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A DEEP LEARNING MODEL FOR EFFECTIVE CYCLONE INTENSITY ESTIMATION

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A B S T R A C T

Tropical cyclones are extremely dangerous weather phenomena that cause significant damage to human life, property, economy, agriculture, and development. Currently, various methods are being used to estimate cyclone intensity. One such method is the objective deviation angle variance technique, which estimates the intensity of tropical cyclones from satellite infrared imagery by performing statistical analysis of the brightness of those images. The limitation of this method is that it requires images with properly marked cyclone centers. Another method to estimate cyclone intensity involves feature engineering and machine learning, however, which is a manual process. To address the limitations associated with the above conventional methods, a new approach is being proposed that uses a deep learning mechanism to design a CYCLONE NETWORK (CY-Net) model. This model will estimate the cyclone intensity by using INSAT-3D infrared (IR) images. The CY-Net model is developed based on structural, intensification, and landfall features along with biasing parameters such as wind speed, sea level pressure, and sea surface temperature. The INSAT 3D data is given as input to the model for training, testing, and validation. It undergoes convolution along with the Re-lu activation function to generate feature maps, max pooling, sub-convolution, and fully connected layers. The stochastic gradient descent factor is measured to implement the backpropagation. The Stochastic gradient and backpropagation network are implemented to obtain the best filter coefficients. The trained, tested, and validated model is deployed in Python-flask for web application and then hosted using the web servers for web application. This approach uses advanced machine learning techniques to estimate cyclone intensity and has the potential to improve accuracy and reduce manual effort.

1. INTRODUCTION

In recent years, the destructive impact of tropical cyclones on human life, property, economy, agriculture, and development has underscored the need for accurate and efficient methods of cyclone intensity estimation. Various approaches, including the objective deviation angle variance technique, feature engineering, and machine learning, have been explored to enhance the precision of these estimations.

The Dvorak technique (DT) reigns supreme for over almost four decades in gauging tropical cyclone (TC) intensity, with subjective estimates rooted in visible and infrared satellite images (Dvorak 1973; Dvorak 1975;

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Dvorak 1984). After the emergence of computing technology, a good number of research workers have followed the same suite that explored the use of computers in the identification of cyclone intensities. For instance, the objective Dvorak technique (ODT) employs a computer-based analysis (Velden et al., 1998) to predict the intensity of the cyclones.

A few regression models (LS-SVM) models were used to forecast the tropical cyclones and it was reported that the established forecast models of 12 hours, 24 hours, 48 hours and 72 hours of tropical cyclone intensity have met the predetermined error requirements (Wang & Yang, 2010). An objective method for estimating TC intensity using historical hurricane satellite data (HURSAT) is developed and tested, which could require a TC's center location to extract azimuthal brightness temperature (BT) profiles from current imagery as well as BT profiles from imagery 6, 12, and 24 hours prior (Fetanat et al., 2013). By doing so, the average mean absolute intensity (AMAI) estimation error reduced significantly, big thanks to the computing power.

However, existing methods face challenges such as the dependence on marked cyclone centers and manual stress involved in feature engineering. To address these limitations, this study proposes a novel approach leveraging deep learning (Diaa, 2024) for cyclone intensity estimation.

Inspired by recent advancements, the study introduces the CYCLONE NETWORK (CY-Net), a deep convolutional neural network (CNN) model designed to analyze INSAT-3D infrared (IR) images. The CY-Net model incorporates structural, intensification, and landfall features along with key parameters like wind speed, sea level pressure, and sea surface temperature. Unlike traditional methods, CY-Net aims to automate and enhance the precision of cyclone intensity estimation without the need for explicit marking of cyclone centers.

2. LITERATURE REVIEW

The utilization of deep learning in cyclone intensity estimation finds its roots in the seminal works referenced as Chen et al. (2019). These pioneering studies harnessed Convolutional Neural Networks (CNNs) (Kumar et al., 2024).to analyze satellite imagery, yielding notable enhancements in accuracy when compared to conventional methodologies. Such advancements underscored the potential of deep learning in revolutionizing cyclone intensity estimation practices.

