Image Processing Technique For Tropical Cyclone Intensity Detection Using Deep Learning Algorithm

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***Abstract*— The prediction and detection of tropical cyclones (TCs) is one of the newest fields of study. Meteorologists employ a variety of ways to anticipate and estimate TC intensity, starting with the Dvorak methodology. We present an image processing-based technique to categorize cyclone strength using feature vectors in this research. The mean, variance, density, and decentricity are used to generate the feature vector of a TC. in machine learning algorithm is the prediction of cyclone image and classification with less efficiency. In this paper we proposed deep convolution neural network scheme is designed for extracted the more feature of images deep learning approach for identifying tropical cyclones (TCs) and their precursors. Twenty year simulated outgoing longwave radiation (OLR) calculated using a cloud-resolving global atmospheric simulation is used for training two-dimensional deep convolutional neural networks (CNNs). Image processing algorithm with feature extraction algorithm is used for extracted feature of image Deep convolution neural network-based algorithm provide the better feature extraction of cyclone images**

Keywords*— Tropical Cyclones, Dvorak Methodology, Intensity, Satellite Photos*, deep learning, CNN.

I.INTRODUCTION

Tropical cyclones (TCs) are known for causing extensive damage and devastation. Forecasting TC intensity assists individuals in preparing for harsh weather and may save lives and property. The main reasons of TC intensity forecasting mistake are rapid intensifications (RI). The RI processes of TCs are influenced by a variety of elements, including sea surface temperature and wind shear. A lot of effort has gone into determining the best mix of circumstances for RI. Apart from Dvorak and modified Dvorak procedures, researchers have developed a variety of strategies for intensity detection. The geometric elements of the TC pictures are the subject of feature-based approaches. Many issues, such as picture classification, have been solved using machine learning techniques. Previously, the MLP algorithm was used to estimate TC intensity, however the method suggested here is based on image-based geometric aspects of TC. The use of sea surface temperature to forecast intensity is a common strategy, and numerous studies have been conducted in this field. A tropical cyclone (TC) is a low-pressure region or whirl in the atmosphere that rotates clockwise or anticlockwise over tropical waterways. Various intensity scales are used to classify tropical cyclones. Knowing the severity of TC is critical information for minimizing the harm caused by TC. The strength of the cyclone must be determined at regular periods of time. As a result, traditional approaches such as visualization of satellite photos are used to evaluate the strength changes of these cyclones at repeated intervals.

Tropical cyclones are spotted from a variety of locations across the world. Tropical cyclones that originate in the Arabian Sea (ARB) and Bay of Bengal are monitored by the Indian Meteorological Department (IMD) (BoB). IMD uses the cyclone categorization scale shown in Table 1.

Table 1. Classification of Cyclone

S. no.	Name given due to intensity	Intensity
1	Depression	31–49 km/h (17–27 knots)
2	Deep depression	50–60 km/h (28–33 knots)
3	Cyclonic storm	62–87 km/h (34–47 knots)
4	Severe cyclonic storm	88–117 km/h (48–63 knots)
5	Very severe cyclonic storm	118–166 km/h (64–90 knots)
6	Extremely severe cyclonic storm	167–221 km/h (91–119 knots)

The India Meteorological Department (IMD) is responsible for monitoring tropical cyclones that form between 100°E and 45°E in the North Indian Ocean (including the Bay of Bengal [BoB]). In the previous 20 years, the North Indian Ocean has seen a lot of cyclones. IMD then created a tropical cyclone measuring scale. This intensity scale is used for the North Indian Ocean and may be divided into several categories, including Depression, Deep Depression, Cyclonic Storm, Severe Cyclonic Storm, Very Severe Cyclonic Storm, Extremely Severe Cyclonic Storm, Super Cyclonic Storm, and others. Table 2 shows the categorization that is depending on wind speed (low to high).

