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Deep Learning Based Cyclone Intensity Estimation

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Abstract
Background/Objectives: *Cyclones are perilous, and disaster management depends heavily on accurate intensity estimation. The primary objective of this research is to develop a deep learning-based technique that uses satellite imagery to assess cyclone intensity. The research involves use of Capsule Convolutional Neural Networks (Caps Nets), which are intended to handle complex patterns and preserve spatial hierarchies. With the ability to preserve positional information and enhance the perception of spatial relationships in satellite imagery, Caps Nets overcome certain drawbacks of conventional Convolutional Neural Networks. Regression modeling was used in this study to forecast cyclone strength based on INSAT 3D satellite imagery, offering a structured technique for evaluating meteorological data and producing precise forecast estimations. The results indicate that the Caps Nets-based approach yields more accurate cyclone intensity estimates compared to traditional Convolutional Neural Networks with a MSE of 1.51 and RMSE of 2.07. The improved pattern identification capabilities of this method contributes to improved estimates of wind speed and evaluations of cyclone intensity. The findings indicate that this technique has the potential to considerably improve disaster response and preparedness by providing more precise and accurate data for evacuation planning and early warning systems. By retaining spatial hierarchies and comprehending complex patterns in satellite imagery, Capsule Convolutional Neural Network offers a novel approach to cyclone intensity estimation, providing improved accuracy and robustness compared to conventional methods.*
Keywords: *Tropical Cyclone, Capsule Convolutional Neural Networks (Caps Nets), Deep Learning, Cyclone Intensity Estimation.*

INTRODUCTION

Accurately predicting cyclone intensity is vital for effective disaster management [24], yet it remains a complex challenge due to the intricate and not fully understood atmospheric and oceanic dynamics involved in cyclone formation [18]. The Indian subcontinent, with a 7,516 km long coastline, is among the most cyclone-prone regions globally. Approximately 10% of the world's tropical cyclones impact India, affecting a 5,400 km stretch of mainland coastline, 132 km in Lakshadweep, and 1,900 km in the Andaman and Nicobar Islands. In total, 84 coastal districts across 13 coastal states and Union Territories (UTs) are vulnerable to cyclonic events. The eastern coast—comprising Andhra Pradesh, Odisha, Tamil Nadu, and West Bengal—along with the UT of Puducherry, and the western coast state of Gujarat, are especially susceptible. Notably, about 40% of India's population resides within 100 kilometres of the coastline.Historical data from 1980 to 2000 indicates that, on average, 370 million people in India were exposed to cyclones annually. Economic analyses show that natural disasters can result in losses amounting to up to 2% of the national GDP and as much as 12% of Central Government revenue. Given the limited availability of direct cyclone wind measurements, meteorological satellite sensors have become essential tools in intensity estimation. Microwave data from geostationary and polar-orbiting satellites are now primary resources for this purpose [25]. While polar-orbiting satellites offer structural insights into cyclones, geostationary satellites provide high-resolution imagery that enables indirect assessment of key cyclone parameters. However, intensity estimates derived solely from satellite data still exhibit considerable uncertainty. For instance, the National Hurricane Center reports a 10–20% margin of error in such estimates, leading to forecast inaccuracies [20]. Enhancing short-term intensity prediction capabilities is therefore critical to improving early warning systems and national disaster preparedness. In recent years, advancements in deep learning have significantly impacted various fields, including meteorology and disaster management [11][13]. The growing frequency and severity of cyclonic storms underscore the need for precise and timely intensity and trajectory estimation to support effective disaster mitigation strategies. Traditional methods like the Dvorak technique [10] have contributed meaningfully to cyclone intensity estimation, but they often involve subjective interpretation and lack the automation and precision of modern computational approaches [14]. This study addresses these limitations by proposing a deep learning-based approach—specifically, the use of Capsule Convolutional Neural Networks (Caps Nets)—to estimate cyclone intensity using raw satellite imagery from the INSAT-3D satellite. INSAT-3D offers high-resolution meteorological imagery, enabling detailed observation of cyclonic systems. By leveraging the pattern recognition capabilities of convolutional neural networks (CNNs), this research aims to develop a more accurate, efficient, and automated framework for cyclone intensity estimation, ultimately contributing to improved disaster response and resilience.

