INCYDE: A large scale cyclone detection and intensity estimation dataset using satellite infrared imagery

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Abstract

Tropical cyclones are devastating natural phenomena that cause a significant amount of damage every year. Conventionally, the Dvorak technique is used to detect cyclones and estimate cyclone intensity from satellite infrared imagery by observing cloud patterns. Satellite infrared imagery provides valuable information for detecting cyclonic storms. Recently, deep CNN models have proven to be highly efficient in detecting relevant patterns in the images. In this work, a novel cyclone detection and intensity estimation dataset called INCYDE (INSAT-based Cyclone Detection and intensity Estimation) dataset is presented. The cyclone images in the dataset are captured from INSAT 3D/3DR satellites over the Indian ocean. The proposed INCYDE dataset contains over 100k cyclone images with augmentations taken from cyclones over the Indian ocean from the year 2013 to 2021. The dataset pertains to two specific tasks: cyclone detection as an object detection task, and intensity estimation as a regression task. In addition to the dataset, this study introduces baseline models that were trained on the newly presented dataset. The results of this research would help develop innovative cyclone detection and intensity estimation models, which in turn could help save lives.

1. Introduction

Tropical Cyclones (TC) are highly destructive natural phenomena and they are one of the costliest natural disasters which cause a wide range of hazards. Tropical cyclones form over warm ocean waters when the water temperature is at least 26.5 degrees Celsius (80 degrees Fahrenheit). As the storm forms, it begins to suck up more and more warm air and moisture from the ocean, which causes it to grow larger and more powerful.

Deep learning has proven to be very efficient in detecting fine patterns in images, the cloud patterns in satellite infrared imagery provide valuable information about the formation of a cyclone. Thus, the usage of deep learning techniques to detect and estimate the intensity of cyclones using infrared satellite images has a lot of potential to be used as an early warning system to predict cyclones. Thus, there is a need to have a large-scale dataset for cyclone detection and intensity estimation to help research and develop deep Convolutional Neural Network (CNN) models that can help provide early warning for cyclones using IR satellite imagery without any human intervention.

In this work, we propose a large-scale dataset called INCYDE dataset for cyclone intensity estimation and cyclone detection. The dataset includes infrared (IR) images from INSAT 3D/3DR [22, 17] satellites from 2013 to 2021 annotated using Indian Meteorological Department's best track data [1].

To summarise, the contributions of this work are as follows:

- A large-scale dataset INCYDE for cyclone detection and intensity estimation is presented.
- Dataset creation pipeline used to curate the dataset has been presented.
- A thorough dataset analysis has been carried out to provide insights relevant to the dataset and a comparison with other state-of-the-art datasets has been carried out.
- Various deep CNN models have been trained on the proposed dataset for cyclone detection, and cyclone intensity estimation to act as baseline models for future work.

The rest of the paper follows the following structure. In section 2, the literature survey is carried out where prior works in the field of cyclone intensity estimation are discussed. In section 3 the methodology used to carry out the experimentation work in this research work is presented. In section 4, the proposed INCYDE dataset is presented along with important characteristics of the dataset like sample images, dataset curation process, dataset split, and comparison with other publicly available datasets. In section 5, the experimentation regarding baseline models trained on the proposed dataset is presented. This research work would help researchers develop robust cyclone intensity estimation and cyclone detection frameworks that have the potential to help save countless lives by providing early warnings for cyclones.

2. Related Work

Dvorak technique [11] 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. [18] presents a novel cyclone dataset FY4A-TC using multispectral images of 81 cyclones captured by FY4A satellite from 2018-2021. Li et al. [18] uses a Convolutional Neural Network (CNN) with a self-label regularizer to increase accuracy. The author proposes a GAN-CNN hybrid model which uses both passive microwave rate(PMW) and Visible channel images.

Tan et al. [30] used Himawari-8 satellite products for cyclone intensity estimation. Tan et al. [30] used a basic convolutional neural network (CNN) and they were able to achieve 4.06 m/s (7.89 knots) RMSE. Their work revealed that the model's performance is highly affected by the initial cloud products.

Chen et al. [6] 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, eliminating the dependence on the PMW channel. They use a hybrid GAN-CNN model, with two generators for producing VIS and PMW images. The generated images are utilized only for training the estimator and are combined with good-quality VIS images to get comparable performance. Their framework is designed to increase the prediction frequency from 3 hours to 15 minutes.