The TC eye detection is a crucial step in the TC intensity detection process. The cloud-free zone of the TC eye is surrounded by dense cloud and little wind, and it is regarded a unique location. The storm's eye usually originates in the center of the Central Dense Overcast (CDO) zone, with a diameter of 10–50 km in most occurrences. The appearance of an eye in satellite imagery is employed in the Dvorak approach to approximate TC intensity.

Table 2. Intensity scale of Tropical Cyclone

Intensity scale	Sustained winds speed (3-min average)
Extremely Severe Cyclonic Storm (ESCS)	90–119 k 166–220 km/h
Very Severe Cyclonic Storm (VSCS)	64–89 kt 118–165 km/h
Severe Cyclonic storm (SCS)	48–63 kt 89–117 km/h
Cyclonic Storm (CS)	34–47 kt 63–88 km/h
Deep Depression (DD)	28–33 kt 51–62 km/h
Depression (D)	17–27 kt 31–50 km/h

II.RELATED WORKS

After the Dvorak technique was widely adopted in 1975, systematic procedures for objectively analyzing and forecasting TC intensity using satellite-based datasets were developed. Using areal histograms to remove subjectivity in interpreting vigor and cloud organization of cloud-top temperatures, as well as Fourier analysis Estimation has been found to improve in the vicinity of the eye.

Similarly, temperature histograms along a TC's radial and angular directions were used to match TC images with similar convective characteristics; a relationship between matched images was then derived to estimate TC intensity.

Another study found that cloud axis symmetric may be measured by calculating deviation angle variances (DAV) of cloud pixels within a 350-kilometer radius of the TC vortex, and that DAV can be used to predict TC intensity. Reference [10] improved on the method by running multiple regressions on seven predictors, including DAV, and achieving an RMSE of 12.01 knots.

Some related work in estimating wind speed from satellite images is discussed here, as well as existing portals that provide real-time tropical cyclone information. We provide background information on convolutional neural networks network, which serves as the foundation for our deep learning model.

A. Dvorak Technique

The Dvorak technique, which uses satellite images to estimate tropical cyclone intensity, has been used for more than 30 years. Variations of the Dvorak technique are considered the gold standard for satellite image-based tropical cyclone intensity estimation among tropical meteorologists, with modifications and improvements over the years, including automated versions [9]. The central premise

The Dvorak technique's shape and coverage of the cloud field are related to the cyclone's intensity. The length and curvature of the storm's outer rain bands are analysed to determine the T-number, as shown in Figure 1. Given this visual analysis, certain objective rules based on prior intensity estimates that are used to determine the current intensity are applied. The Dvorak technique's longevity in the tropical community demonstrates that there is a physical relationship between spatial cloud patterns and tropical cyclone intensity. However, because the Dvorak technique is based on human interpretation of features in a tropical cyclone cloud field, two well-trained analysts can assign different intensities. Furthermore, minor variations

b. Advanced Dvorak Technique

Olander and Velden expanded on the manual Dvorak technique by introducing the Advanced Dvorak Technique. which feeds satellite imagery into an automated algorithm that generates a T-number Additional enhancements have been incorporated into the ADT, such as the incorporation of aircraft measurements, as well as passive microwave data as enhanced tropical cyclone centering; an important component of the computerized algorithm While the ADT evolves, model performance issues with the manual Dvorak technique on weaker storms with disorganised cloud formations To constrain, distribution and empirical thresholds are retained. the variation in cyclone intensity over time

B. Deviation-Angle Variance Technique (DAVT)

Pineros et al. and Ritchie et al. described and applied the deviation-angle variance technique (DAVT) to the North Atlantic, and Ritchie et al. [13] to the North Pacific. The symmetry of tropical cyclones in infrared (IR) satellite imagery is quantified using this technique. It analyses the brightness of those images using a directional gradient statistical analysis. The gradient vector's level of alignment is the amount of deviation from the perfect radial axis. The variance of this deviation angle is used in cyclone quantification. This technique has two major limitations: I it requires images with properly labelled tropical cyclone Centre's, and (ii) it employs different models and fitting parameters for tropical cyclones in different regions, limiting broader, global applications.