RESEARCH CONTRIBUTION

Recent advancements in deep learning have significantly contributed to the field of tropical cyclone intensity estimation and prediction. Maskey et al. (2020) introduced *Deepti*, a real-time deep learning-based system designed to estimate the wind speeds of tropical cyclones solely from satellite imagery [1]. Their study demonstrates the effectiveness of convolutional neural networks (CNNs) in capturing complex patterns in satellite data to accurately estimate cyclone wind speeds, thereby enhancing forecasting capabilities. They also propose future research directions, including the extension of their model to less intense cyclones using passive microwave data and the detailed analysis of specific cyclone events—particularly those involving rapid intensification—to better understand the model's performance under varying meteorological conditions.Similarly, Nandhini et al. (2020) [4] explored cyclone classification and prediction using deep learning architectures, with a focus on CNNs and recurrent neural networks (RNNs). Their experimental results reveal that CNNs outperform RNNs in classification accuracy, achieving a success rate of 83.8% using 1,380 input features. This study underscores the utility of deep learning techniques in cyclone modelling and highlights the need to investigate various network architectures to further optimize prediction accuracy and robustness.In contrast, Kabir et al. (2016) [6] focused on cyclone intensity estimation using the traditional Dvorak Technique (DVKT), a longstanding method based on satellite image interpretation. By integrating satellite technology with digital interpretation tools, their research emphasizes the continued relevance of DVKT in real-time cyclone monitoring. While not based on deep learning, this study contributes to the broader understanding of cyclone dynamics and supports the refinement of conventional intensity estimation techniques through modern technological enhancements.

RESEARCH GAPS

Despite the notable advancements in applying deep learning techniques to tropical cyclone intensity estimation and prediction [16][19], several critical gaps remain in the existing body of research. One key limitation is the insufficient exploration of deep learning models across cyclones of varying intensities, particularly weaker systems. Expanding model applicability to such cases is essential for enhancing the generalizability and accuracy of forecasts across the full spectrum of cyclonic events. Moreover, although convolutional neural networks (CNNs) have demonstrated strong performance in cyclone classification tasks, further investigation into alternative deep learning architectures—such as Capsule Networks, Transformers, or hybrid and ensemble models—could yield improved predictive accuracy and model robustness.Another important area requiring deeper analysis is the influence of environmental factors and structural changes within cyclones, especially during phases of rapid intensification. Current models often struggle to maintain accuracy under such dynamic conditions, highlighting the need for more comprehensive approaches that integrate physical and contextual storm parameters. Addressing these gaps will not only enhance the scientific understanding of tropical cyclone behaviour but also support the development of more reliable early warning systems, ultimately strengthening disaster preparedness and risk mitigation strategies.

Research Questions

This research is guided by the following key questions:

1. Can Capsule Networks (Caps Net) effectively learn and extract relevant features from raw satellite imagery to accurately estimate cyclone intensity and classify cyclone severity?
2. To what extent does temperature variation around the cyclone's eye enhance the accuracy of intensity estimation?
3. Can deep learning models reliably predict the immediate trajectory of tropical cyclones with high spatial and temporal precision?
4. How dependable are predictions regarding cyclone weakening or strengthening when based on the analysis of swirl asymmetry or skewness emanating from the storm's eye?

ABOUT THE DATA

The dataset utilized in this study is the INSAT-3D Infrared and Raw Cyclone Imagery, published as open-source by the Indian Space Research Organisation (ISRO) on Kaggle**.** This dataset comprises satellite images of tropical cyclones over the Indian Ocean**,** covering the period from 2012 to 2021**.** It includes both infrared (IR) and raw grayscale images, capturing various phases of cyclone development.For the purpose of this research, the raw cyclone images are primarily used, as they preserve essential unprocessed visual features necessary for deep learning-based analysis. The dataset is labelled**,** with each image associated with an intensity value (in knots) provided in a CSV file in tabular format. These intensity annotations serve as ground truth for model training and performance evaluation.

