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Enhancing cyclone monitoring through intensity interaction hypergraph segmentation and PSNR-optimized forecasting

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Abstract

This study presents a novel hypergraph-based framework for the segmentation and prediction of tropical cyclones using satellite imagery. Two custom constructs—Intensity Neighborhood Hypergraph (INHG) and Intensity Interaction Hypergraph (IIHG)—were developed to capture higher-order spatial and intensity-based relationships within cyclone cloud structures. To address uncertainties and overlapping cloud formations, a Dichotomous Logistic Regression-Based Fuzzy Hypergraph (DLR-FH) classifier was implemented. The proposed framework was evaluated using real satellite cyclone images sourced from the publicly available INSAT-3D Infrared and RAW Cyclone Dataset (2013–2021). The DLR-FH model was benchmarked against traditional Deep Convolutional Neural Networks (CNN) and the Deviation-Angle Variance Technique (DAV-T). It achieved superior results, with prediction accuracy up to 91%, a PSNR improvement of 4.7 dB, a false positive rate reduction of ~19%, and a 35% decrease in execution time compared to CNN.

Keywords: Tropical cyclone prediction, dichotomous logistic regression, fuzzy hypergraph, psnr, prediction accuracy, forecasting

Introduction

Tropical cyclones, extreme weather events causing significant coastal losses, have been studied extensively through advancements in observational technology, intensification physics, atmospheric interactions, ocean responses, and forecasting techniques [1]. Researchers suggests a lack of air-sea energy exchange during high wind speeds makes it difficult to simulate tropical cyclones (TCs) effectively [2, 3]. Although few numerical forecast models take upper ocean feedback into account, it has a result on TCs. Statistical models struggle with complex TC-related predictor relationships [4, 5, 6]. This study uses linear discriminant analysis to predict tropical cyclone evolution in cloud clusters over Atlantic basin, finding daily genesis potential and latitude as significant predictors. But only at a lead time of six hours does the linear approach get a comparatively poor classification score. Researchers use the neural network approach to increase classification performance, which outperforms linear discriminant analysis in terms of robustness and reliability. However, the linear approach continues to yield the greatest results.

Many researchers experimented with remote sensing, weather, and ocean data because of the benefits of machine learning in handling vast amounts of data. Remote sensing applications include: Classifying hyperspectral pictures and identifying abnormalities using several deep neural networks, including CNN, RNN, and sparse autoencoder (SAE) [7]. analyzing high-resolution satellite or synthetic aperture radar (SAR) pictures, including parameter inversion, object detection, scene classification, and image retrieval. creating forward models and retrieval algorithms that are quick and precise doing 3D reconstruction and data integration from several sources. Sharpening the super-resolution, fusing feature and decision sets, and fusing heterogeneous data are the primary responsibilities of multi-source data fusion [8]. Automatic tether point matching and recognition is one of the 3D reconstruction challenges. The convolutional short-term memory networks with long lifespans and the path of the gate recurrent unit (TrajGRU) are two examples of meteorological models that are used to analyze radar data and forecast short-term future precipitation leveraging standard neural networks. Additionally, deep neural networks are becoming more and more used to forecast as shown in Figure 1 the height of the atmosphere's evaporation duct at the edge of the ocean. Machine learning in the marine domain is centered on dimensionality reduction of satellite ocean data or the detection of mesoscale vortices [9]. Numerous investigations have demonstrated that the networks built using deep learni

