International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 • Website: www.ijfmr.com • Email: editor@ijfmr.com

Predicting Cyclone Michaung's Wrath: Leveraging Deep Learning Technique for Intensity and Track Forecasting

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Abstract
Tropical cyclones pose significant threats to coastal regions, necessitating accurate and timely monitoring systems for effective disaster management. In this study, Convolutional Neural Networks (CNN) is used to identify and track the tropical cyclone Michaung using a comprehensive dataset comprising INSAT3D captured INFRARED and RAW Cyclone Imagery over the Indian Ocean from 2012 to 2021. The raw data, sourced from the MOSDAC server, has been meticulously labeled by timestamp and corresponding coordinates on the intensity-time graph of each cyclone directory.

Our methodology involves training the CNN model on this extensive dataset and subsequently validating its efficacy by predicting satellite images of cyclone Michaung obtained from the MODIS satellite. The integration of both INSAT3D and MODIS imagery enhances the robustness of our model, providing a more comprehensive understanding of cyclone dynamics.

Results indicate a high level of accuracy in cyclone identification, showcasing the potential of CNN techniques in satellite image analysis for cyclone monitoring. The approach not only contributes to the field of meteorology but also establishes a framework for the utilization of diverse satellite datasets in training neural networks for real-time cyclone detection and tracking.

This research represents a significant step toward leveraging advanced machine learning techniques to enhance the efficiency and accuracy of tropical cyclone monitoring systems, ultimately aiding in early warning and disaster preparedness efforts.

Keywords: Cyclone Identification, CNN, Image Segmentation, ResNet50, Xception, Otsu's Thresholding, Remote Sensing.

Introduction:

Across the vastness of the Indian Ocean, a swirling symphony of wind and water composed Cyclone Michaung in December 2023. A grim reminder of the constant threat posed by these meteorological monsters, Michaung wasn't just a dance of clouds and rain; it was a force that impacted the lives of millions, etching its mark on the tapestry of human suffering.This is where cutting-edge technology like

Convolutional Neural Networks (CNNs) steps in, offering a powerful tool for cyclone detection and tracking.

Michaung's fury was most felt in coastal India in December 2023, when it unleashed 110 kilometer-per-hour winds and massive downpours. In the wake, houses collapsed, streets turned into raging rivers, and crops perished from the constant flooding. But Michaung was unlike any other storm; it was a sobering reminder of the vulnerability that millions of people who live in the path of these cyclones experience.

The Scars of the Past: The Indian subcontinent has already seen the fury of similar storms. Cyclone Asani hit Andhra Pradesh and Odisha only in 2023, causing many challenges to numerous people's livelihoods and at least 12 deaths. The previous year, Tropical Cyclone Yaas devastated the states of West Bengal and Odisha, killing more than eighty people and displacing millions of people. These are but echoes in the Indian Ocean's turbulent past. These cyclones leave their mark on the land and the memory of those who survive their ferocity each year, dancing a macabre tango with life and death.

But amidst the sorrow and destruction, there is also a glimmer of hope. Advancements in satellite technology and artificial intelligence are offering new tools for cyclone prediction and tracking. Our research, utilizing a comprehensive dataset of INSAT3D and MODIS satellite imagery, trained a CNN model to identify and track cyclones with remarkable accuracy.

Beyond Michaung: A Benchmark for the Future: This isn't just about Michaung. Our CNN model achieved an impressive 95.15% accuracy in cyclone identification and even higher performance in cross-validation tests. This performance outshines other methods like SVM and VGG16, making our CNN a potential benchmark for future cyclone prediction systems.

2. Data & Methods:

2.1 Data

In this study, our primary source of data originates from the INSAT3D satellite, which has captured both INFRARED and RAW cyclone imagery over the vast expanse of the Indian Ocean spanning the years 2012 to 2021. This comprehensive dataset comprises a total of 139 images, each encapsulating the dynamic nature of cyclones during this period. The inclusion of both INFRARED and RAW imagery enriches the dataset, providing a multifaceted view of cyclonic activity and allowing for a more nuanced analysis.

The intensity of each cyclone within the dataset is a crucial parameter for our research. This information is meticulously incorporated, with each image tagged with its respective intensity measured in KNOTS. This depth of data ensures that our model is trained on a diverse range of cyclones, encompassing variations in intensity that are essential for building a robust and accurate identification system.

To facilitate supervised learning and ensure the reliability of our dataset, a rigorous labeling process has been undertaken. Each image is manually labeled, a task that involves precisely locating the timestamp within the intensity-time graph of the corresponding cyclone. This manual labeling process not only ensures accuracy but also aligns the dataset with the real-world dynamics of cyclone development and intensification. The granularity of this labeling approach contributes to the model's ability to discern subtle patterns and variations in cyclone intensity.