A representative sample of a raw cyclone image and its corresponding infrared image of the same event is displayed below to illustrate the dataset's visual characteristics and diversity.

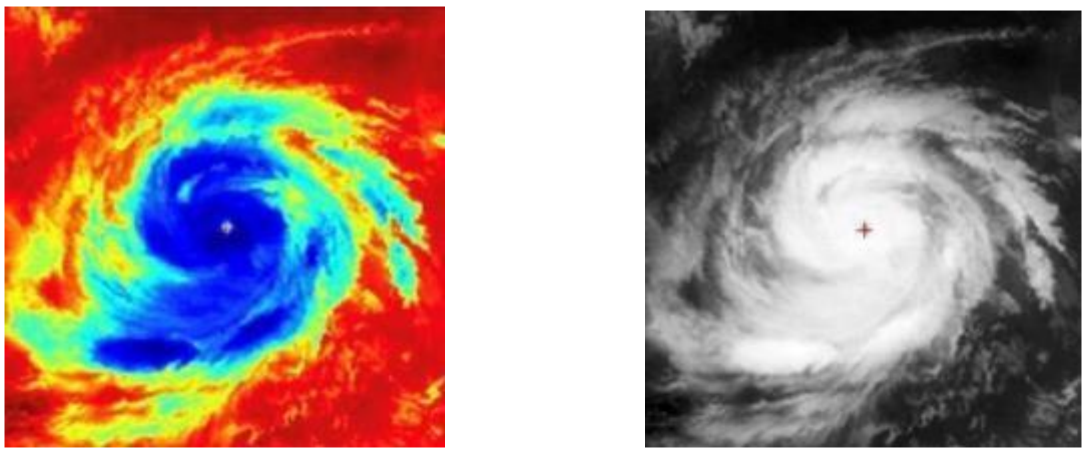

Fig. 1. Figure shows image of a cyclone captured by INSAT3D (both Infrared and Raw) displayed side-by-side

Methodology

Image Processing

Image processing plays a critical role in extracting meaningful features from satellite imagery to determine the strength and trajectory of cyclones. It involves a range of computer vision techniques, each designed to identify and analyze specific aspects of cyclone imagery. Computer vision algorithms act as our detectives, meticulously analyzing satellite images to identify characteristics that foreshadow a cyclone's intensity.

Cyclone's Shape: Contour Detection

Imagine tracing the outline of the cyclone in the image. Computer vision algorithms achieve this by identifying pixels with significant intensity variations at the edges. These variations often mark the boundaries between the cyclone's cloud formations and the surrounding environment. Common algorithms for contour detection include:

Active Contours (Snakes): It is used to trace and follow the boundaries of objects within an image, crucial for identifying the outer contours of cyclones. These algorithms work by minimizing an energy function, which balances smoothness and the force to adhere to high-gradient areas, allowing them to flexibly adjust to cyclone shapes and structures. By tracking these contours, deep learning models can focus on the areas where the cyclone's cloud formations meet the surrounding atmosphere, which is often indicative of the cyclone's overall intensity.Level Sets: It offers an alternative approach to contour detection, representing boundaries as the zero- level of a higher-dimensional function. This technique iteratively adjusts the curve's shape, enabling the precise identification of complex cyclone contours, especially when dealing with more challenging image characteristics such as occlusion or irregular shapes.

Cyclone Edges: Edge Detection

Another crucial aspect involves edge detection. Edges often represent significant changes in intensity within an image and can reveal important structural details of the cyclone. Edges can be identified using various algorithms, including: Sobel Operator: It is a fundamental edge detection technique used to detect changes in intensity within an image. It can identify significant gradients, indicating the boundaries between different cloud formations. It utilizes a filter that calculates the approximate derivative of the image intensity in horizontal and vertical directions. Significant values in the resulting image correspond to potential edges. This is critical for determining the structure and organization of a cyclone, which in turn can provide insights into its intensity.
Canny Edge Detection: It is another popular edge detection method, incorporating a multi-stage process that includes gradient calculation, non-maximum suppression, and edge linking. It helps in capturing precise edges and reducing noise, allowing for a cleaner extraction of cyclone-related features.

