep Learning to Estimate Tropical Cyclone Intensity from Satellite Passive Microwave Imagery”, AMS Journals, vol. 147, issue 6, pp. 2261-2282,1 June 2019, doi: 10.1175/MWR-D-18-0391.1.

[2] Buo-Fu Chen, Boyo Chen, Hsuan-Tien Lin, and Russell L. Elsberry, “Estimating Tropical Cyclone Intensity by Satellite Imagery Utilizing Convolutional Neural Networks”, vol. 34, issue 2, pp. 447-465, 1 Apr 2019, doi: 10.1175/WAF-D-18-0136.1.

[3] Devraj J, Ganesan S, Elavarasan RM, Subramaniam U, “A Novel Deep Learning Based Model for Tropical Intensity Estimation and Post-Disaster Management of Hurricanes”, Appl. Sci., 2021, 11, 4129, doi: 10.3390/app11094129.

[4] Shay, Lynn K. "Air-sea interactions in tropical cyclones." In Global Perspectives on Tropical Cyclones: From Science to Mitigation, pp. 93-131, 2010, doi: 10.1142/7597.

[5] Song, Jinjie, Philip J. Klotzbach, Jianping Tang, and Yuan Wang. "The increasing variability of tropical cyclone lifetime maximum intensity." Scientific reports 8, no. 1 (2018): 16641, doi: 10.1038/s41598-018-35131-x.

[6] Roy, Chandan, and Rita Kovordányi. "Tropical cyclone track forecasting techniques—A review." Atmospheric research 104 (2012): 40-69, doi: 10.1016/j.atmosres.2011.09.012.

[7] Mooers, Griffin, Mike Pritchard, Tom Beucler, Prakhar Srivastava, Harshini Mangipudi, Liran Peng, Pierre Gentine, and Stephan Mandt. "Comparing storm resolving models and climates via unsupervised machine learning." Scientific Reports 13, no. 1 (2023): 22365, doi: 10.1038/s41598-023-49455-w.

[8] B. Jangir and D. Swain, "Validation of Tropical Cyclone Heat Potential (TCHP) derived from satellite products over the North Indian Ocean," 2019 URSI Asia-Pacific Radio Science Conference (AP-RASC), New Delhi, India, 2019, pp. 1-1, doi: 10.23919/URSIAP-RASC.2019.8738449.