In the subsequent research endeavor denoted as (Chen et al., 2021), the introduction of Deepti, a CNN-based system dedicated to tropical cyclone intensity estimation, marked a significant milestone (Maskey et al., 2020). Notably, Deepti not only delivered objective and consistent results but also showcased the reliability of CNN architectures in capturing the intricate dynamics of cyclone formations and intensifications.

Further innovation was witnessed in Kusiak (2020) where a sophisticated deep learning model emerged by fusing Generative Adversarial Networks (GANs) with CNNs. This novel approach enabled real-time estimation of tropical cyclone intensity using temporally-heterogeneous satellite data, remarkably reducing estimation intervals to less than 15 minutes. Such advancements hold immense promise for enhancing early warning systems and disaster preparedness efforts.

Exploring deeper into the domain, (Wang & Li, 2023) delved into the application of CNN models specifically tailored for tropical cyclone intensity estimation over the Northwest Pacific Ocean. This study emphasized the pivotal role of input channels in influencing model performance, while also addressing challenges related to sample imbalances. Moreover, it underscored the efficacy of deep learning methodologies in extracting critical information such as intensity and wind radius from satellite infrared imagery, thereby enriching the predictive capabilities of cyclone forecasting systems.

The comprehensive review presented in (Wang et al., 2022) elucidated the broader landscape of machine learning techniques in tropical cyclone forecasting. By highlighting the potential of these methodologies in addressing forecasting challenges, the study underscored the transformative impact of deep learning in advancing our understanding and prediction capabilities of cyclone dynamics.

Contributing further to this burgeoning field, (Uma et al., 2024) conducted a meticulous comparative study focusing on deep learning-based cyclone intensity estimation utilizing INSAT-3D IR imagery. Through rigorous evaluation of various model performances, this research shed light on the strengths and limitations of different deep learning approaches, thereby paving the way for future advancements.

Innovating on the forefront of deep learning methodologies, Tian et al. (2023) proposed a groundbreaking model for tropical cyclone intensity estimation. By integrating rotation equivariant convolution and transformer architectures, this novel approach aimed to capture both local and global spatial contextual information, thereby enhancing accuracy. Furthermore, the integration of multi-platform satellite remote sensing data and physical environmental field information represented a significant leap forward in improving the predictive capabilities of cyclone intensity estimation models.

3. DATA SETS & METHOD OF ANALYSIS

The INCYDE (INSAT-based Cyclone Detection and Intensity Estimation) dataset serves as a valuable resource for cyclone detection and intensity estimation tasks, leveraging images captured from INSAT 3D/3DR satellites over the Indian Ocean. The dataset comprises over 100,000 cyclone images with augmentations, sourced from cyclones occurring between 2013 and 2021. Data collection involved gathering satellite imagery of cyclones over the Indian Ocean during this period, ensuring a comprehensive representation of cyclonic events. Each image in the dataset is labeled with metadata indicating cyclone detection and intensity estimation information, facilitating both object detection and regression tasks. The data analysis process involves preprocessing the images, including augmentation techniques to enhance the diversity and robustness of the dataset. Techniques such as rotation, flipping, and scaling may be employed to augment the dataset and improve model generalization.

Upon preprocessing, the dataset is partitioned into training, validation, and test sets to facilitate model training and evaluation. Baseline models are then developed and trained on the INCYDE dataset, serving as benchmarks for future research and comparison. These models may utilize convolutional neural network (CNN) architectures tailored for both cyclone detection and intensity estimation tasks.