Advanced Feature Extraction

Beyond contours and edges, deep learning-based cyclone intensity estimation benefits from more advanced computer vision analytical techniques to extract additional features that provide insights into cyclone intensity. Here are some potential areas of exploration:
Density Analysis: Statistical measures can be employed to quantify the distribution of pixels within the cyclone region. This can reveal information about the compactness or dispersion of clouds, potentially offering clues about the cyclone's organization and strength.Skewness Measurement: Asymmetry in the cyclone's cloud formations can be indicative of its rotational characteristics and potential intensity changes. Skewness, a statistical measure of asymmetry, can be calculated to quantify the deviation from a symmetrical distribution.Trajectory Prediction: By analyzing the cyclone's contour and density distribution in multiple satellite images captured over time, computer vision algorithms can potentially estimate the cyclone's immediate movement and trajectory. This can involve techniques like optical flow, which tracks the motion of apparent patterns in image sequences. [9]By strategically combining these computer vision techniques, the model meticulously prepares the satellite images for the Caps Net. The extracted features, encompassing the cyclone's shape, edges, density distribution, and potentially its trajectory, provide valuable insights that the Caps Net can leverage to estimate cyclone intensity with remarkable accuracy. This paves the way for early warnings and improved disaster preparedness efforts.

Flow of Deep Learning Model

This work proposes a deep learning- based approach [12] for estimating cyclone intensity using Capsule Convolutional Neural Networks (Caps Net) [5]. Caps Nets are a recently proposed deep learning model that is designed to overcome the limitations of CNNs in capturing complex patterns and relationships in the data. The proposed approach takes a sequence of satellite images of a cyclone as input and outputs the estimated intensity label. The mode is trained end-to-end using a supervised learning approach with a loss function that minimizes the difference between the predicted and ground truth intensity labels. A diagram illustrating the model is shown below in fig 2: -

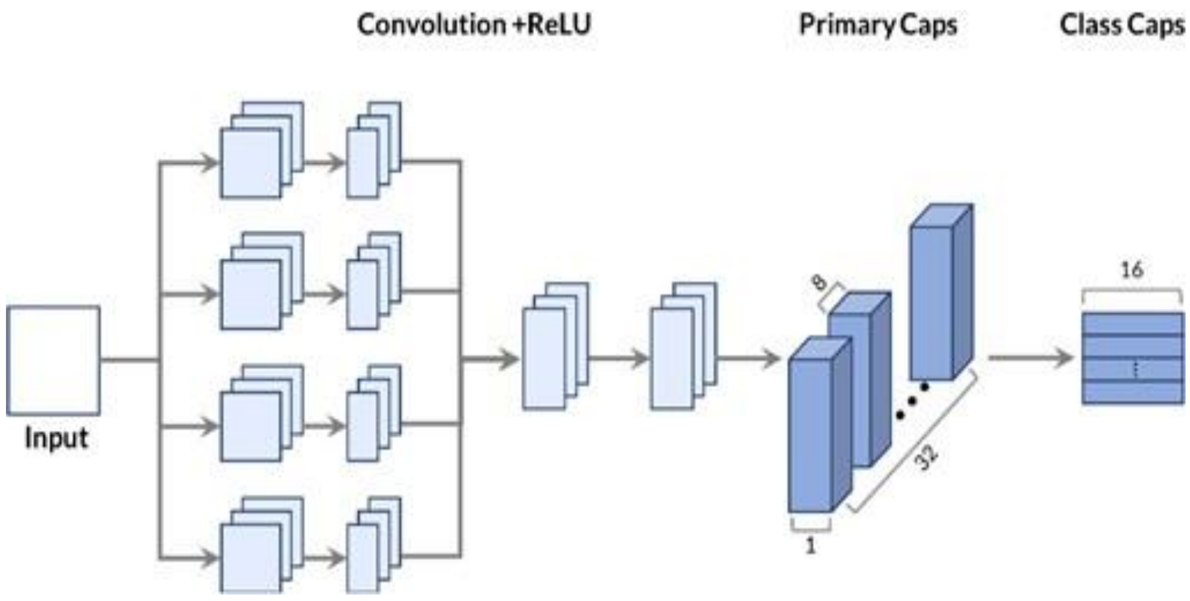

Fig. 2. Figure shows proposed CapsNet model.