C. Passive Microwave Imagery-based Tropical Cyclone Intensity Estimation

Passive microwave satellite measurements provide extra information on the cyclone's inner structure. Microwaves can see through clouds and show precipitation. amongst the storm. Initial estimation efforts straight from passive microwave tropical cyclone strength However, [34] have added microwave data into the ADT, reducing estimation errors. The ADT uses microwave data only when the storm is intensifying and there is no visible eye. The reduced temporal frequency of observations when compared to infrared geostationary satellite measurements is one of the key drawbacks of employing passive microwave data for operational diagnosis of cyclone intensity.

E. Convolutional Neural Network

Learning "features" is a core idea behind deep learning, which consists of machine learning, computer vision, and pattern recognition algorithms that have multiple layers, where each layer performs feature detection. The fundamental issue in image classification is bridging the semantic gap of using low-level features (image pixels) to derive high-level abstractions. Deep learning's hierarchical layered learning approach attempts to bridge that semantic gap. Recent advancements in deep learning techniques have produced state-of-the-art image classification results in many domains [25] mostly using convolutional neural networks (CNN)

Convolutional neural networks (CNNs) have been used for many different computer vision tasks ranging from image classification [17], [18], [19] to object detection [20] and even visual saliency detection [23]. Each task uses a slightly different network layout depending on the objective. However, their basic components are all very similar, consisting of convolutional layers, pooling layers, and fully connected layers.

Convolutional neural networks (CNNs) have been utilized to solve a variety of computer vision problems, including picture categorization, object identification [20], and object recognition. even detection of visual saliency [23]. Each assignment requires a somewhat different approach Depending on the goal, multiple network layouts are used. However, Convolutional layers, pooling layers, and fully linked layers are all present in their basic components.

The convolutional layer's main job is to learn feature representations of the inputs, where a feature is any form of input pattern (for example, a cloud band in a satellite image). The weights of the convolution filters are learned during each iteration of the network during convolution, which is the major action in this layer. Feature maps are created by convolutionally filtering the input and then applying an element-wise non-linear activation function to the output. Nonlinearities are introduced to the network by the activation function, which is commonly the rectified linear unit (ReLU)

Pooling layers are typically placed between convolutional layers. It is employed to reduce the spatial size of the representation, thereby reducing the number of parameters and computations in the network. The pooling layer operates independently on each input (feature map) and spatially resizes the input using average or maximum pooling [24]. By stacking more and more convolutional and pooling layers, the network may be able to generate progressively more abstract features at higher representational layers.

After numerous convolutional and pooling layers, the fully connected layer is similar to a traditional neural network, with full connections to all activations in the previous layer. The fully connected layer's job is to do high-level reasoning and classification, which is usually done with a softmax classifier. The most frequent back propagation algorithm used to update the parameters during training is stochastic gradient descent (SGD) SGD calculates each parameter update in terms of a micro batcht.

A CNN has been successfully utilised to estimate tropical cyclone classifications in our prior work. When compared to existing approaches, our results suggest that CNNs perform better. With data from the Naval Research Laboratory, we used up to 5 interval estimation of wind speed. We build on previous work by incorporating additional real-time Geostationary Operational Environmental Satellite (GOES) images, improving the model to estimate wind speed at 1 kt intervals, conducting thorough testing, and installing a production system.

