A Survey Of Deep Learning Based Cyclone Intensity Estimation

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***Abstract*— Throughout climate research, predicting the intensity of meteorological events, like hurricanes, has proven to be a difficult task. To this end, numerous deep-learning models have been constructed. When a catastrophic hurricane hits a coastal area, there are significant risks to human life and ecosystems. Additionally, there are significant financial losses. Models must be created to increase prediction accuracy and prevent such large losses in all areas. However, forecasting or tracking each storm formation in real-time is unfeasible. While several methods, including recurrent neural networks (RNN), convolutional auto-encoders, and convolutional neural networks (CNN), are available for determining the intensity of a tropical cyclone [2]. By using infrared satellite imagery data and wind speed data, an enhanced deep CNN model is utilized to forecast the intensity values of the weakest to fiercest hurricanes. Determining a cyclone's intensity is the primary goal of this research project since cyclones can pose a serious threat and harm [1].**

Keywords—Deep Learning, convolutional neural network (CNN), Recurrent Neural Network (RNN)

I. Introduction

One of the most damaging kinds of extreme weather disasters are tropical cyclones (TC). They come from over the warm waters of the tropics and have a big impact on the world economy. Hurricanes in the western North Pacific, cyclones in the Atlantic, and cyclones in the Bay of Bengal are the names given to these storms when they reach their highest strength [5]. It was widely acknowledged that tropical cyclones have a negative impact on people's lives, property, and transportation. The severity of the injury may vary according on its size, location, and intensity. [8]. Cyclones, which can cause serious destruction to the environment, wildlife, and human life, can contain rain and strong gusts. Among the damages include communication system failures, waterborne infections, fires, and floods [10].

Forecasters often rely on satellite-based methods to calculate the intensity of tropical cyclones (TC) in ocean basins that lack aircraft reconnaissance capabilities. The Dvorak technique (DT) is a commonly used approach for assessing TC intensity. This technique uses manual pattern recognition to calculate the intensity of TC based on cloud patterns seen in satellite infrared images. For almost 30 years, the Dvorak methodology has been widely used to estimate the severity of tropical storms based on satellite images.

There are several techniques to estimate the strength of tropical cyclones (TC) using satellite data. Some of the popular ones are consensus techniques and microwave sounders-based techniques. The traditional Dvorak approach is one such method that links the strength of a TC to its rotation, eye shape, and deep thunderstorms. This approach assumes that cyclones of similar strengths follow similar paths. A specialist can visually analyze the shape of a TC cloud in visible and infrared photos. However, the latest version of the Dvorak approach eliminates human subjectivity by using automated algorithms [9].

This survey research aims to compare the performance of various deep learning models used to estimate cyclone strength. We explore different methods of calculating cyclone intensity from satellite imagery in this survey.

II. Deep Learning

In recently years, deep learning techniques have gained popularity, especially in the domains of natural language processing and computer vision. Segmentation and convolutional Bi-Directional Gated Recurrent Unit (GRU) networks are two instances of these techniques [1]. In the history of climate science, predicting severe weather events, like hurricanes, has always been a difficult task. Several deep learning models have been developed to predict the intensity of weather events. Numerous high-impact weather applications can benefit from the application of machine learning and deep learning, and accurate forecast outcomes can be attained. When modeling complex problems, deep learning models can capture higher level feature representation. With a lot of training data, DL models perform well, and hybrid models still improve the efficiency. The difficulty of estimating cyclone intensity has been significantly solved in recent years by deep learning-based approaches. These methods make use of deep neural networks' potent representation learning skills to assess the strength of the cyclone and extract valuable information from satellite data. Unfortunately, majority of deep learning- based methods already in use concentrate on visible light images, which has limitations when it comes to capturing a cyclone's underlying dynamics and structure [3].

When classifying satellite data, deep learning approaches have demonstrated their dependability by yielding optimal results even with unstructured data and producing high detection accuracy with low processing time [10]. Artificial neural networks, including recurrent neural networks, convolutional neural networks, MLP and deep belief networks, are used in deep learning (DL), a subset of machine learning techniques [11].

A. *CONVOLUTIONAL NEURAL NETWORK*

In many papers, convolutional neural network was programmed to estimate the cyclone intensity as it was a robust algorithm [1]. One type of deep learning technique for analyzing data arranged in a grid format is the convolutional neural network (CNN). They are a type of deep learning technique used for spatial or temporal information analysis. Compared to other neural net types, CNN has an additional layer of complexity due to the use of a convolutional layer stack.The more features a model can learn from the images it is fed, the more complex the model gets[5].