The proposed system for cyclone intensity estimation leverages the power of deep learning and, specifically, incorporates the innovative Capsule Network (CapsNet) architecture. CapsNets have demonstrated the ability to capture hierarchical and spatial relationships within images, making them an ideal choice for recognizing intricate structures and patterns in cyclone satellite imagery.

Input Layer: The system takes INSAT 3D satellite images as input. These images are preprocessed to ensure consistency in format, remove noise, and enhance their quality.Convolutional Layers (Primary Capsules): The initial layers of the CapsNet consist of a series of convolutional layers. These layers aim to extract low-level features from the input images, such as edges, shapes, and basic structures.[2][3]Primary Capsules: The primary capsule layer follows the convolutional layers. In this layer, capsules are used to group low-level features into higher-level structures. Capsules are groups of neurons that work together to recognize more complex patterns and spatial relationships. For cyclone intensity estimation, these primary capsules focus on identifying features like cloud formations, eyewall organization, and spiral band structures, which are indicative of cyclone strength.Routing by Agreement: The heart of CapsNets is the "routing by agreement" mechanism, where the primary capsules collaborate to recognize complex patterns. During this process, capsules communicate and "vote" on the presence of specific features. This iterative routing mechanism helps establish the relationships between different features and components of a cyclone.Digit Capsules: The digit capsule layer is responsible for further consolidating the information and relationships established by the primary capsules. It learns to recognize and represent more abstract and high-level features that are indicative of cyclone intensity. Intensity Estimation: The final layer of the CapsNet is responsible for estimating the cyclone's intensity. It takes the output from the digit capsules and computes an estimate of the cyclone's intensity, which can be a numerical value or a category representing the cyclone's strength. The proposed system's CapsNet architecture offers a promising approach to cyclone intensity estimation, with the potential to outperform traditional methods by capturing intricate features and spatial relationships crucial for accurate predictions. The integration of CapsNets into the deep learning model enhances its ability to understand and estimate cyclone intensity, ultimately contributing to more effective early warning systems and disaster preparedness.

Metrics for Evaluation of Model

The output that is to be produced is intensity of the cyclone in knots. Since it is a numeric continuous value, the metrics to measure performance of the neural network model would be the following: -

Mean Squared Error (MSE): The MSE is calculated by taking the difference between the forecasts made by our model and the actual data, squaring it, and averaging it over the entire dataset. Since we are constantly squaring the errors, the MSE can never be negative. The following expression provides the official definition of the MSE:

$$\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

Where, n is the number of samples under consideration, Yi is the desired / expected / actual value and Ŷi is the calculated / observed value.

Root Mean Squared Error (RMSE): The square root of the mean of the square of all errors is known as the root mean squared error (RMSE). RMSE is frequently employed and is regarded as a superior all- purpose error measure for numerical predictions.

$$\sqrt{\frac{1}{n} * \sum (X_p - X_t)^2}$$

Where, n is the number of observations that can be used for analysis, Xt are the observations, and Xp are the predicted values of a variable.

Since RMSE is scale-dependent, it should only be used to evaluate forecasting errors of various models or model configurations for a single variable and not between variables.

Pseudo Code

The pseudo code for deep learning [7] based cyclone intensity estimation is as follows: -

BEGIN

Data Preparation

Load INSAT 3D dataset

Preprocess images (resize, normalize) Prepare meteorological data

Deep Learning Model Setup

Choose architecture (CNN, Capsule Network) Define model structure (layers, parameters) Compile model (loss, optimizer, metrics)

Model Training
Split dataset (train, validation sets) Train model using training data
Monitor training progress (loss, accuracy)
Model Evaluation
Evaluate model using validation set
Calculate performance metrics (MSE, R-squared) Visualize results (predicted vs. actual intensity)
Prediction
Prepare new/unseen cyclone images and meteorological data Use trained model to predict intensity
Post-processing
Interpret and analyze prediction results Apply post-processing as needed
Reporting
Generate reports or visualizations of cyclone intensity Communicate results to stakeholders
END

The system processes and analyzes these input data to estimate the intensity of cyclones. Deep learning models, such as convolutional neural networks (CNNs) and capsule networks (CapsNets), are trained on historical and labeled data to make predictions based on new satellite imagery and meteorological observations.