CNNs have also been employed in other research projects to estimate storm intensity. Using passive microwave imaging (37, 89 Ghz bands) as input to the model, Wimmers et al. used CNNs to predict cyclone intensity. The method employs photos from 1987 to 2012. In 5 kt intervals, the wind speed labels are derived from the best track records in the hurricane database (HURDAT2) and the joint typhoon warning centre. The wind speed estimations for training photos are then calculated using linear interpolation. In the test set obtained between 2007 and 2012, the model achieves an RMSE of 14.3. 3-dimensional CNNs were employed by Lee et al. [38] to estimate storm intensity. Satellite imagery from the Communication, Ocean, and Meteorological Satellite - Meteorological Imager is used as input to their suggested model.

Gifford-Roisin et al. [37] build a model based on track data and 3D reanalysis data, as well as additional variables such as location information and maximum sustained windspeed, Models of storm tracks They define the difficulty of tracking. as well as calculating the distance between your current position andcyclone's future location Other CNN variants (CNN Long Short Term Memory (Consett), U-Net) have also been developed.

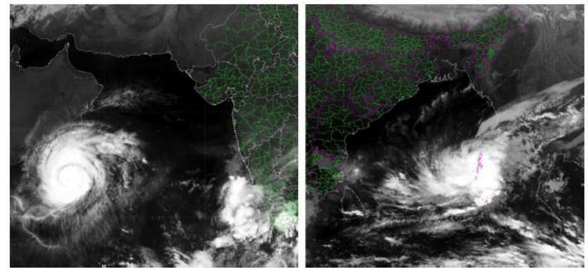

Fig. 1 Tropical cyclone images

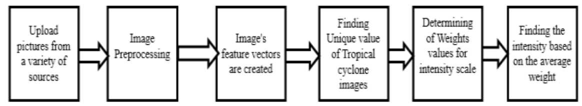

Fig. 2 Proposed system Block Diagram

III. METHODOLOGY

The diagnostic tropical cyclone intensity estimation system was developed and deployed using the end-to-end machine learning lifecycle described by Maskey et al. [29].The machine learning lifecycle is a systematic iterative process of training, testing, and deploying a model in order to create an optimised model ready for ingestion into a production system and consumption by the intended end users.

A. Machine Learning Lifecycle

The four phases of the machine learning lifecycle are problem formulation, data collection and analysis, and model development. development, testing, and deployment to the production system Many machine learning projects come to an end after demonstrating the model's accuracy improvement over the state of the art. Thus, the steps of the machine learning lifecycle that are frequently overlooked are robust evaluation in order to understand how the model makes decisions and deployment of the model in a production environment where the model can be evaluated with new real-time data. We use the full machine learning lifecycle as a road map to develop our production system in this paper.

2) Data Collection and Analysis: The initial training image dataset for this application was created using tropical cyclone satellite images from the Marine Meteorology Division of the United States Naval Research Laboratory (NRL) (http://www.nrlmry.navy.mil). These satellite infrared

(IR) images are captured every 15 minutes and include additional information such as the hurricane's year, date, time, and name.

After several iterations of the early stages of the machine learning lifecycle, we realised that the NRL image database was insufficient and that more samples at a higher temporal frequency were required. Real-time image generation from NRL data, on the other hand, was not possible. As a result, we switched to raw GOES data from NOAA's Comprehensive Large Array-data Stewardship System (CLASS) [30], as well as wind speed information from HURDAT2, the tropical cyclone best track reanalysis data [40]. HURDAT2 is a tropical storm database that provides various characteristics of any tropical storm. We make use of the database's location, time, and wind speed features. Storms from 2000 to 2019 are used, with storms from 2000 to 2016 used for training and storms from 2017 used for testing.

1. Upload pictures from a variety of sources.

Images of cyclones were obtained from the Indian Meteorological Department's Cooperative Institute of Meteorological Satellite Studies and National Satellite Meteorological Center websites.

2. Image Preprocessing

The original image, which we obtained from the aforementioned sources, was cropped manually by observing the region of interest.

To preserve uniformity amongst photos, the clipped image is resized to 100 x 100 pixels.

For the next steps, the enlarged picture was transformed from grayscale to binary.