Our mission revolved around tapping into the power of infrared (IR) images sourced from the Indian national satellite system (NSAT-3D) via the mosdac portal [https://www.mosdac.gov.in/insat-3d]. These IR images provide a unique window into cyclones, crucial for building a robust intensity estimation model. We store this invaluable data in a structured hierarchical data format 5 (HDF5), ensuring efficient management of vast and diverse datasets. Getting started means meticulously gathering ir images from the INSAT-3d repository on the mosdac portal. With data organized in HDF5, our approach guarantees a methodical setup conducive to in-depth analysis. Python's arsenal of standard libraries becomes our go-to toolkit for data handling and pre-processing, setting the stage for feature extraction from ir images. This ensures that our data is primed and ready for training a cnn down the line.

At the heart of our dataset preparation lies an effective labeling strategy. Labeling data is pivotal for training a dependable intensity-estimation model. Our labeling process revolves around identifying structural and intensification cues within cyclone imagery. To achieve this, we meticulously categorize the dataset into classes aligned with intensity classifications defined by the Indian Meteorology Department (IMD).

Table 1. The Classification of cyclonic images based on MSW

Type of cyclone	**Notation**	**MSW**
DEPRESSION	D	17 to 27 kt 31-49 kmph
DEEP DEPRESSION	DD	28 to 33 kt 50-61 kmph
CYCLONIC STORM	CS	34 to 47 kt 62-88 kmph
SEVERE CYCLONIC STORM	SCS	48 to 63 kt 89-117 kmph
VERY SEVERE CYCLONIC STORM	VCS	64 to 119 kt 118-221 kmph
SUPER CYCLONIC STORM	Su-CS	>= 120 kt >= 222 kmph

The above (Table 1)classification is performed by considering important parameters, such as sea level pressure and wind speed, such that the model can predict the wind speed range and estimated sea level pressure from an image provided by the user. The classification of cyclone intensities by considering parameters such as sea-level pressure and wind speed is given in Table 2.

4. DATASETS USED IN THIS RESEARCH

a) CY-Net Convolution Neural Network:

CY-Net, a novel Convolutional Neural Network (CNN), was designed to estimate cyclone intensity. Figure 1 shows the representation of the CY-Net. The network uses Resnet50 – one a powerful network in powerful image classification models that can be trained on large datasets. CY-Net takes a unique approach by incorporating biasing parameters, such as cyclone structure, wind speed, and sea surface temperature, from previous cyclones. The training process involved evaluating the Root Mean Square (RMS) error and Stochastic Gradient Descent (SGD) factors in each epoch. This comprehensive approach aims to enhance the accuracy of cyclone intensity predictions.

Table 2. Representing category wise cyclone strength description

Type of Cyclone	**Notation**	**MSWS**
DEPRESSION	D	17 to 27 kt 31-49 kmph
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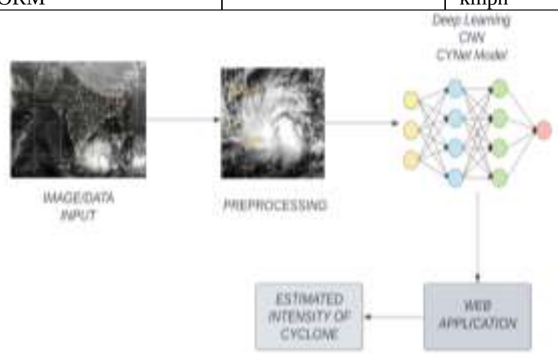

Figure 1. CY-Net Convolution Neural Network Representation

CY-Net is structured to analyse and understand the intricate relationships between cyclone images and various biasing parameters. The CNN architecture comprises multiple convolutional, pooling, and fully connected layers. These layers collectively learn and extract features from input images while considering historical parameters for a holistic understanding of the cyclone intensity.

The success of building an accurate CNN such as CY-Net depends heavily on the quality of the training data and preprocessing steps. The main dataset used to train CY-Net is infrared image acquired from INSAT 3D. These images were systematically stored in the HDF5 format, ensuring a high-performance system suitable for subsequent analysis and training. HDF5 provides a standardized way to handle large amounts of data while maintaining information integrity. The standard Python library plays an important role in the data-preprocessing pipeline. These libraries were used to manipulate the datasets.