RESULTS

Intensity Prediction: The intensity prediction module is tested against historical cyclone intensity data to assess its ability to accurately predict cyclone intensity levels. Performance metrics such as mean absolute error and correlation coefficient are calculated to quantify the model's accuracy and precision.

Fig. 3. Wind speed intensity output

Wind speed is typically quantified in kilometers per hour (kmph) and is determined by analyzing intensity data provided in a .csv file, which aligns with the parameters the model has been trained on. These intensity values are utilized to assess the accuracy of the model's predictions through metrics like mean absolute error. Table 4.4.3 showcases the corresponding values for loss and root mean square error (RMSE), offering insights into the model's performance evaluation.

Table 1: Model Training Result

Performance Measure	Value
Mean Squared Error	1.5196
Root Mean Squared Error	2.0730

Thus it can be understood that the model is performing well on unseen data.

Severity Classification: The severity classification module is tested against ground truth severity labels (e.g., Low Pressure Area, Depression, Cyclonic Storm) to evaluate its classification accuracy. Metrics such as accuracy, precision, recall, and F1-score are computed to assess the model's effectiveness in categorizing cyclone severity levels.

Fig. 4. Classification based on intensity value

Classification of intensity is done by referring to the values mentioned in the table below: -

Table 2: Classification of cyclone into its type of disturbance based on its wind speed.

Type of Disturbances	Associated Wind Speed in the Circulation
Low pressure Area	Less than17 knots (<31 kmph)
Depression	17 to 27 knots (31 to 49 kmph)
Deep Depression	28 to 33 knots (50 to 61 kmph)
Cyclonic Storm	34 to 47 knots (62 to 88 kmph)
Severe Cyclonic Storm	48 to 63 knots (89 to 118 kmph)
Very Severe Cyclonic Storm	64 to 119 knots (119 to 221 kmph)
Super Cyclonic Storm	119 knots and above (221 kmph and above)

A conditional statement, using if-else logic, is employed to classify disturbances, which informs the formulation of a mitigation plan recommended to the user.

Trajectory Prediction: The trajectory prediction module [17] is validated against observed cyclone trajectories to measure its predictive accuracy. Metrics such as root mean square error (RMSE) and mean absolute error (MAE) are calculated to quantify the model's trajectory prediction errors.

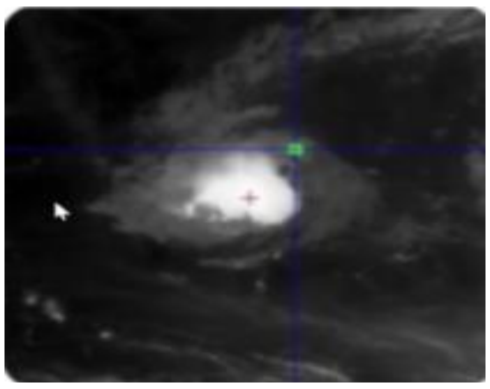

Fig. 5. Image showing next immediate trajectory of the cyclone

In this stage, the goal is to predict the imminent path of the cyclone, specifically pinpointing the location of its eye in the upcoming minutes. This prediction is achieved by examining the perimeter of the cyclone and analyzing its configuration. Sections of higher density within the cyclone indicate a greater likelihood of the prevailing winds redirecting the cyclone along that particular trajectory.

Potential Weakening Assessment: The potential weakening assessment module is tested against historical cyclone data to evaluate its ability to predict potential weakening events. Performance metrics such as sensitivity, specificity, and receiver operating characteristic (ROC) curve analysis are used to assess the model's predictive capability.