Bloemendaal et al. [3] uses STORM dataset [4] for TC wind speed estimation. The author uses historical best track data from the International Best Track Archive for Climate Stewardship (IBTrACS20) and generates tropical cyclone data comparable to 10,000 years with the current climate constraints. The authors propose the STORM dataset and use it to find the return periods of a Tropical cyclone hazard.

Chen et al. [8] 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 use 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. [24] 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. [20] used IR satellite images from 2006 to 2010 for cyclone intensity estimation. Pradhan et al. [25] used a deep CNN for cyclone intensity estimation and achieved state-of-the-art RMSE for cyclone intensity estimation. Luo et al. [21] presented a novel DR-transformer for tropical cyclone intensity estimation. Their proposed model is able to achieve a state-of-the-art RMSE of 7.6 knots. Their transformer-based model extracts Distance-consistency(DC) and rotation invariance(RI) features in TC images. These features extracted can overcome the issues faced by classical CNN models in differentiating highly similar visual features. Additionally, they also repurpose their model to incorporate the evolution of the cyclone through time and intensity.

Various machine learning algorithms were used by [2], [10] for predicting hurricanes intensity using IR satellite imagery data. Devaraj et al. [10] also uses a VGG 19 model to predict the extent of the damage. Maskey et al. [23] 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.

3. Methodology

In this work, a novel dataset INCYDE is presented. The images in the dataset were collected from INSAT 3D and 3DR satellites [22, 17] and the labels were collected from IMD best track data. The IMD best track contains cyclone information like latitude, longitude, maximum sustained wind speed, timestamp, etc. The data in the best track data has a frequency of 6 hours but the INSAT 3D/3DR satellite IR imagery is available in 30/15 minutes intervals. So, in order to efficiently use all the images available, it was imperative to generate more labels for the images in the dataset using the available data from IMD's best track data. So, we used interpolation to generate more labels between two consecutive timestamps in the best track data for the corresponding images.

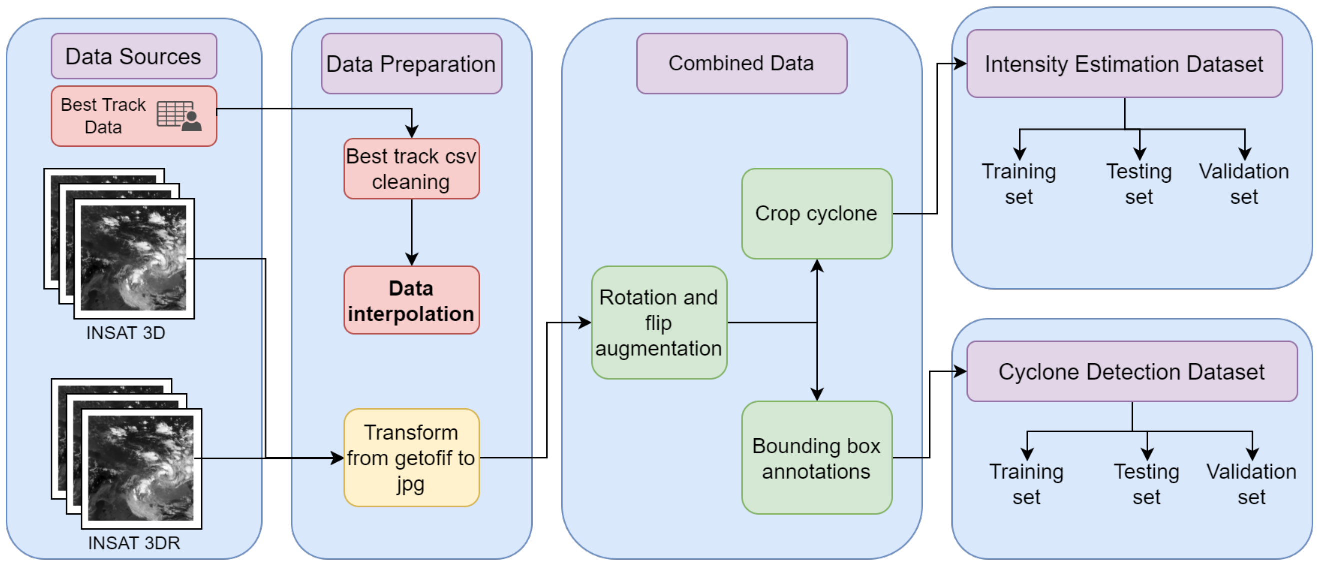


Figure 1. Workflow for curating the INCYDE dataset from best track data and satellite images for cyclone detection and intensity estimation task

4. Dataset

The proposed dataset, i.e., INCYDE contains 22k images or over 100k images with augmentation from INSAT 3D and INSAT 3DR satellite IR imagery [22, 17] of cyclones between the years 2013-2021. The INSAT 3D/3DR provides IR imagery in 6 different bands, in this work, the thermal infrared (TIR1) band has been used. In this section, all the relevant information regarding the INCYDE dataset is presented.