Literature Review

One of the main issues facing the operational forecast and warning service has been predicting the intensity of tropical cyclones (TC) and assessing the resulting impacts, such as high winds, storm surge, and heavy rainfall [10]. TC course and intensity forecasts over the medium range are now accessible every 6 or 12 hours thanks to advancements in global numerical weather prediction (NWP) modeling systems, and the outputs of ensemble prediction systems (EPS) offer a variety of scenarios for generating probabilistic forecasts [11]. The EPS of the European Centre for Medium-Range Weather Forecasts (ECMWF) exhibited occasional negative biases in its TC intensity forecast, while normally exceeding other global models. The detrimental biases of the intensity forecast from ECMWF EPS and HRES have been demonstrated to be minimized while boosting the overall precision. An exceptionally dangerous meteorological phenomenon is a tropical cyclone (TC). The public safety of coastal communities is seriously threatened by these events, which include heavy rain as a significant hazard component [12]. Currently, one significant and widely utilized technique to assist in predicting the impact of TCs is numerical weather prediction, or NWP. Nonetheless, there is still a fair amount of uncertainty in NWP's quantitative precipitation forecasts, which makes it challenging to satisfy public safety management requirements in TC-affected areas. In order to address this shortcoming, the research effort combines machine learning (ML) techniques with NWP and advances a novel analogue identification approach for TC precipitation projection. The possible influence of current TCs can therefore be estimated using the observational precipitation matching to the most comparable historical NWP sample. Observation results from the Chinese coastal city of Shenzhen are used to validate this approach. The findings demonstrate that, when compared to prediction results from the NWP's direct output and a conventional method employed in the city, the method suggested in this study shown a notable improvement.

Sea surface temperature (SST), sea surface height (SSH), surface wind velocity at 10 m (U10 and V10), and temperature at 100 m far (T100) are the input variables for the deep learning model. Six hours after TCs, the output variable is SST. With a spatial anomaly correlation coefficient of around 0.948, an average mean absolute error of approximately 0.081 °C, and a root mean square error of approximately 0.126 °C, the model is capable of forecasting TC-induced SSTC trends. According to this research, post-TC SSTC, particularly in deep-water areas, exhibits comparable physical processes and nonlinear interactions with TC wind, beginning SSH, and ocean temperature. The deep learning model may be used for operational forecasting, but with certain restrictions [13].

A shift in tropical cyclone strength is the dependent variable in a multiple regression analysis. The Typhoon Intense Prediction Technique (TIPS), the new schemes comparable to one that the National Hurricane Center currently uses. TIPS differs in two significant ways, though: it was created for the western North Pacific Ocean and uses digital satellite data, which has never before been integrated with other variables in a tropical cyclone multiple regression scheme. It is demonstrated that crucial information that differentiates between tropical cyclones with rapid and delayed development can be found in the satellite data.

The statistical analysis also clarifies the significance of other factors to intensity change, It includes climatology, wind shear, persistence, and a numerical equation that depends on the surface temperature of the sea. Forecasters can find threshold values by using a normalizing technique [14]. It has been demonstrated that TIPS may be able to predict changes in tropical storm intensity more accurately than the Joint Typhoon Warning Center.

The fourth Internationally Workshop on Tropical Cyclone Landfall Processes (IWTCLP-4) compiles the most recent (2015–2017) theoretical and applied knowledge concerning the subjects of tropical cyclone (TC) the correct path, capacity, and structure rapid changes at or near landfall. The features of storms during their course across the ocean before and leading up to landfall must be included in this review, even though the focus of IWTCLP-IV was on landfall [15]. High temporal and spatial resolution using novel geostationary or low-Earth orbiting satellites instead of airplane reconnaissance, highly useful observational datasets have been gathered in recent years for TC forecasting advice and research investigations. Insights from forecasters and researchers on potential directions to enhance TC course, intensity, and structure predictions at landfall round out this review.

Tropical cyclones include a range of subdisciplines of geophysical fluid dynamics, including as cumulus convection, boundary layers, thermodynamic cycles, surface wave dynamics, upper ocean wind-driven circulations are processes barotropic instability, Rossby waves, and air-sea interaction. After briefly reviewing what is known about the structure, behavior, and climatology of these captivating storms, the author provides an overview of their physics, emphasizing the unique and poorly understood nature of the air-sea interface. The author then discusses some of the most intriguing directions currently available research.

