# Cyclone Vision: A Comprehensive Deep Learning Framework and Web App for Early Cyclone Detection and Monitoring

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## Abstract

*Cyclones are a devastating natural phenomenon that causes massive destruction in coastal regions. The unpredictable nature of cyclones also makes them very challenging to forecast. Satellite infrared images are an invaluable source of information for estimating cyclone intensity and providing necessary information to predict cyclones early. Deep learning has revolutionized computer vision in recent times, empowering significant advancements and breakthroughs. Also, the proliferation of web technologies and smartphones has helped the general public become more accessible to the power of AI. In this work, we have developed a very large dataset used to train a deep CNN model with a novel custom loss function for training the model specifically penalizing error for high-speed cyclones, and we developed a web app that integrates various components, serving as a public-facing platform to showcase the application of AI in cyclone detection and intensity estimation. It offers features that can be utilized in disaster management crises.*

## 1. Introduction

Cyclones are highly destructive and can cause widespread devastation, leaving a trail of destruction in their path. The unpredictable nature of cyclones and their immense destructive power pose a significant threat to coastal regions worldwide. It is crucial to develop a cyclone intensity estimation model that would help detect cyclones early during their formation, so necessary actions can be taken to help save lives. Conventionally, the Dvorak technique was used to estimate cyclone intensity. Dvorak technique relies on manually analyzing cloud patterns in satellite infrared images to estimate cyclone intensity. In recent times, deep learning has shown a lot of potential in finding intricate patterns within vast and diverse datasets. The task of detecting and estimating cyclone intensity can also be automated using deep learning thus providing a tool for real-time monitoring and early warning systems for cyclones.

In this study, we present an improved version of the INCYDE dataset by incorporating additional infrared bands (TIR1, TIR2, WV, MIR) obtained from INSAT 3D/3DR [12, 9]. The dataset was curated using the same pipeline as INCYDE [7] utilizing Indian Meteorological Department (IMD) best track data [1] as labels and INSAT [12, 9] images as input. We also introduce a deep Convolutional Neural Network (CNN) model for cyclone intensity estimation, accompanied by a novel loss function that penalizes errors more severely for high-speed cyclones, enhancing the model's accuracy in such cases. Furthermore, we develop a user-friendly web application that integrates various components, allowing the general public and authorities to identify imminent cyclones and visualize the estimated intensity.

In conclusion, the contribution of this work is as follows:

- Introduction of a novel dataset for cyclone intensity estimation with multiple bands.
- Proposal of a unique loss function that addresses errors for high-speed cyclones.
- Development of a CNN model architecture utilizing a 4-band input for cyclone intensity estimation.
- Creation of a user-friendly web application for easy satellite image visualization and accessible display of cyclone intensity estimation.

## 2. Application Context

Cyclones pose a significant threat to coastal regions worldwide, it is of great importance to develop solutions to predict the onset of a cyclone before it can do much damage. Automating cyclone detection and intensity estimation, in other words, prediction using deep learning can prove to be immensely helpful to people living in cyclone-prone regions. In this work, a novel dataset for cyclone intensity estimation is presented which is used to train a deep CNN model with a customized loss function, and a user-friendly public-facing web app is also presented. The work aims to address concerns in humanitarian assistance and disaster response operations by providing timely and accurate information for cyclone prediction. The dataset encompasses diverse satellite infrared images during cyclone periods from 2013 to 2021 in Indian Ocean Region, serving as a valuable resource for training deep learning models. The deep CNN model captures intricate patterns in cyclone data, while the customized loss function enhances accuracy. The web application integrates all components, enabling users to assess the potential threat of an imminent cyclone. This work has been made possible through our collaboration with Indian Space Research Organisation (ISRO), leveraging their expertise and guidance.

## 3. Related Work

In this section, some related works for cyclone intensity estimation are briefly discussed. The conventional means of cyclone intensity estimation is the Dvorak technique [6]. Dvorak technique [6] uses satellite images to estimate the intensity of a tropical cyclone using its cloud pattern. The cloud pattern is analyzed in terms of the distribution of cloud cover and the temperature of the cloud tops. The cyclone is classified using a combination of cloud pattern features such as the size, shape, and temperature of the cloud tops, as well as the presence of an eye or the center of the storm. Once the storm has been classified, the Dvorak technique provides an estimate of the maximum sustained winds and the central pressure of the storm. This information can be used to issue forecasts and warnings to people in the path of the storm. While the Dvorak technique is the conventionally used tool for estimating the intensity of tropical cyclones, deep learning techniques can provide a faster and more accurate way of estimating cyclone intensity without human intervention.