The infrared images were resized and normalized to facilitate effective image training. Resizing keeps the resolution of the images consistent, allowing the model to handle information consistently. Normalization, on the other hand, standardizes the pixel values, removes biases, and ensures that the CNN consistently interprets the data in the dataset. Data enhancement techniques were used to increase the strength of the model and encourage generalization. Enhancements introduced changes to the dataset by applying rotation, float, and zoom adjustments to the images. This configuration not only increases the diversity of the training set but also enables CY-Net to handle real changes in the shape of the storm.

A unique feature of CY-Net is the inclusion of the bias parameters for historical storms. Factors such as storm structure, wind speed, and sea surface temperature were carefully incorporated into the dataset. They are derived from historical records and formatted in the CSV format, allowing seamless alignment. Data labeling is essential to perform model training; hence, all the datasets are labeled according to biasing parameters such as wind speed, sea level pressure, and Image Intensity prediction.

The datasets were then divided into training, testing, and validation datasets. During Training the Cyclone Net (Cy-Net) trains itself with the input training dataset images and the biasing parameter values that are provided. At each epoch, the Root Mean Square (RMS) Error and Stochastic Gradient Descent Factor were calculated, and accuracy and loss were obtained. As the Epoch increases, the loss decreases, and the accuracy increases. When the model is introduced to an unseen dataset, which is a validation dataset, an accurate prediction is observed.

b) Integration of CY-Net Model to a Web Application

Figure 2 shows the flowchart representation of CY-Net Model. To obtain intensity estimates, a trained CNN model was used in the web applications. This web interface allows users to upload an IR image, and the model provides real-time estimates of the storm intensity. The application was designed to be easy to use, making it a valuable tool for meteorologists, disaster managers, and the general public.

Implementing CY-Net, a sophisticated CNN for hurricane intensity forecasting, using Flask and hosting on a cloud server, the following steps need to be followed: First, install the Flask app, create a virtual environment, and install the necessary packages. The CY-Net model script, which is responsible for defining and installing the model, is included in the Flask app. For real-time forecasts, a specific API endpoint is established to facilitate communication with the model. Subsequent hosting on a cloud server, modeled using Heroku, ensures availability and scalability.

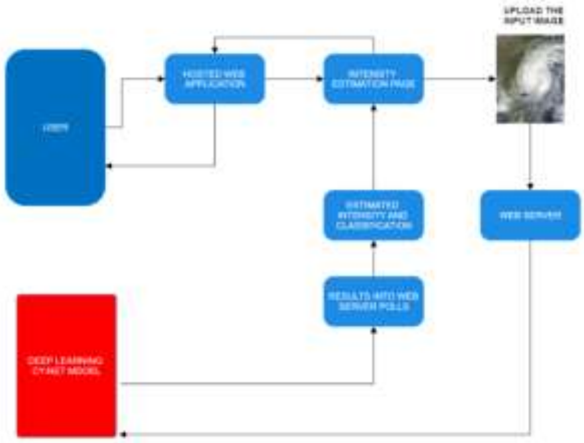

Figure 2. Flowchart representation of the CY-Net Model

By following this guide, developers can easily use the CY-Net model as a web application, delivering a user-friendly and cloud-based solution for the hurricane intensity forecast.

5. ADVANTAGES

The proposed CY-Net model for cyclone intensity estimation using INSAT-3D IR images offers several advantages: CY-Net leverages deep learning to automate the cyclone intensity estimation process. This reduces the manual effort required for feature engineering and center marking, thereby enhancing the efficiency of predicting cyclone intensity. The use of deep learning algorithms ensures a more objective and consistent approach for cyclone intensity estimation. The model relies on patterns learned from data and reduces subjective interpretation compared with traditional methods. CY-Net incorporates various features, including structural, intensification, and landfall characteristics, along with biasing parameters, such as wind speed, sea level pressure, and sea surface temperature. This comprehensive approach enhances the model's ability to capture diverse aspects of cyclone behavior.