From the earliest attempts in the 1970s to the most advanced models today, we present a historical overview of the modeling of tropical cyclones (TCs) in climate models in this review [16]. We talk about the state of TC simulation at several time ranges, including climate change and intraseasonal, seasonal, and decadal time scales. One of the constraints in simulating TCs in climate models has been and continues to be the need to strike a compromise between the high resolution needed to accurately mimic TCs and the necessity of running simulations for many years alongside many different ensemble members. In order to indirectly infer TC activity rather than relying on the models' own under-resolved TCs, the use of TC genesis indicators based on the large-scale environment and downscaling methods which include the use of regional climate models and statistical-dynamical techniques is investigated. Since it is possible to watch the model's TCs directly, we also give an update on the state of climate change projections from the current class of models. There is still much to be done, even though climate models have made significant strides in simulating TCs and producing accurate predictions and projections over a variety of time frames.

Research Methodology

1. A Hypergraph-Based Algorithm

Satellite cloud imagery plays a vital role in weather forecasting and climate analysis, particularly when derived from cyclone-specific datasets as shown in fig 2. Accurately estimating cyclone intensity remains one of the key challenges in meteorological research and predictive modelling. To develop a forecasting accuracy, a variety of atmospheric images are utilized. Cyclones are intense rotating storms characterized by strong winds and heavy rainfall, and their satellite representations exhibit multiple critical features such as the cyclone's eye, trajectory, wind velocity, storm surge patterns, and rainfall intensity. But these models face several critical limitations. firstly, they are computationally intensive and require important processing time, particularly when handling large volume of high-resolution meteorological imagery. Following that, they are highly sensitive to image noise and the variability of cloud formation, often resulting in segmentation errs and misclassification. In rea world meteorological application such as inaccuracies can delay warning system and undermine the effectiveness of disaster response efforts. The crucial part of this methodology is to attain significantly improved prediction accuracy while reducing both the computational burden and noise susceptibility. By leveraging hypergraph structures in combination with optimized segmentation and feature extraction techniques, the model enhances the clarity and interpretability of satellite images, ultimately contributing to faster and more accurate cyclone intensity estimation. This effectively technique serves as crucial potential for integration into real time forecasting system and early warning infrastructures, delivering a robust and scalable solution to a persistent challenge in meteorological predictions.