4.1. Pipeline

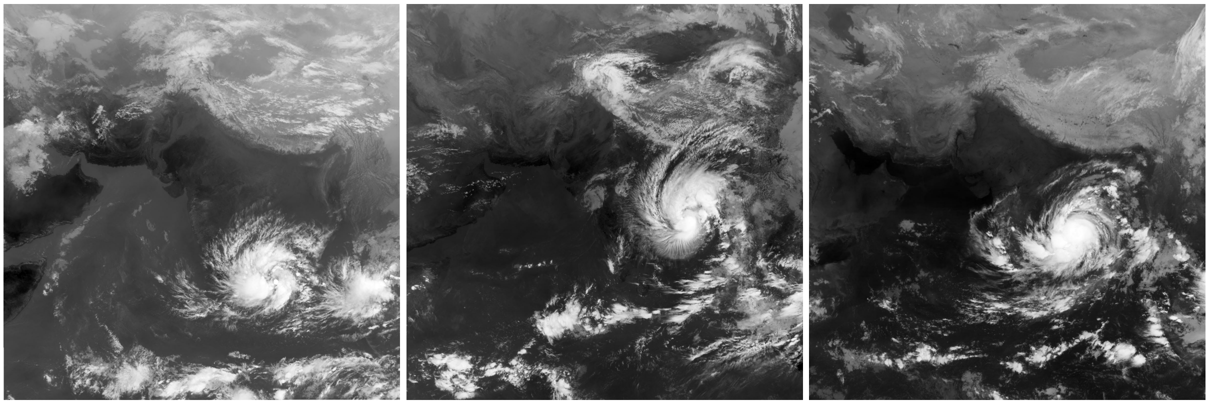
In order to create an end-to-end cyclone intensity estimation solution, the task can be divided into two parts, i.e, object detection and intensity estimation. In the first step, an object detection algorithm can be used to identify and localize cyclones in the image, and in the second step, the cropped cyclone image can be used as input to the intensity estimation model to get the intensity (MSWS) of the cyclone. Thus, the entire solution is able to output cyclone intensity as well as its location in the image. This pipeline also allows focusing research on cyclone detection and intensity estimation independently. So, in this work, we have presented a dataset with both types of annotations. Figure 1 shows the process we used to curate the dataset. We have used INSAT 3D/3DR [22, 17] satellite infrared images for cyclone periods from 2013-2021, and for the labels, we have used IMD best track data [1] that contains relevant information regarding cyclones from 1982 to 2022. The data from INSAT 3D/3DR has been transformed from GeoTIFF format to jpg for usage in deep learning frameworks while the best track data is first compiled for each year, cleaned, and then standardized in a CSV format. Additional cyclone label data has been generated using interpolation of the existing best track data. The combined data is then augmented using various augmentation techniques and then split into training, validation, and testing sets according to the distribution of cyclone categories in the dataset. The process of interpolation, dataset augmentations, and dataset splits are explained thoroughly in later sections.

4.2. INCYDE

In this work, we propose a novel dataset called INCYDE, which stands for INSAT-based Cyclone Detection and Intensity Estimation. Figure 2 shows some sample images from the proposed INCYDE dataset for cyclone detection from satellite IR imagery. Similarly, Figure 3 shows some sample images from the proposed INCYDE dataset for cyclone intensity estimation, the cropped images are taken from full INSAT 3D/3DR imagery and cropping 15 degrees latitude and longitude around the cyclone center in the satellite image. The INCYDE dataset presents the intensity estimation annotations in CSV format and cyclone detection annotations in COCO [19] format.