The model was specifically tailored to utilize INSAT-3D IR imagery. This adaptability ensures optimal performance because the model is designed to work seamlessly with the characteristics and nuances of the chosen satellite data. The deployment of CY-Net as a web application allows for real-time accessibility. This feature enhances the utility of the model in operational settings, facilitating timely decision making in response to cyclone threats.

By leveraging deep learning and image processing, CY-Net has the potential to analyze cyclones in their initial stages, providing valuable insights early in their development. This early stage analysis can contribute to improved forecasting and disaster-management strategies. The CY-Net model reduces reliance on human expertise for specific tasks such as center marking. This can be advantageous in situations where human resources may be limited, or in cases where consistency across analysts is challenging to maintain. When properly trained and validated, deep learning models have the potential to provide highly accurate and reliable predictions. The CY-Net model's incorporation of an advanced convolutional neural network architecture aims to enhance the accuracy of cyclone intensity estimation.

The deployment of CY-Net in web applications allows widespread accessibility. This integration can facilitate collaboration among meteorologists, researchers, and policymakers, enabling them to conveniently access and utilize the model's predictions.

6. RESULTS

The cyclone intensity estimation system, featuring an innovative CY-Net integrated with effective data labeling and a user-friendly web application, demonstrated promising results during testing.

To know the efficacy of this estimation system, we have considered four cyclones occurred over China region and these cyclone images were downloaded from the Tropical Cyclone Data Centre that is being maintained by the China Meteorological Administration Website. Figures 3.1–3.4 present a visual representation of the outcomes generated by the CY-Net model, illustrating the comparison between predicted and actual cyclone intensities. Upon examination, a striking resemblance between the predicted and actual intensity values is evident across the depicted cyclonic events. This observation underscores the efficacy and accuracy of the CY-Net methodology in forecasting cyclone intensity.

The close alignment between predicted and actual intensities signifies the robustness of the CY-Net model in capturing the complex dynamics of cyclonic systems. This alignment indicates that the model has successfully learned and generalized from the input data, enabling it to provide reliable estimates of cyclone intensity. Such consistency between predicted and observed values instills confidence in the validity and applicability of the CY-Net approach.

The disparity observed in the levels of actual and projected intensity may be attributed to a limited quantity of available datasets. In order to mitigate this incongruity, it is imperative to gather data consistently and systematically. Subsequently, achieving a more definitive understanding of cyclone intensity and trajectory tracking within a particular geographical area can be facilitated with reduced ambiguity.

The system is designed to consolidate cyclone-related information in one accessible portal, potentially integrating with the IMD portal to offer weather reports at 30-minute intervals on the website. The main page of the portal, depicted in Figure 4, serves as a centralized hub for comprehensive cyclone-related information. This user-friendly interface facilitates easy access to the critical data. Integration with the IMD portal ensures timely and relevant updates for users. The results of the model were published in the following images while making predictions on the test dataset.