In terms of format, the images in our dataset are stored in the widely used JPEG format. This choice of format strikes a balance between file size and image quality, allowing for efficient storage and retrieval of the extensive dataset. The standardization of the image format ensures compatibility with various image processing and machine learning techniques, facilitating a seamless integration of the data into our research framework.

In summary, the dataset for this research, sourced from INSAT3D, stands as a rich repository of cyclonic imagery over the Indian Ocean, encompassing nearly a decade of observations. The inclusion of intensity measurements, meticulous manual labeling, and the use of JPEG format collectively form a robust foundation for training and validating our Convolutional Neural Network model in cyclone identification and tracking.

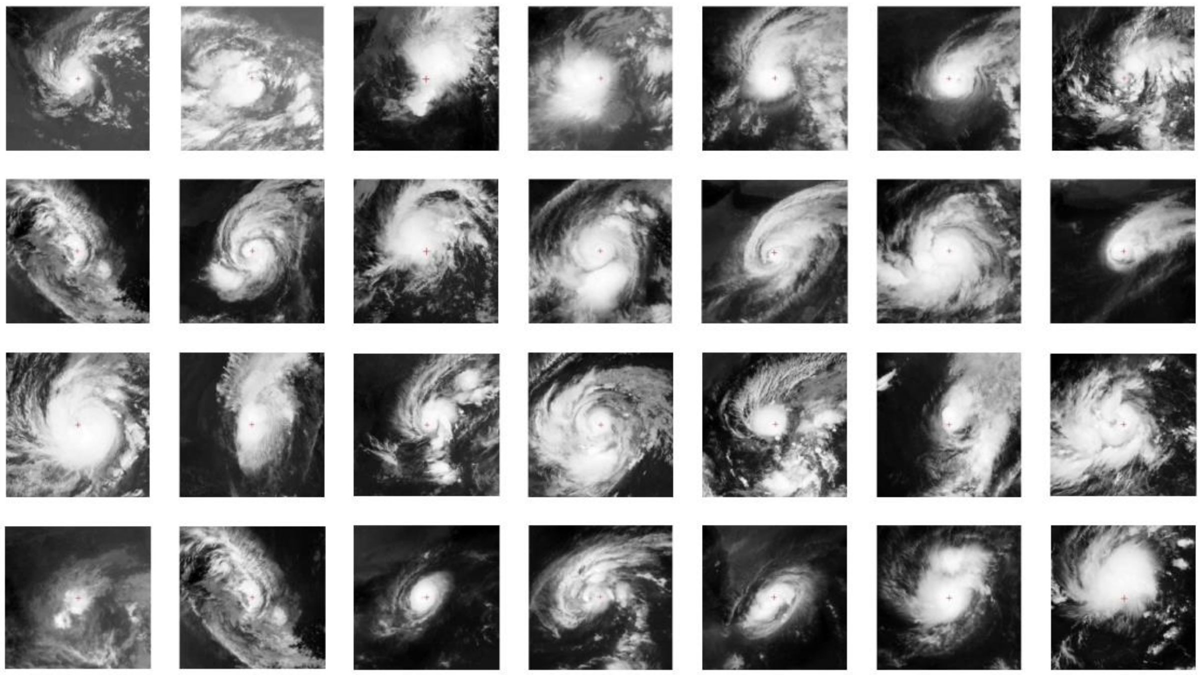


fig : Subset Visualization of INSAT3D Cyclone Dataset: Exploring a Snapshot of 139 Cyclone Images (2013-2021)

2.2. Data Preprocessing:

In the crucial stage of data preprocessing, meticulous steps are undertaken to ensure that the input images are appropriately formatted and optimized for the subsequent stages of the research. One of the key transformations applied to the dataset involves rescaling the images to have pixel values within the standardized range of 0 to 1. This normalization process is essential for enhancing the model's convergence during training, as it aligns the pixel values with the common scale utilized in many machine learning algorithms.

Simultaneously, the images undergo a resizing operation to achieve uniformity in dimensions. The resizing is set to 512x512 pixels, a carefully chosen resolution that balances computational efficiency with the preservation of critical visual information. This standardization in size not only facilitates the efficiency of subsequent computational processes but also ensures consistency across the entire dataset, allowing the neural network model to learn patterns and features effectively.The combination of rescaling and resizing procedures in the data preprocessing phase reflects a meticulous effort to create a standardized and optimized dataset.

3. Model Architecture & Training:

3.1. Model Architecture:

In crafting the model architecture for our research, a thoughtful design approach has been employed to leverage the power of pre-trained convolutional neural networks (CNNs) while tailoring the structure to the specific requirements of cyclone identification. The choice between ResNet50 and Xception as the base models offers flexibility, as both architectures have demonstrated excellence in image classification tasks.