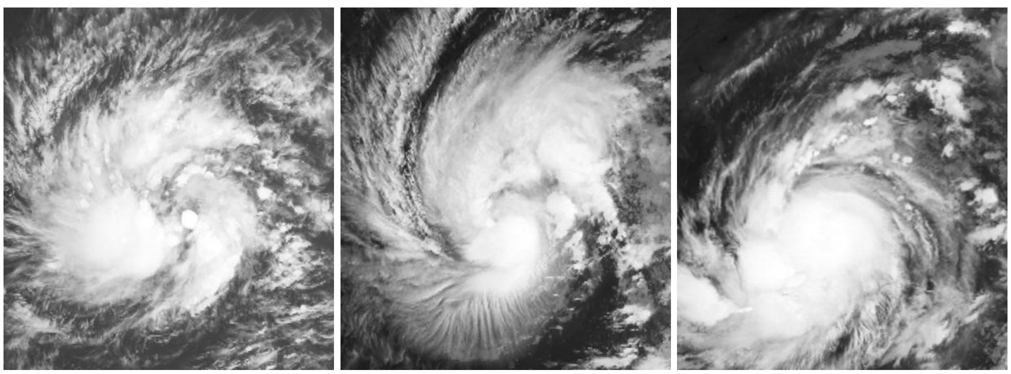
4.3. Interpolation of Labels

The INSAT 3D/3DR satellite images are in the interval of 30/15 minutes but the IMD best track data is the interval of 6 hours. So, in order to efficiently use all the infrared satellite imagery available for a particular cyclone, it is imperative to use satellite images with timestamps lying in between consecutive best-track data labels. We used interpolation to generate more labels from existing labels for the satellite images. Figure 4 shows the process of interpo-



(a) 1 December 2020 (b) 8 November 2019 (c) 10 October 2014

Figure 2. Infrared satellite images during cyclone period



(a) 1 December 2020 (b) 8 November 2019 (c) 10 October 2014

Figure 3. Cropped cyclone images

lation of labels. First, the step size is calculated using two consecutive rows in the best track data for latitude, longitude, and MSWS. The stepsize is then added to the first row of best track data in multiples of the number of steps. The process is then continued for the entire best track data to generate over 20k labels from existing 4k labels.

4.4. Dataset Augmentation

Augmentation has been used to increase the size of the dataset. Specifically, horizontal flip, vertical flip, and 90° rotations are used. Using these augmentations the resulting dataset size increased from 22k images to over 100k images. We have used openCV [5] and PIL [9] libraries to augment the images.

Figure 5 shows augmented satellite images for cyclone detection in the proposed CycloneSat dataset. We have performed horizontal flip, vertical flip, 90° rotation, 180° rotation and 270° rotation. Similarly, the dataset was also augmented for the cyclone intensity estimation task using the same augmentations.

4.5. Dataset split

The dataset has been split into training, validation, and testing sets based on sequences of cyclones in the dataset. Every storm was given a unique id and the highest grade it reached. According to the highest wind speed recorded, the cyclone sequences were assigned classes based on the IMD best track cyclone classification [1]. The dataset was divided to ensure equal representation of the different cyclone sequence classes, for instance, for the highest class of cyclone i.e., Super Cyclonic Storm (SuCS), there were only 4 cyclone storm sequences in the combined dataset, the split was made in such a way that the final training set contains 2 SuCS sequences, validation, and testing sets get 1 SuCS sequence each. The rest of the dataset was split into the train, test, and validation sets by randomly sampling 70% of the sequences into the train, 15 % into the test, and 15% into the validation set according to different grades. To avoid data leakage in the dataset, it was crucial to split the data in a way that ensures an image from one sequence is not included in more than one set, given that consecutive images in a sequence are highly similar. The final split resulted in