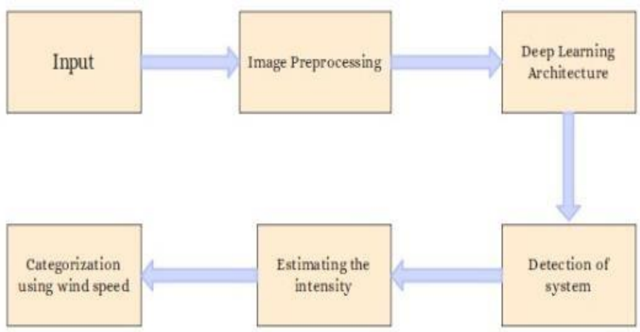

Figure 1: Convolutional Neural Network [1]

Different layers such as convolutional, pooling, and fully connected (FC) layers can be found in a basic CNN model. Convolutional layer it extracts features from images. The maximum value of these features is then filtered by the pooling layer to lower the total number of features. After learning every feature, the FC layer outputs the outcomes. A dropout layer, which sets the partial weight to zero, is typically added before the FC layer to prevent over-fitting [9]. CNNs are excellent at extracting data because they are made to use a sequence of convolutional layers that learn progressively more complicated representations of the visual data in order, to extract features from images in an orderly fashion [1].

In order, to categorize cyclones into distinct intensity categories based on picture data, CNNs are a good option since they can handle the image data well and learn the pertinent characteristics and patterns [1].

Convolutional neural networks, or CNNs, are immensely effective classifiers that have been the subject of extensive research in recent years. Several CNN versions, including as LeNet, GoogLeNet, and ResNet, were put forth and achieved impressive results on a variety of vision tasks. The assessment of cyclone intensity for infrared (IR) pictures has been effectively accomplished recently with CNN [4].

B. *RECURRENT NEURAL NETWORK*

Recurrent Neural Networks (RNNs) are a type of ANN in which the network has internal loops that exhibit dynamic temporal activity. In machine learning, recurrent neural networks (RNNs) are nonlinear dynamical models that are frequently used to represent complex sequential or dynamic interactions between variables. Robust spatiotemporal processes, like predicting hurricane paths, are a type of complex systems where RNNs may have some utility. The precision of projected path estimates could be enhanced by an RNN that can simulate the intricate nonlinear temporal interactions of a hurricane [13].

RNNs have been used, for instance, to forecast events in the real world. RNNs are often fully linked networks that are trained using connection weights. On the other hand, processing units (neurons), hidden layer count, and network topology all have a significant impact on network efficiency. Furthermore, fully connected networks may have unneeded linkages, increasing their complexity. Conversely, sparse (non-fully linked) networks offer faster processing times, more generalization, and a larger store capacity per connection.[14]

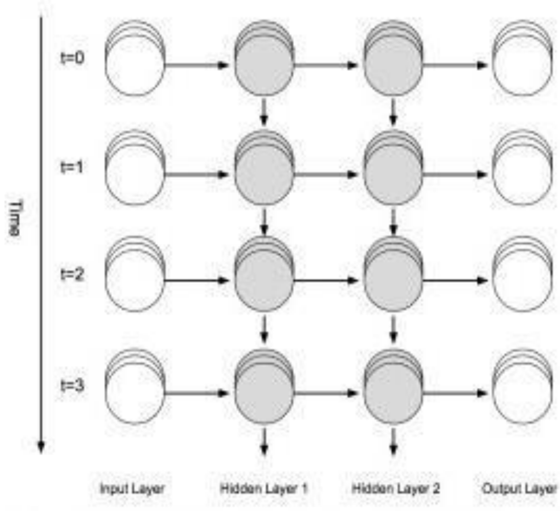

Figure 2: Recurrent Neural Network [13]