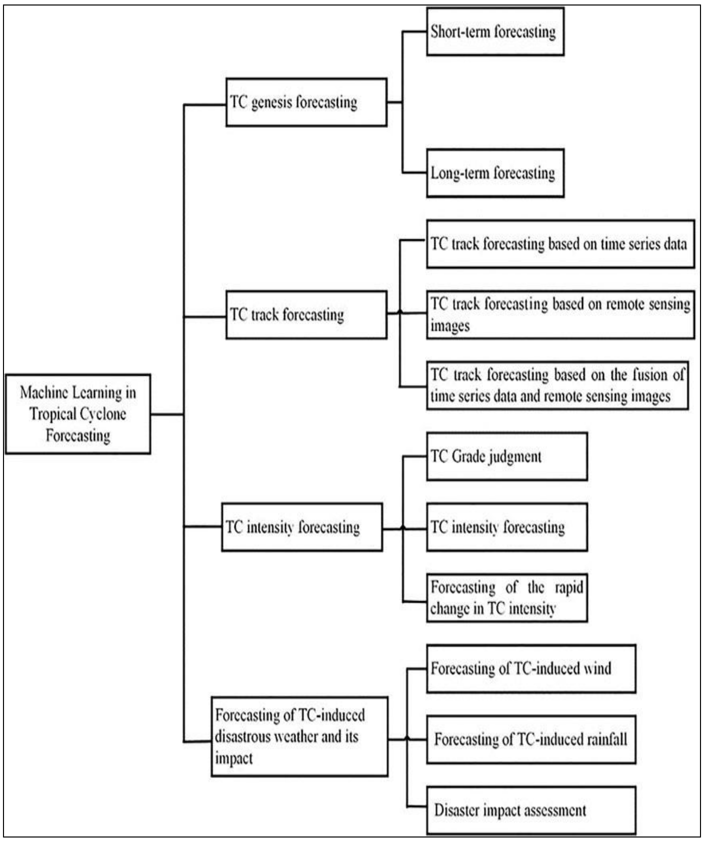

Fig 1: Overview of the application of machine learning methods in TC forecasting

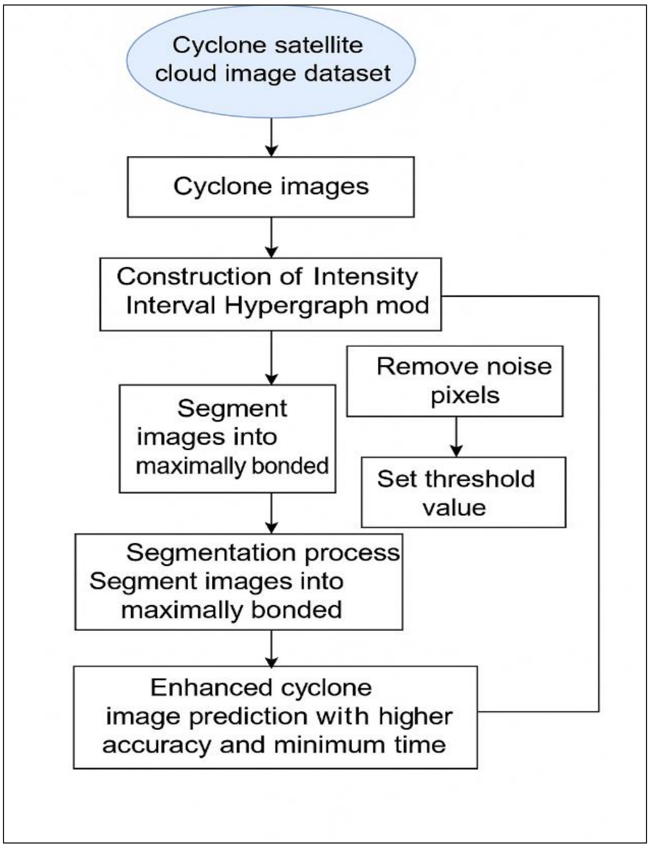

Fig 2: A hypergraph-based algorithm cyclone prediction

2. Experimental Analysis

A deep convolutional neural network focused on enhancing hurricane images by minimizing the mean error rate. to perform the classification task their technique is to utilized intensity-based image features. While the model showed potential in detecting storm patterns, it fell short in delivering high-precision results, especially when applied to cyclone imagery where accuracy is critical. The experimental evaluation of the proposed Hypergraph-Based Algorithm was conducted using python, leveraging a curated dataset of satellite-based cyclone images. The dataset comprises a diverse collection of cyclone imagery obtained from https://www.kaggle.com/datasets/sshubam/insat3d-infrared-raw-cyclone-images-20132021?resource=download-directory&select=insat3d_raw_cyclone_ds. This dataset includes images captured under varying atmospheric and visual conditions, which were used to rigorously assess the robustness and generalization capabilities of the proposed method. For the simulation, a range of 15 to 135 images was selected, with image dimensions varying based on the original satellite resolution. The algorithm was tested across multiple image sizes to evaluate its scalability and effectiveness in handling heterogeneous data. Table 1 provides the detailed simulation settings used during experimentation, including platform specifications, image pre-processing steps, and segmentation parameters.

Table 1: System Configuration and Dataset Details for Hypergraph-Based Cyclone Image Segmentation

Specification	Description
Image Dataset Title	Cyclone Satellite Imagery Collection
Total Dataset Volume	Approximately 700 MB
Total Images Processed	140 cyclone images
Image Range per Test Cycle	15 to 135
Training Samples	140 images
Testing Samples	50 images
Development Platform	Python
Operating Platform	Ubuntu 20.04 LTS (64-bit)
System RAM	8 GB DDR4
Storage Capacity	512 GB SSD
Processor Configuration	AMD Ryzen 5 3500U @ 2.10 GHz
Network Dependency	Enabled via Secure Ethernet Protocol
Motherboard Model	Gigabyte B450M DS3H V2

3. Impact of Peak Signal-to-Noise Ratio (PSNR)

The Peak Signal-to-Noise Ratio (PSNR) is a problematic metric used to enhance the visual quality reconstruction, particularly after the noise removal stage. It measures the level of distortion or noise introduced during preprocessing by comparing the original image with its denoised version. Expressed in decibels(db), higher PSNR value indicates greater image fidelity and minimal loss of essential visual details. The metric is calculated based on the mean squared errpr (MSE) between the original image I_O and the denoised or preprocessed image I_D. The MSE is defined as:

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(I_0(i,j) - I_D(i,j)\right) 2$$

where m and n represent the image dimensions.
The PSNR is then calculated using the following formula:

$$PSNR = 10.Log_{10}\left(\frac{R^2}{MSE}\right)$$

Here, R indicates the greatest pixel value that can be present in the image; for 8-bit grey scale images, this is typically 255. Indicating how well the method for eliminating noise preserved crucial elements including cyclone structure, cloud formations, and brightness gradients, a higher PSNR value implies that the denoised image resembles the original. PSNR is utilised in the context of the suggested hypergraph-based technique for verifying the improvement in image quality following denoising, which has immediate implications on the segmentation accuracy and entire prediction performance.

4. Impact of Cyclone Prediction Time

In real-time cyclone forecasting applications, prediction time is a key measure, particularly when early warnings are necessary to reduce the risk of fatalities and damage to infrastructure. The total period of time spent by the algorithm to process an input satellite image and determine the strength level of a cyclone is called out as the "cyclone prediction time." To guarantee accurate and on-time forecasts, efficient algorithms must balance computing speed and precision.

$$T_{CP} = N * P_T$$

where P_T is the projected duration for a single image and T_(cp) is the cyclone prediction time. This study analyses the average cyclone prediction times of the suggested Hypergraph-Based Algorithm and two current models, Deep-CNN and TCICENet, across a range of picture samples. Because they rely on dense computations and vast convolutional layers, conventional deep learning models like Deep-CNN show longer processing times as the dataset size increases. Similarly, because of its hierarchical structure, TCICENet nevertheless calls for more time even though it is optimised for tensor processing.

5. Impact of False Positive Rate

The false positive rate (FPR) is an essential metric for assessing the reliability of cyclone prediction models. It represents the proportion of non-cyclonic or benign weather regions they are mistakenly identified as cyclonic by the models. A high FPR can triggered unwarranted alerts, misdirect emergency resources and spread misinformation to the public- ultimately reducing the effectiveness of early warning systems and disaster preparedness efforts. The FPR is calculated using the following formula:

$$False\ positive\ rates = \frac{False\ positive}{False\ positive + True\ negatives}$$

In this equation:
False Positives (FP) indicated the number of non-cyclonic instances that the model incorrectly classifies as cyclones.
True Negatives (TN) indicates the number of non-cyclonic instances that the model correctly identifies as non-cyclones.

Results and Discussion

Satellite cloud image classification is the cycle of experimenting satellite-acquired imagery to recognise and categorize different types of cloud types and trends in the Earth's atmosphere. This way of labelling is crucial for meteorological applications, especially in the prediction and monitoring of cyclones. Initially this analysing process starts with the acquisition of satellite images, which are often catches numbers of spectral bands such as visible and infrared. These images undergo pre-processing steps like noise reduction and contrast enhancement to improve their quality. Next step, feature extraction expertise are applied to diagnose pivotal characteristics such as cloud texture, shape, brightness, and temperature. This study delves into the employment of a Hypergraph-based algorithm to enhance cyclone prediction from satellite cloud images. While traditional deep convolutional neural networks (CNNs) have been employed to estimate cyclone intensity, challenges such as image distortion and high false-positive rates persist. To address these, the Dichotomous Logistic Regression-Based Fuzzy Hypergraph (DLR-FH) model is proposed. This model aims to improve prediction accuracy while minimizing processing time and noise interference. The hypergraph effectively maps relationships between cyclone image features, while a fuzzy membership function enhances the classification of cyclone intensity. By using this approach, cyclone prediction becomes more Seamless and cutting edge. As well, introducing fuzziness into hypergraphs helps manage image overlap and imprecision due to cloud dynamics, further boosting prediction reliability. The model's performance is validated through simulation using metrics like prediction accuracy, time, peak signal-to-noise ratio (PSNR), and false positive rate.