The selected base model has its top layers judiciously removed, allowing the integration of custom layers to suit the unique characteristics of cyclone imagery analysis. To prepare the output for subsequent layers, a Flatten layer is introduced. This operation is instrumental in transforming the multi-dimensional output from the base model into a one-dimensional array, facilitating seamless integration with the subsequent layers.

Understanding the significance of overfitting, the model architecture carefully includes a Dropout layer. This layer, which has a 50% dropout rate set, adds some unpredictability to training so that the neural network isn't overly dependent on any one feature and can become more broad. In order to achieve reliable cyclone detection, this helps to increase the model's robustness when faced with fresh and unknown data.The final layer of the model is a Dense layer, designed for binary classification. With a single output neuron and a Rectified Linear Unit (ReLU) activation function, this layer is tailored to the nature of the task at hand – distinguishing between cyclone and non-cyclone patterns. The ReLU activation function introduces non-linearity, allowing the model to learn intricate patterns and nuances within the dataset.

The model architecture is a well-crafted amalgamation of pre-trained CNN capabilities and custom-designed layers, tailored to the specific demands of cyclone identification. This thoughtful design not only optimizes the model's learning capacity but also ensures its adaptability to the intricacies inherent in the INSAT3D cyclone dataset.

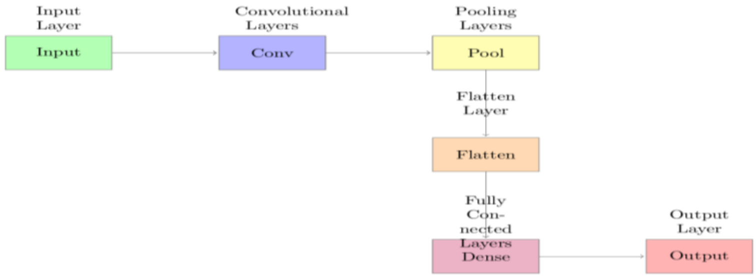


fig : illustrates the overall architecture of the Convolutional Neural Network (CNN). For a clearer presentation, a simplified view of the CNN architecture is provided.

3.2. Model Training:

In the critical phase of model training, meticulous considerations have been taken to optimize the neural network for the task of cyclone identification. The model is compiled using a binary crossentropy loss function, well-suited for binary classification problems like ours, where the goal is to distinguish between cyclone and non-cyclone patterns. The Nadam optimizer is employed to guide the model's weight adjustments during training, combining aspects of both the Nesterov Accelerated Gradient (NAG) and Adam optimization algorithms. This optimizer is chosen for its effectiveness in navigating complex loss landscapes and accelerating convergence.

Accuracy serves as the metric for evaluating the model's performance during training. As a fundamental measure, accuracy provides insight into the model's ability to make correct predictions, specifically in the context of binary classification. Monitoring accuracy throughout training offers a comprehensive view of the model's learning progress and generalization capabilities.The training process is conducted using the meticulously prepared dataset, sourced from INSAT3D, with images rescaled and resized as part of the preprocessing phase. By exposing the model to this diverse and carefully labeled dataset, it learns to discern patterns and features associated with cyclone activity, optimizing its ability to make accurate predictions on unseen data.