Li et al. [10] presents a cyclone dataset FY4A-TC using multispectral images of 81 cyclones captured by FY4A satellite from 2018-2021.

Tan et al. [17] used Himawari-8 satellite products for cyclone intensity estimation. Tan et al. [17] used a basic convolutional neural network (CNN) and they were able to achieve 4.06 m/s (7.89 knots) RMSE for their dataset

Chen et al. [3] presents a framework for tropical cyclone intensity estimation using Generative Adversarial Network (GAN) to handle temporally heterogeneous datasets. Their model uses IR1 and WV channels for prediction.

Chen et al. [4] used a deep CNN model for estimating TC intensity using satellite IR brightness temperature and microwave rain rates together with additional TC information like the basin, day of the year, local time, etc. They managed to achieve an RMSE of 8.79 knots for a subset of 482 samples. They used a 4-layer CNN model with three fully connected layers with random rotation as preprocessing and post-analysis smoothing to achieve lower RMSE.

Miller et al. [14] used GOES IR images for historical tropical storms in the Atlantic and Pacific basins from the year 2000 to 2015. Miller et al. used the HURDAT2 dataset for labels. Lu et al. [11] used IR satellite images from 2006 to 2010 for cyclone intensity estimation. Pradhan et al. [15] used a deep CNN for cyclone intensity estimation and achieved state-of-the-art RMSE for cyclone intensity estimation.

Various machine learning algorithms were used by [2], [5] for predicting hurricanes intensity using IR satellite imagery data. Devaraj et al. [5] also uses a VGG 19 model to predict the extent of the damage. Maskey et al. [13] developed a simple deep CNN with 6 CNN with max-pool layers and 3 fully connected layers at the end. Their model was able to achieve 13.24 knots. They also developed a web application to visualize historical data of cyclones and get current cyclone intensity estimation predictions.

## 4. Methodology

In this section, the methodology employed in this work would be discussed briefly, including the dataset curation pipeline, the deep CNN model details, the loss function, and the web app.

The dataset is the most crucial part of any deep-learning task. In this work, we present a large-scale dataset for cyclone intensity estimation. The work builds upon the INCYDE dataset [7] and improves it by adding more infrared bands. More images are added using the same dataset curation pipeline as INCYDE [7]. The labels are taken from IMD best track data [1]. The images are taken from INSAT [12, 9] satellites. The dataset includes images for cyclone periods from 2013 to 2021 in the Indian Ocean. The labels

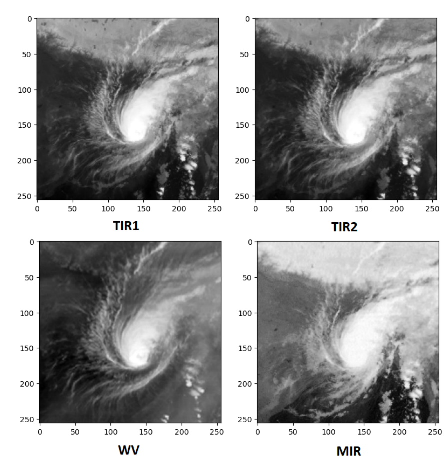


Figure 1. TIR1, TIR2, WV and MIR bands of the infrared satellite imagery from INSAT 3D/3DR satellite