The preceding processes may result in picture noise, which is eliminated by morphological procedures such as erosion and dilation.

3.Image's feature vectors are created

Construction of a TC image's unique feature vector using the approach suggested by several scholars for constructing Character Unique Feature Vector (CUFV). Calculating the mean, variance, density, and decentricity yields the CUFV. The suggested study is influenced by Onodera et al., Barnes, and Manic's work.

The training dataset for the intensity estimation model is generated using the following steps: • Identify HURDAT2 storm intensity, time, and location (latitude, longitude of storm center) • Create a bounding box around storm using start and end date time of the storm • Use the bounding box and time to download GOES8, GOES-10, GOES-11, GOES-12, GOES-13, GOES15, and GOES-16 IR channel (band 4 GOES-8 through GOES-15 and band 13 for GOES-16) data from NOAA CLASS data catalog • Create a padding of +/-5 degrees from the center of the storm on both latitude and longitude for every file available through NOAA CLASS • Match HURDAT2 wind speed to the closest file if there is not an exact match in time • Inperpolate location information and wind speed (1kt interval) between consecutive HURDAT2 observations • Apply random rotation, random shear, random zoom on training data to create more training samples (only for training set)

Any image that had more than 70% missing data was removed from the training set. Please keep in mind that the training set included all wind speeds. Year data and images from the East Pacific and Atlantic From 2000 to 2016, All wind speed data were included in the validation set. as well as images from the East Pacific and Atlantic for the year 2017. The All wind speed data and images from East were included in the test set. For the years 2018 and 2019, the Pacific and Atlantic will be used. As a result, There were 97152 training samples and 4840 validation samples in each set. as well as 6118 test samples Figure 2 depicts the total number of tropical Training cyclone images at 1 kt wind speed intervals from 20 to 140 knots

3. model development

Using this training dataset, we create a deep learning model for objectively estimating tropical cyclone intensity on satellite images using a convolutional neural network (CNN). To arrive at the final model configuration, the CNN required several iterations through the machine learning lifecycle. Further model iterations since Pradhan et al. 2018 [28] revealed that image classification to Saffir-Simpson scale storm intensity and 5 kt wind speed intervals did not perform as well as linear output at 1 kt wind speeds. As a result, this model takes in training samples at 5 kt speed intervals and outputs a maximum wind speed at 1 kt resolution; however, model precision cannot exceed the 5 kt resolution of the input training.

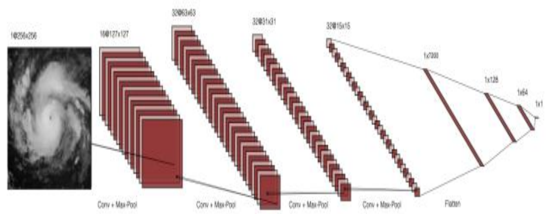

Figure 4:CNN model

data. Overall, the linear model RMSE for all storms in the Atlantic and Eastern Pacific Ocean basins in 2018 and 2019 was 13.62 kts (Table I).

4) Metrics of Performance: The metrics used to evaluate model performance in Table I are as follows:

• Absolute Mean Error (MAE)

$$\frac{1}{n} * \sum |X_p - X_t| \quad \ldots\ldots\ldots\ldots\ldots.(1)$$

$$\frac{1}{n} * \sum (X_p - X_t) \quad \ldots\ldots\ldots\ldots\ldots\ldots.(2)$$

Relative Root Mean Squared Error (RRMSE)\

$$\frac{\sqrt{\frac{\sum (X_p - X_t)^2}{n-1}}}{\overline{X_p}} \quad \ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Where Xp in predicted intensity value and Xt is actual intensity value. n denotes the number of samples depicts the final CNN model architecture. Computing employs a mean squared error (MSE) loss function. difference between real and projected wind speed speed. As a result, the output is considered like a regression output. than the result of a classification The design we selected is a VGG-16 model variation. It is distinct from VGG-16. The VGG-16 model employs 13 convolutional layers. between each two or three consecutive max-pooling layers 4 convolutional layers are included in our CNN model. After each layer, there is a max-pooling layer. This heuristics were used to reduce model complexity and avoid Overfitting the model In addition, our model has four dense layers. The output layer, for example, uses linear activation.