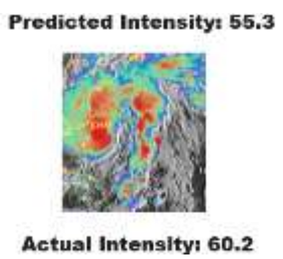

Figure 3.1

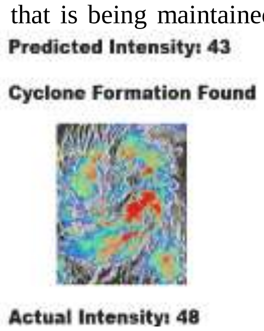

Figure 3.2

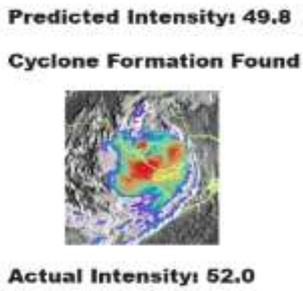

Figure 3.3

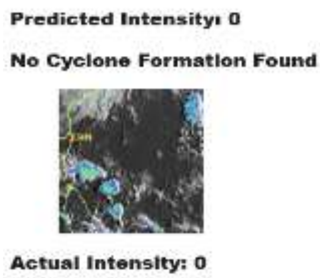

Figure 3.4

Figure 3. Cyclon prediction and formation

Figure 5 illustrates the Cyclone Intensity Estimator page, where the model processes infrared (IR) images to estimate the cyclone formation and intensity. The system predicts crucial parameters such as cyclone structure, intensity level, sea level pressure, and wind speed based on geographical statistics.

Figure 4. Home Page of Web Application

Figure 5. Intensity estimation page of web application

In a specific test case, as shown in the picture below, we uploaded
cyclone Hudhud's image, which was given by a satellite on October 8, 2014, and the model accurately identified the intensity of the cyclone. Similarly, we uploaded many other satellite images where there was clear cyclone formation, and the model accurately predicted its feature values. In a comparison between the actual cyclone parameters and the model's predictions, the original wind speed of the cyclone was in the category of a severe cyclone, and the model predicted the cyclone under the class SCS. The observed accuracy of the deep learning model was an impressive 96%. The model's training dataset comprised 5000 images of various cyclones captured at different intervals. To enhance accuracy further, it is recommended to expand the dataset by incorporating more diverse images into the training process. This augmentation would contribute to the model's ability to provide increasingly precise information about cyclones, thereby improving its overall performance and reliability.

7. CONCLUSION

The presented cyclone intensity estimation system, driven by the innovative CY-Net model, represents a significant leap forward in cyclone monitoring and response capabilities. By providing accurate and timely information, empowering decision-makers, and adapting to changing conditions, the system contributes to improved preparedness and response efforts in the face of these natural disasters. Therefore, the CY-Net model represents a significant advancement in cyclone intensity estimation, boasting the incorporation of biasing parameters and dynamic learning mechanisms. These features endow the model with remarkable accuracy, particularly in gauging cyclone intensity. What sets CY-Net apart is its user-friendly interface, specifically designed to empower meteorologists and emergency responders with accessible, timely, and reliable information. Through its intuitive interface, the system facilitates swift decision-making in critical scenarios. Meteorologists can swiftly interpret the data provided by CY-Net, aiding in the formulation of effective response strategies.

In addition, one of the most notable aspects of CY-Net is its adaptability. The system continuously monitors cyclonic patterns, adapting its algorithms to reflect evolving conditions. This adaptiveness is crucial in ensuring resilience in the face of ever-changing weather dynamics. By staying attuned to the latest developments in cyclone behavior, CY-Net remains a dependable tool for cyclone monitoring and response.

On the flip side, the proposed cyclone intensity estimation system does not operate in isolation; rather, it forms part of a comprehensive approach to cyclone preparedness and response. Secondly, while the system claims to adapt to evolving cyclonic patterns, it's essential to verify its performance during extreme weather events, such as Category 4 or 5 cyclones. Extreme events often exhibit unique characteristics that may challenge the adaptability and resilience of the model. Rigorous testing under various cyclone intensities and conditions is necessary to assess its reliability in extreme scenarios.

As far as the future research work is concerned, the effectiveness of any machine learning model, including CY-Net, heavily relies on the quality and quantity of the data used for training and validation. It is essential to assess the representativeness and completeness of the cyclone intensity data utilized to train the model. Moreover, incorporating additional diverse datasets may improve the model's robustness and predictive capability. In this context, ongoing efforts will focus on refining the model, incorporating additional data sources, and staying abreast of emerging technologies (Rajendran & Shanmugam, 2024).

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