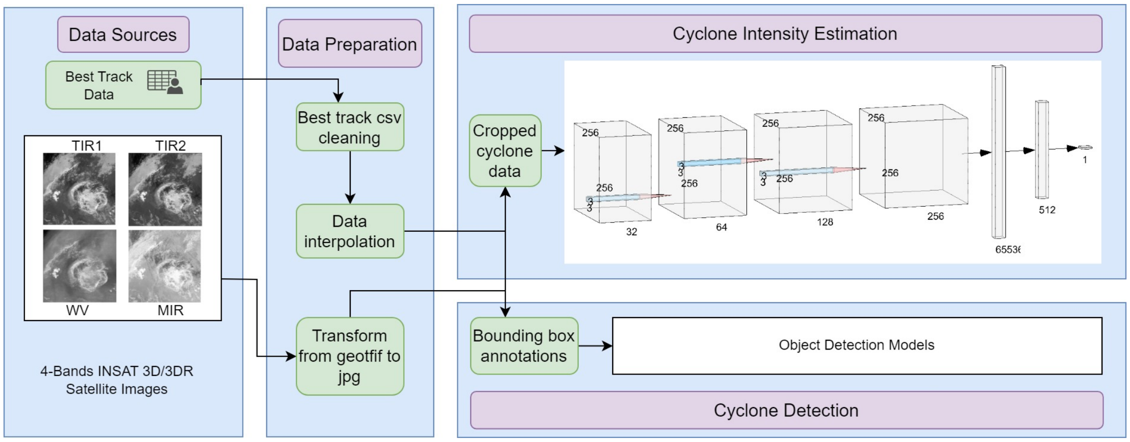


Figure 2. Workflow of the dataset curation and model training pipeline for cyclone detection and cyclone intensity estimaton

are available at 6-hour intervals, while the images are available at 15-minute intervals. In order to utilize all the images available, interpolation has been used to create more labels from existing labels. The images are available in 6 different bands, i.e., thermal infrared 1 (TIR1), thermal infrared 2 (TIR2), middlewave infrared (MIR), shortwave infrared (SWIR), visible (VIS), water vapor (WV). The INCYDE dataset contains only the TIR1 band for simplicity, we have added TIR2, MIR, and WV bands to the dataset. The SWIR and VIS bands are not utilized in our methodology due to their limited effectiveness during nighttime, as they exhibit blank or insufficient data coverage, thus including these bands would result in half the dataset having empty images. Figure 1 shows the images from 4 infrared bands used in this work. The 4 images are used as a stacked input to the CNN model. The dataset contains over 20000 images per band.

A custom loss function is also presented for training the deep CNN models for cyclone intensity estimation. The loss function provides a penalty term that scales up when the predicted value deviates too much from the target value at higher ranges. The loss function is given as:

$$\text{loss} = \frac{1}{N}\sum_{i=1}^{N}\left((pred_i - target_i)^2 \cdot (1 + \frac{|pred_i - 140|}{140})\right)$$

where $pred_i$ represents the predicted value for the $i$-th sample, $target_i$ represents the target value for the $i$-th sample, and $N$ is the total number of samples. The motive behind this loss function is to penalize the model more when the predicted cyclone intensity deviates too much from the target intensity at high-intensity values near 140. 140 is chosen as it is the highest value of cyclone intensity in our dataset and it represents the highest grade of tropical cyclone according to IMD [1].

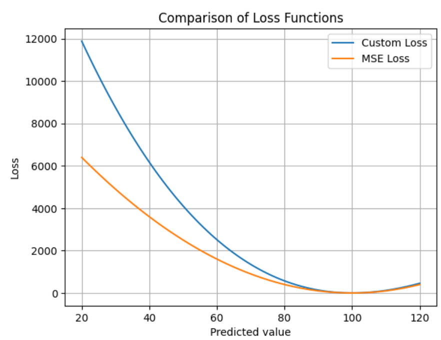


Figure 3. Comparison of the custom loss function as compared to the MSE loss, when the target value is 100 knots

The CNN model for cyclone intensity estimation is shown in figure 2. The model contains 4 CNN layers and 2 fully connected layers. The input to the deep CNN model is a 4-channel input matrix which includes the 4 channels in the dataset stacked together. The output is a single-valued number representing cyclone intensity in terms of maximum surface wind speed (MSWS) in knots.

## 5. Results

In this section, the results of the deep CNN models are briefly discussed. The metric used to evaluate the performance of the deep CNN model for cyclone intensity estimation is root mean squared error (RMSE) since the intensity is a single continuous numerical value. The metric used for cyclone detection is the same as the metric used to report results for object detection tasks, that is, mean average precision (mAP). RMSE is calculated using the following formula:

$RMSE = \sqrt{\Sigma(pr - ob)^2}$

where, pr = predicted value and, ob = observed value The YOLOv5 object detector for cyclone detection is able

Table 1. Comparison of loss functions when used with the CNN model for cyclone intensity estimation

| Loss Function | RMSE (knots) |
|---|---|
| MSE Loss | 20.2 |
| **Custom Loss** | **19.8** |

to achieve 63.35 mAP. The CNN model for cyclone intensity estimation is able to achieve 19.8 knots RMSE in 20 epochs while using the custom loss function, meanwhile the CNN model was able to achieve 20.2 knots RMSE when using the MSE loss, thus showing improvement over MSE loss.