5.Determining of Weights values for intensity scale

The following categories might include a test TC image: Cyclonic Storm, Super Cyclonic Storm, Extremely Severe Cyclonic Storm, Very Severe Cyclonic Storm, Severe Cyclonic Storm, Cyclonic Storm, Deep Depression, and Depression are all terms used to describe a cyclonic storm. Based on training photos, the following method is used to compute weight range and average weight for each category:

$$C = \frac{1}{n}\sum_{k=1}^{n} W_k \quad (10)$$

The weight values of k^{th} image is the W_k.

6. Finding the intensity based on the average weight

To anticipate the intensity of a test image, we use the last 6 hours of photos. For example, if we want to forecast the intensity TC picture of Synoptic Time (YYYYMMDDHH) 2016120800, we must take into account photographs taken after 2016120718. Finally, the average weight of the previous six hour photos predicted the intensity of a test image. Based on computed weight and average weight scale, the category of an input image is determined.

IV.EXPERIMENTAL RESULTS

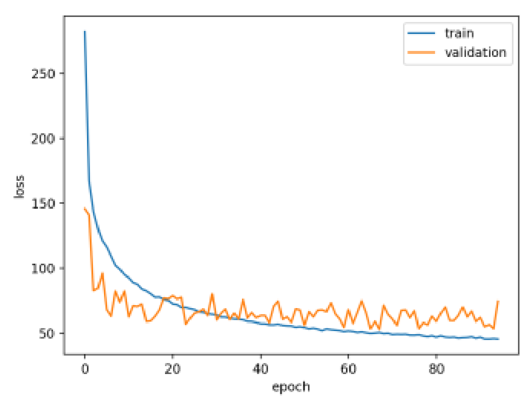

Figure: Training accuracy: model loss means squared error

One of the major criticisms of machine learning techniques from subject matter experts is that it is difficult to determine what the model is actually learning to make classification decisions. Thus, there is a trust factor between the machine learning experts and the physical science community that hinders the transition of these models into a production system. As part of our model evaluation, we use techniques to understand how cyclone intensities are determined within the CNN. Our approach includes tracing the CNN's final intensity back to the original image to discover which pixels contributed most to the classification by using class activation maps (CAMs) [31]. CAMs show which parts of the image the machine learning model uses to determine the maximum wind speed. Encouragingly, the features (and location of pixels) that contribute most to the model output are also present in the cloud patterns used within the Dvorak technique

IV.CONCLUSION

In this paper, we present an end to end deep learning based wind speed estimation system of tropical cyclones that is triggered in real time. The system include the development of a new convolutional neural network model used to objectively estimate tropical cyclone wind speed using just satellite images. The model is extensively evaluated and systematically transitioned to production by comparing features identified in CAMs to Dvorak T-number images. We also a present a novel way to monitor for new storms and launch the workflow to provide wind speed estimates in real time using a situational awareness portal. In addition, we find that the amount of time spent on development of algorithm is considerably lower than creating a large-scale reliable training dataset of images and corresponding wind speeds. Deployment of the machine learning model is a non-trivial task and requires several iterations with updated training data and model configurations. From the software engineering perspective, the model was treated like source code and versioned appropriately. Finally, for the successful execution of an end to end machine learning project, a diverse team of machine learning experts, domain experts, end users, software engineers, and user interface designers is needed. Various future work could be considered including use of passive microwave data to estimate wind speed for tropical cyclones at lower intensity as in [34]. In addition, a detailed analysis of a particular storm to understand model performance with storm structural changes during rapid intensification is another future work that could be studied

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