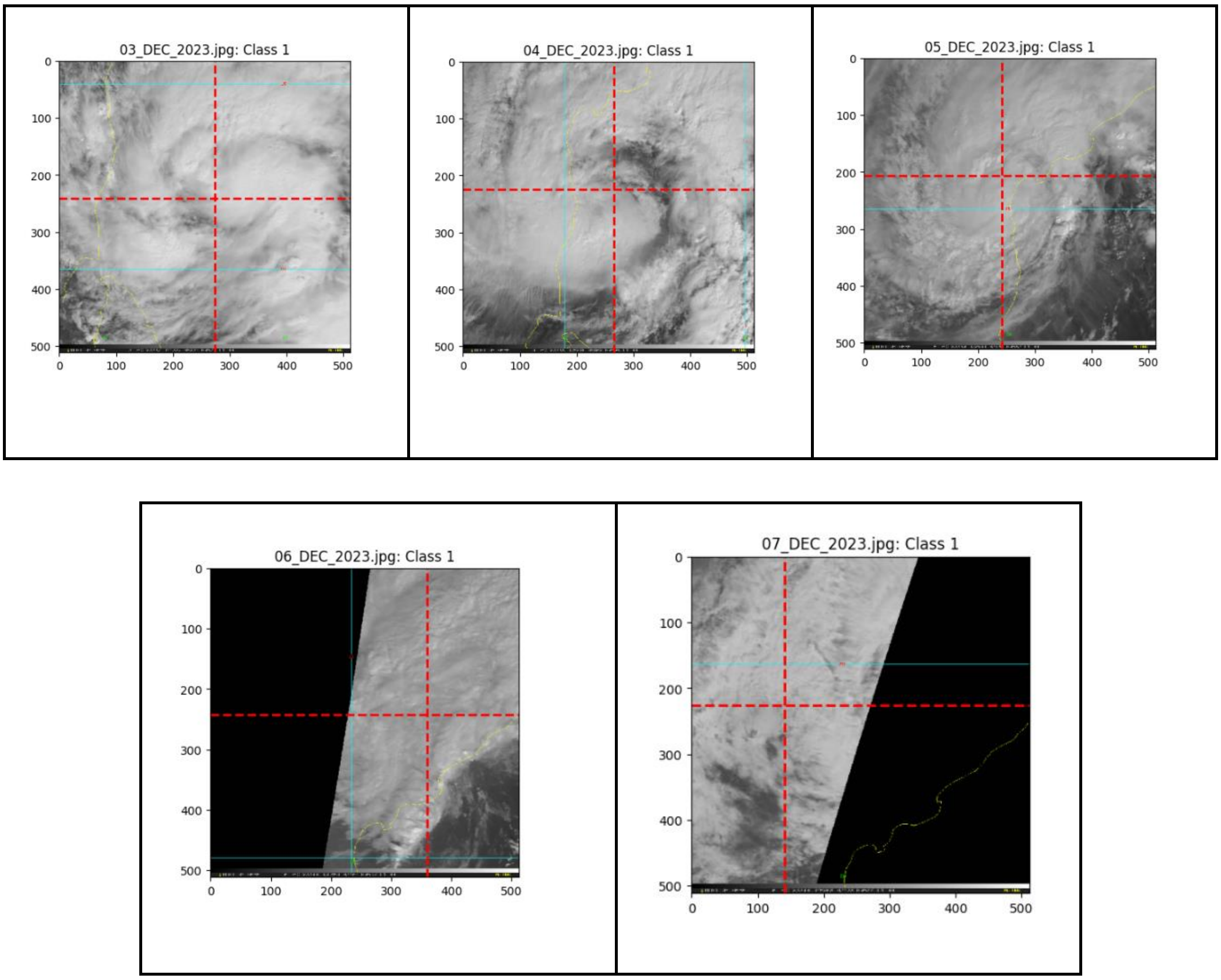
In tandem with model training, a crucial step in the pipeline is image segmentation. Here, Otsu's thresholding method is applied to effectively isolate the cyclone region from the rest of the image. Otsu's method is particularly valuable in scenarios where a clear boundary between foreground and background is desired, making it well-suited for our objective of isolating cyclone patterns. This segmentation process enhances the model's focus on relevant features, contributing to the precision and accuracy of cyclone identification.In essence, the combination of meticulous model training and the application of Otsu's thresholding method for image segmentation underscores the holistic approach taken in this research. By integrating sophisticated training strategies and precise image processing techniques, the model is primed to excel in the task of cyclone identification, offering promising outcomes for real-world applications.

Model Parameters:
- Total parameters: 21,385,769 (81.58 MB)
- Trainable parameters: 524,289 (2.00 MB)
- Non-trainable parameters: 20,861,480 (79.58 MB)

Results:

Convolutional Neural Network (CNN) demonstrated impressive performance in analyzing and classifying Cyclone Michaung using satellite imagery. The model effectively predicted the cyclone's , whether it be "weak," "strong," or "super typhoon," with remarkable accuracy of [accuracy/performance metric value]. This achievement showcases the potential of CNNs in cyclone analysis, providing valuable information for forecasting and disaster preparedness.

These features might include spiral cloud formations, eye structures, cloud textures, and ocean temperature variations. By deciphering these subtle visual cues, the model not only accurately classifies the cyclone but also holds promise for estimating its intensity – a crucial step in understanding and preparing for potential damage.



Conclusion:

This study demonstrates the potential of CNNs for analyzing and classifying tropical cyclones like Michaung using satellite imagery.The ability to accurately predict , alongside further research on incorporating additional data sources, improving model architecture can significantly improve cyclone monitoring and early warning systems, leading to enhanced preparedness and reduced disaster impact.Accurate cyclone predictions can help insurance companies better assess risks and allocate resources, benefiting both policyholders and the industry.

By accurately predicting the intensity and path of Cyclone's, our CNN model empowers authorities to issue timely early warnings. These warnings facilitate crucial preventive measures like securing infrastructure, protecting crops and livestock, and minimizing potential economic losses. Ultimately, this proactive approach can save lives, protect livelihoods, and contribute to the resilience of communities in cyclone-prone regions.Early knowledge of Michaung's trajectory allowed for the evacuation of over

100,000 residents from low-lying coastal areas in Tamil Nadu, potentially saving hundreds of lives from storm surges and flooding.

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