Table 1 shows the RMSE achieved by the CNN model when used with MSE Loss, and the custom loss. It can be observed that there is a slight improvement, but also since the loss function increases the penalty factor more when the predicted value deviates too much from the high target values, there are less instances of false negatives. Table 2 shows some object detection algorithms for cyclone detection trained on the INCYDE dataset [7], the object detection models are trained on single channel data as opposed to the multichannel input for the model presented in this work. Based on these results, the YOLOV5 object detector is used in the web app. But it would be interesting to observe the effect of multichannel inputs for object detection as well, we leave it for future work.

Table 2. Object detection models trained on the INCYDE dataset [7] for cyclone detection

| Model Name | Validation mAP | Epochs |
|---|---|---|
| **YOLOv5** [8] | **63.35** | **20** |
| FasterRCNN [16] | 48.5 | 20 |
| EfficientDet [18] | 40.5 | 20 |
| YOLOv5-Aug [8] | 42.37 | 20 |

## 6. Web-application architecture

The web app integrates everything together to build a platform for visualizing satellite images and a platform to act as an early warning system for cyclones, Figure 4 shows the architecture of the web app. The web app is hosted on AWS for scalability. The images for the web app are taken from INSAT 3D/3DR satellite [12, 9] through the MOSDAC framework. The images are preprocessed and fed into a YOLOv5 object detector trained on the cyclone detection dataset from the INCYDE dataset [7], and deployed on AWS Sagemaker. The resulting bounding box is cropped, stored in an AWS S3 bucket, and then fed into a deep CNN model for cyclone intensity estimation trained on the proposed dataset, the model for cyclone intensity estimation is also deployed on AWS Sagemaker. The inputs to the deep CNN model are a 4-channel matrix that includes the 4 infrared bands of the satellite imagery provided by INSAT 3D/3DR. The resulting inference is stored in another S3 bucket which is then consumed by the web app. The

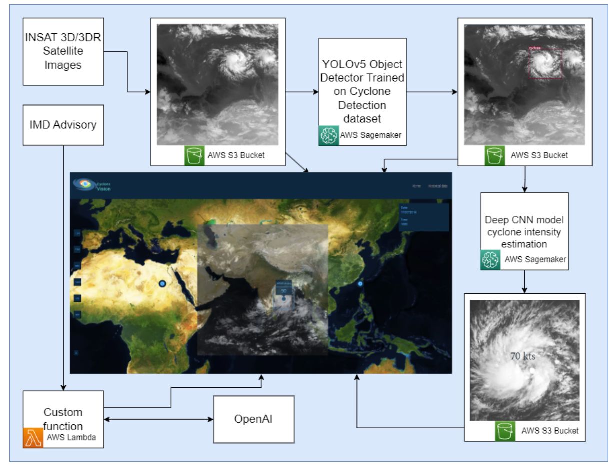


Figure 4. Architecture of the web app

user-facing client of the web app shows the satellite images, the bounding box generated by the YOLOv5 object detector, and the estimated cyclone intensity in one place. The web app uses an open-source framework called Mapbox for visualizing the map within its interface. Apart from cyclone detection and cyclone intensity estimation, the web app also uses OpenAI ChatGPT API to summarize the IMD advisory in a layman's language to provide any cyclone-related information when there isn't any visual information available.

## 7. Conclusion and future work

In this work, we presented a comprehensive end-to-end framework for cyclone detection and cyclone intensity estimation called Cyclone Vision. The deep CNN model is able to accurately predict cyclone intensity. The model can be enhanced further by using a more complex CNN architecture. In the future, we would also explore augmentation techniques to generate more data for training. The work would be enhanced further by training the models for more number of epochs. Furthermore, model interpretability frameworks can be employed to help experts understand more about cyclones. A comparative study can be carried out comparing all the models in the literature on a standard dataset. An even larger dataset can be created combining all existing datasets for cyclone intensity estimation. The 4 channel input model can also be replicated for cyclone detection task. This work leverages deep learning techniques and web technologies to empower stakeholders with valuable insights for improved preparedness and decision-making in the face of cyclonic events. Our future work involves collaborating with Indian Space Research Organisation (ISRO) to implement the project on a larger scale.

## 8. Acknowledgement

We extend our heartfelt appreciation to the Indian Space Research Organisation (ISRO) for their collaboration and support in implementing this project on a larger scale. Their expertise and guidance have been invaluable in making this work a reality.

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