Ref	Forecasting Model	Severe Weather Type	Data Source, Data Set, Sample Size and Location	Model Evaluation	Purpose of Prediction	Limitations
[1]	INSAT 3D pictures and CNN	Tropical cyclones	INSAT3D: 2012–2021 Infrared and Raw Cyclone Imagery	Mean Absolute Error (MAE) and Mean Squared Error (MSE) are evaluation metrics.	Enhancing the speed and effectiveness of cyclone monitoring by automating the intensity estimation process	Depends on analysts' subjective interpretation of cyclone cloud patterns, which leads to discrepancies.
[3]	CNNs with convolutional layers, like ResNet-50 and Inception-V3,	Severe natural disasters, such as cyclones	400,000 photos of the Arabian Sea and the Gulf of Bengal from INSAT-3D infrared imaging; sample size ranges from 20 to 120 km..	R-squared score, Mean Absolute Error, and Mean Squared Error (MSE)	To provide precise and timely estimations of cyclone intensity in order, to enhance disaster management.	It has limitations because, in contrast to MSE or MAE, R-squared could not be as good at identifying and penalizing huge errors.
[4]	CNNs with convolutional layers for FY-4 multispectral images (MSI)	Cyclones in the tropics	5243 multispectral image (MSI) sets that the FY-4 weather satellite acquired With 14 bands and 240 x 240 pixels, each MSI shows a cyclone at a 4000 m spatial resolution.	The Kappa coefficient and overall accuracy (OA)	precisely predict the intensity of a storm ahead of time, particularly in coastal regions vulnerable to strong tropical cyclones	The dearth of accurately labelled samples, particularly in the context of estimating cyclone severity
[5]	Neural network using bounding box convolution (BBCNN)	Cyclone that forms over warm water	Infrared and Raw Cyclone Imagery from INSAT3D (2012–2021) pictures taken by the satellite KALPANA 1	F1-score, recall, and precision	Created a cutting-edge deep learning method to identify the eye's cyclone intensity for forecasting and surveillance needs.	The difficulty of obtaining high precision with few training examples in image recognition is known as limitation.
[6]	CNN	Tropical storms in the Northern Pacific region's west	Track data, 3D reanalysis data, and a dataset from the U.S. Naval Research Laboratory's (NRL) Marine Meteorology Division,	13.24 knots for the Root Mean Squared Error (RMSE)	The primary objective is to precisely calculate the intensity of tropical cyclones using satellite data to enhance preparedness and response for disasters.	The drawback of previous methods, like as Dvorak, was their reliance on human interpretation of cloud feature data to estimate the severity of tropical cyclones.
[7]	RNNs and CNNs	Cyclones	India Meteorological Department's infrared imagery from INSAT-3D (2014 to 2019)	CNN and RNN had mean absolute errors (MAE) of 5.21 and 5.52 knots, respectively.	Assessing the performance of CNN and RNN, two deep learning models, in forecasting cyclone intensity based on images	–
[8]	CNN	Typhoons, high winds, and rain	Tropical Cyclone Wind Estimation Competition Dataset comprises of 366x366 black and white photos of storms from the Atlantic and East Pacific Ocean.	Categorical cross-entropy in the multi-class classification mode	The primary purpose is to estimate the severity of tropical cyclones in order, to reduce risks to human lives and environmental damage caused by severe weather occurrences.	Limitations include issues linked to generalization to varied cyclone patterns and potential biases in the training sample.

[9]	DCNN	Tropical cyclones in the Northwest Pacific Ocean	Advanced Himawari Imager onboard the Himawari-8 geostationary satellite (2015 - 2018)	Root mean square error (RMSE) of 5.24m/s (meters per second).	The goal of this project is to create an objective approach for evaluating tropical storm intensity using deep CNN.	The constraint was properly resolving the issue of data imbalance.
[10]	DCNN	Cyclones are severe circular storms known as typhoons.	INSAT-3D has channels such as visible and short-wave infrared.	Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE)	The major goal is to detect cyclones and predict their intensity prior to eye formation.	The limitation is the probable loss of microscopic details about cyclones when lowering image sizes for CNN processing.
[11]	3D-CNN	TC	Data from the western North Pacific over a span of 22 years (1997-2018)	Mean absolute error (MAE)	To improve the accuracy of forecasting tropical cyclone (TC) intensity fluctuations during a 24-hour warning period using deep learning techniques.	The challenge is to determine how different combinations of atmospheric layers affect the model's convergence and prediction accuracy.
[12]	Machine Learning model, specifically a Multilayer Perceptron (MLP)	Tropical cyclones in the Atlantic, Central, and Eastern North Pacific	Atlantic dataset covers from 1982 to 2017 and contains approximately 11,000 cases.	Mean Absolute Error (MAE) and MLP	Predicting variations in tropical cyclone intensity for better preparedness and risk reduction methods.	The restriction is potential bias and systematic errors found in forecasting extreme intensity variations.

Table 1: Survey table on different models of deep learning

III. Conclusion

After reviewing the reference papers, it can be concluded that deep learning models have potential to improve TC intensity forecasts. It shows that using CNNs and RNNs shows promise. These models improve early warning systems for disaster preparedness by providing automation, uniformity, and robustness in intensity estimation. Even though these models are more accurate and efficient than previous methods, there are still several limits that need to be investigated. These include the inability to forecast dramatic changes in intensity, difficulties obtaining data, and difficulties with image preprocessing. All things considered, deep learning-based methods show great promise for improving the precision of cyclone strength estimation and aiding in disaster relief operation.

In order, to overcome obstacles such data scarcity, subjectivity in conventional approaches, and the effects of climate change, strong methodologies are required. The literature review highlights the benefits and drawbacks of various models. When it comes to cyclone intensity estimation, the suggested deep learning models often beat conventional methods in terms of automation, accuracy, and efficiency. With timely and accurate predictions, these developments have the potential to completely transform early warning systems.

Every work presents novel perspectives, exemplifying the ongoing innovation in model structures, through the application of attention layers, hybrid similarity assessments, or INSAT-3D imaging. Numerous studies do admit certain difficulties, though, such as data imbalance, a lack of training cases, and computational complexity.

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