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Blue areas are skewed, indicating potential weakening of the cyclone.
Blue areas are scattered, indicating a weak cyclone.
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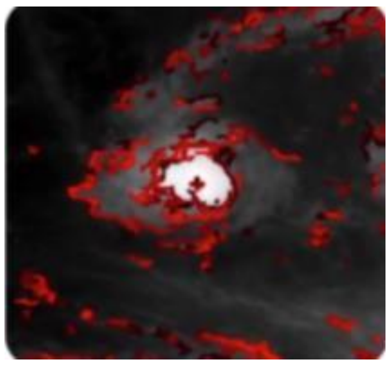
Fig. 6. Image showing output for skewness and symmetry analysis of cyclone

Density-based computations are utilized to assess the concentration of stormy regions, determining their compactness. Skewness, alongside the intensity of concentration, is computed to gauge the deviation of the cyclone's structure from its central eye. This measurement serves as an indicator of the cyclone's potential weakening, attributed to the disruptive effects of wind shear. A greater skewness suggests a higher probability of storm deterioration, as it signifies the dispersion and fragmentation of storm clouds due to environmental forces.

Edge Detection: The edge detection module is validated against ground truth edge maps of cyclone



imagery to measure its performance in detecting cyclone boundaries. Metrics such as precision, recall, and F1-score are computed to evaluate the accuracy of edge detection outputs.

Fig. 7. Image showing areas that the model determines as important features

In this context, the model identifies and emphasizes essential features within the figure to enhance its understanding of the cyclone. The highlighted regions, depicted in varying shades of red, represent the edges or curves of the cyclone. The intensity of the red hue correlates with the density of these areas, with darker shades indicating higher density and greater significance of these features in characterizing the cyclone.

Temperature Estimation: The temperature estimation module is tested against observed temperature data around cyclone eye walls to assess its ability to estimate average temperatures accurately. Mean absolute error (MAE) and correlation coefficient are calculated to quantify the model's temperature estimation errors.

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Average temperature around the eye of the cyclone: 19.874719730941703
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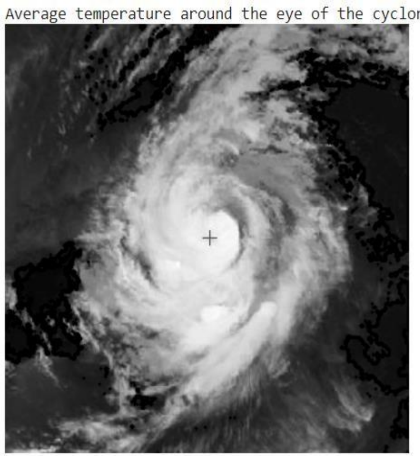

Fig.8. Image showing output for average temperature of wall of the eye of cyclone

Utilizing the temperature values across the cyclone and considering the density of specific regions enables the calculation of the average temperature surrounding the eye wall of the cyclone. This process serves to validate the cyclone's intensity, as a higher intensity cyclone typically exhibits a colder eye wall.

DISCUSSION

The Deep Learning-based Cyclone Intensity Estimation project employs the Capsule Neural Network (CapsNet) model to achieve remarkable accuracy across multiple crucial tasks in cyclone monitoring and forecasting. The model accurately predicts cyclone intensity levels, classifies severity, forecasts trajectories [15], detects cyclone boundaries in satellite imagery, and estimates temperatures around the eye wall. These capabilities enhance decision-making processes for stakeholders involved in disaster preparedness and response, offering valuable insights into cyclone characteristics and behavior. By leveraging advanced deep learning techniques and comprehensive meteorological data, the project contributes to improved disaster resilience, climate adaptation strategies, and the advancement of scientific knowledge in meteorology [23], machine learning, and disaster management.

CONCLUSION

In this study, a deep learning-based approach for cyclone intensity estimation using Capsule Convolutional Neural Networks (CapsNets) has been proposed. The results demonstrate that this method outperforms traditional Convolutional Neural Networks, offering a more accurate and robust means of predicting cyclone intensity from satellite imagery. The implementation of CapsNets for cyclone intensity estimation has the potential to transform disaster management [22] and evacuation planning. The more precise forecasts enable authorities to make better-informed decisions, thereby reducing the risks associated with severe weather events [8]. This study underscores the value of deep learning [21] in addressing critical real- world challenges, offering a promising direction for further research and development.

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