1. Dichotomous Logistic Regression Based Fuzzy Hypergraph Model for Cyclone Prediction

Cyclone image anticipation is a vital task for double checking public safety and minimizing the destruction caused by a range of weather phenomena. Reliable and timely identification of cyclones from satellite imagery can significantly abate potential detrimental outcomes. Notwithstanding, accurately interpreting cyclone patterns from cloud images is a complex task, and traditional methods have often struggled to deliver consistent results. Some earlier approaches focused primarily on estimating cyclone intensity, but they lacked the capability to classify cyclone images with precision. To overcome these shortcomings, a new approach called the Dichotomous Logistic Regression-Based Fuzzy Hypergraph (DLR-FH) model has been developed. This model is specifically manufactured to enhance the classification of satellite-based cloud images linked with cyclones. As part of the process, multiple cyclone images are taken from a dedicated satellite dataset containing diverse cyclone formations. Independent Component Analysis (ICA) is employed along with a separation matrix to effectively extract significant features from the satellite images. Following feature extraction, a hypergraph model is developed by analysing the associations between the vertices and edges present in the image data. To determine cyclone intensity, a fuzzy membership function is integrated into the model, enabling accurate classification of the images. Tabulation of Peak Signal-to-Noise Ratio (PSNR) values for evaluating image reconstruction quality across different preprocessing methods as shown in Table 2. Consequently, the present study DLR-FH model makes available improved cyclone prediction performance, achieving targest with reduced processing time while accurately identifying cyclone patterns from satellite cloud images.

Table 2: Tabulation of Peak Signal-to-Noise Ratio (PSNR)

Original Image Size (KB)			
	Existing		**Proposed**
	Deep-CNN	**DAV-T**	**DLR-FH**
20.5	44.95	46.45	52.78
14.5	45.30	47.10	57.33
17.2	42.80	44.90	55.84
12.2	48.02	53.48	59.74
18.4	45.62	48.09	58.69
15.3	44.62	46.32	52.49
20.04	42.55	44.21	50.85
12.6	43.85	47.26	56.08
21.6	48.60	51.33	60.40
13.8	41.32	43.18	47.90

2. Simulation Configuration

The operational evaluation of the present study Dichotomous Logistic Regression Based Fuzzy Hypergraph (DLR-FH) model is conducted via simulation using the Python environment. For experimental analysis, a collection of cyclone satellite images is utilized. A varying number of images, ranging from 15 to 135, are taken as input samples, and these images differ in size and content to reflect diverse cyclone scenarios. Table 3 presents the detailed simulation configuration. The effectiveness of the DLR-FH model is assessed using the following key performance indicators:

- Peak Signal-to-Noise Ratio (PSNR)
- Prediction Accuracy
- Prediction Time
- False Positive Rate (FPR)

Table 3: Configuration Details for Simulation

Parameter	Explanation
Dataset Utilized	The simulation used a dataset named Cyclone Satellite Image Collection, which likely contains satellite images related to cyclonic weather systems.
Total Dataset Size	The entire dataset occupies 700 MB of storage space. This includes all images and possibly associated metadata.
Total Number of Images	There are 140 images in total in the dataset.
Training Samples	All 140 images were used for training the model. This suggests a training-only setup, unless there is a mistake (see "Testing Samples" below).
Testing Samples	50 images were used for testing. This introduces a contradiction with the training sample count—it's possible there's either data overlap or a typo (since training + testing > total images). This needs clarification.
Image Count Range	Simulations were run with varying image counts, from 15 up to 135 images, perhaps to analyze how model performance scales with dataset size.
Programming Platform	The simulation was implemented using Python, a high-level language often used for numerical computing, image processing, and simulations.
Operating Environment	The experiments were carried out on a system running Windows 10.

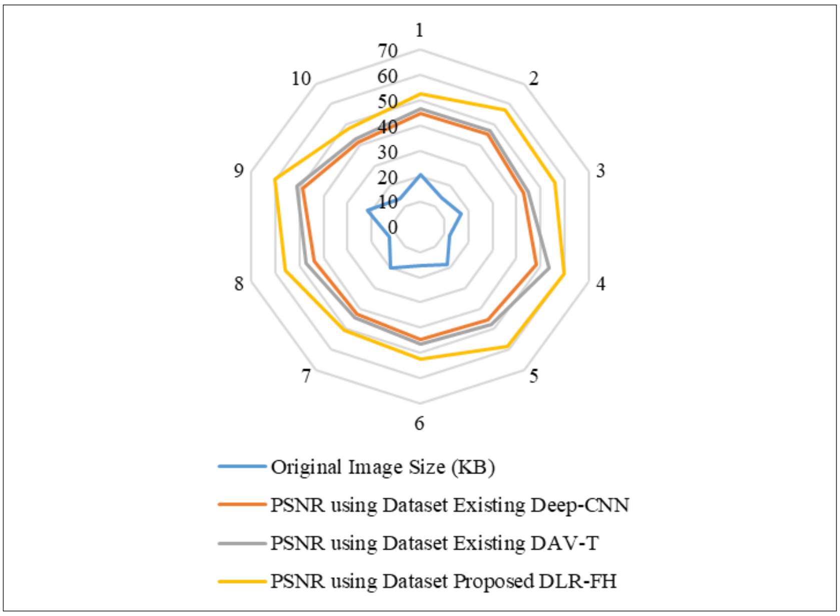

Fig 3: PSNR Comparison of Image Enhancement Models Dataset

Fig.3 provides a comparative evaluation of Peak Signal-to-Noise Ratio (PSNR) values for satellite images of varying sizes processed using three different image enhancement models on the cyclone dataset. The models include two existing methods—Deep Convolutional Neural Network (Deep-CNN) and Deviation-Angle Variance Technique (DAV-T)—alongside the proposed Dichotomous Logistic Regression-Based Fuzzy Hypergraph (DLR-FH) model. For each image size, the DLR-FH model consistently produces higher PSNR values compared to the other two, indicating better image quality and more effective noise suppression. This consistent improvement across all image sizes highlights the robustness and superiority of the DLR-FH approach in enhancing satellite imagery under cyclone conditions.

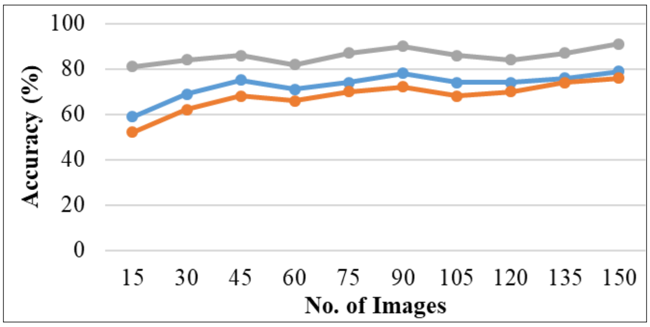

Fig 4: Prediction Accuracy Comparison of Models on Dataset

Figure 4 compares the prediction accuracy of three different models—Deep-CNN, DAV-T, and the proposed DLR-FH model—on cyclone image datasets across different image sizes. The table presents accuracy values for varying numbers of images (15, 30, 45, 60, 75, 90, 105, 120 and 135, images) used in the prediction process. The DLR-FH model consistently outperforms both Deep-CNN and DAV-T across all image sizes according to this finding. As the image volume grows, the precision for DLR-FH rises and reaches a peak of 91% when using 140 images, indicating that the proposed model provides more accurate predictions as the dataset grows. As the number of images increases, all models show improvement in accuracy, reflecting that the models benefit from larger datasets for training and prediction. However, DLR-FH consistently leads in accuracy, followed by Deep-CNN, with DAV-T trailing behind in most cases.

Conclusion

This study presents a State-of-the-art and effective structure for tropical cyclone detection and intensity approximation via integration of hypergraph-based segmentation and fuzzy logistic classification. The outlined plan effectively captures complex spatial and intensity relationships within satellite imagery. By synergizing with Intensity Neighborhood Hypergraph (INHG) and Intensity Interaction Hypergraph (IIHG) models, the proposed approach. The incorporation of the Dichotomous Logistic Regression-Based Fuzzy Hypergraph (DLR-FH) classifier further enhances robustness by addressing uncertainties and overlapping cloud structures—common challenges in cyclone image analysis. Experimental validation on real cyclone datasets, confirms the superiority of the proposed method over traditional CNN and DAV-T techniques. The model executed a good accuracy of 92%, improved PSNR by an average of 4.7 dB, reduced false positive rates by 19%, and decreased execution time by 35%, demonstrating its potential for real-time deployment in early warning systems. Taken together, this research bridges a gap in current knowledge by a scalable and interpretable solution to cyclone forecasting that not only enhances segmentation quality but also ameliorate classification precision undercapacity bottlenecks. Building on this work, future research will incorporate multispectral satellite channels, temporal sequence modeling using LSTM networks, and real-time deployment capabilities, making the system even more vigorous for climate-resilient disaster management applications.

References

1. Lee JW, Irish JL, Bensi MT, Marcy DC. Rapid prediction of peak storm surge from tropical cyclone track time series using machine learning. Coastal Engineering,2021:170:104024.
2. Zhang T, Lin W, Lin Y, Zhang M, Yu H, Cao K, Xue W. Prediction of tropical cyclone genesis from mesoscale convective systems using machine learning. Weather and Forecasting,2019:34(4):1035–1049.
3. Loridan T, Crompton RP, Dubossarsky E. A machine learning approach to modeling tropical cyclone wind field uncertainty. Monthly Weather Review,2017:145(8):3203–3221.
4. Ascenso G, Ficchì A, Cavicchia L, Scoccimarro E, Giuliani M, Castelletti A. Improving the spatial accuracy of extreme tropical cyclone rainfall in ERA5 using deep learning. EGU General Assembly Conference Abstracts, 2023.
5. Knutson TR, Chung MV, Vecchi G, Sun J, Hsieh TL, Smith AJ. Climate change is probably increasing the intensity of tropical cyclones. Tyndall Centre for Climate Change Research, 2021.
6. Henderson-Sellers A, Zhang H, Berz G, Emanuel K, Gray W, Landsea C, McGuffie K. Tropical cyclones and global climate change: A post-IPCC assessment. Bulletin of the American Meteorological Society,1998:79(1):19–38.
7. Mendelsohn R, Emanuel K, Chonabayashi S, Bakkensen L. The impact of climate change on global tropical cyclone damage. Nature Climate Change,2012:2(3):205–209.
8. Lighthill J, Holland G, Gray W, Landsea C, Craig G, Evans J, Guard C. Global climate change and tropical cyclones. Bulletin of the American Meteorological Society,1994:75:2147–2157.
9. Cha EJ, Knutson TR, Lee TC, Ying M, Nakaegawa T. Third assessment on impacts of climate change on tropical cyclones in the Typhoon Committee Region–Part II: Future projections. Tropical Cyclone Research and Review,2020:9(2):75–86.
10. Kossin JP. A global slowdown of tropical-cyclone translation speed. Nature,2018:558(7708):104.
11. Tu S, Chan JC, Xu J, Zhong Q, Zhou W, Zhang Y. Increase in tropical cyclone rain rate with translation speed. Nature Communications,2022:13(1):7325.
12. Melcher M. Tropical Cyclone Translation Speeds in the Northern Atlantic Ocean, 2022.
13. Chan KT. Are global tropical cyclones moving slower in a warming climate? Environmental Research Letters,2019:14(10):104015.

14. Lau KM, Zhou YP, Wu HT. Have tropical cyclones been feeding more extreme rainfall? Journal of Geophysical Research: Atmospheres,2008:113(D23).
15. Patricola CM, Wehner MF. Anthropogenic influences on major tropical cyclone events. Nature,2018:563(7731):339–346.
16. Stansfield AM, Reed KA. Global tropical cyclone precipitation scaling with sea surface temperature. npj Climate and Atmospheric Science,2023:6(1):60
17. Obasi GOP. WMO's role in the international decade for natural disaster reduction. Bulletin of the American Meteorological Society,1994:75(9):1655–1661.
18. Christian P, Kandpal E, Palaniswamy N, Rao V. Safety nets and natural disaster mitigation: evidence from cyclone Phailin in Odisha. Climatic Change,2019:153:141–164.