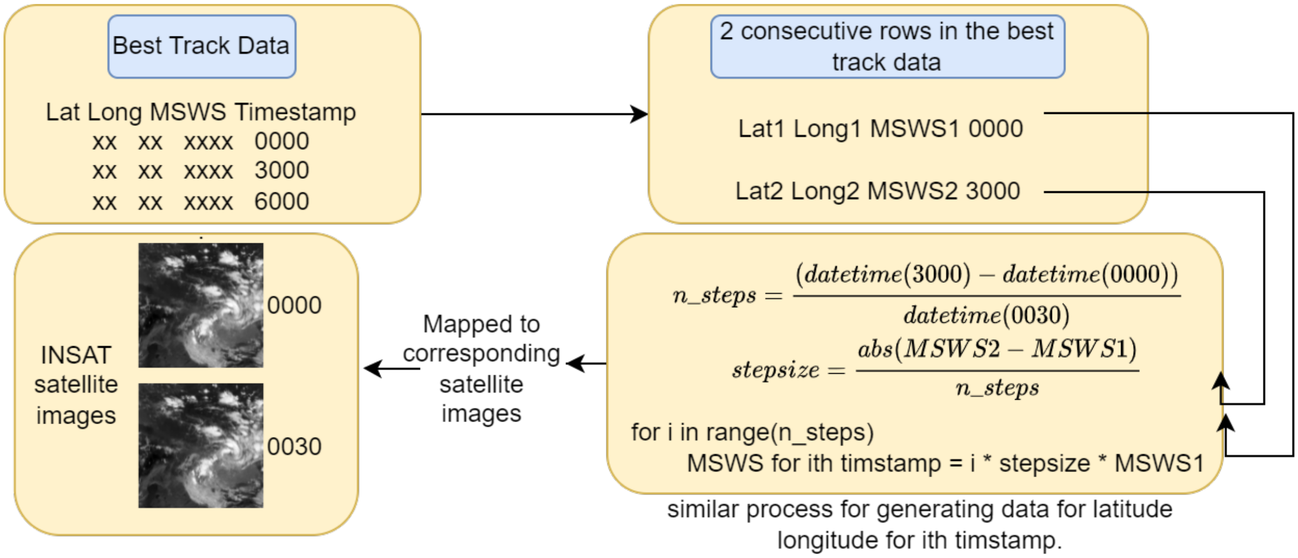
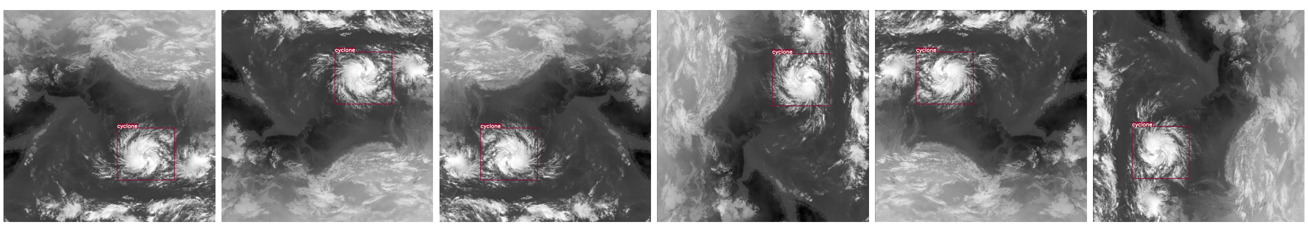


Figure 4. Process of generating new labels through interpolation of existing labels



(a) Original (b) Horizontal Flip (c) Vertical Flip (d) Rotation 90 (e) Rotation 180 (f) Rotation 180

Figure 5. Augmented infrared satellites images for the INCYDE dataset with the bounding box for the cyclone in the image

16k training set images, 2.5k test set images, and 2.9k validation set images. The split was performed in this way so as to create completely unseen sets for test and validation set as consecutive images in a sequence of a cyclone have very similar images and thus randomly sampling all the images in a naive approach would result in data leakage.

4.6. Dataset Statistics

This section presents some statistics about the proposed dataset. Figure 7 shows the histogram of mean sustained wind speed (MSWS) which is a metric for cyclone intensity in nautical miles per hour (knots) for the proposed INCYDE dataset and other datasets for cyclone intensity estimation as found in the literature. It can be observed in the figure that a lot of images have cyclones with speeds around 20-40 knots and very less images have cyclone intensity higher than 100 knots and it is consistent across all datasets for cyclone intensity estimation. It is in line with the fact that in the entire lifecycle of a cyclone, for most of the part, the cyclone has speeds in the range of 20 to 40 knots and for very less time the cyclone actually achieves the highest MSWS at its peak. Detection and intensity estimation of cyclones during the first phase is crucial for building a robust early warning system for cyclone prediction as during the initial phases, the cyclone has not yet formed spiral-like cloud patterns that are associated with cyclonic storms. This also implies that the cyclone intensity forms a bell curve which can be validated in figure 6. Figure 6 shows cyclone intensity in terms of MSWS over the course of the entire cyclone sequence for 5 random cyclones in the dataset. It can be observed that cyclones have a lifespan where they follow a normal distribution of wind speed during their lifespan. Figure 8 shows the category-wise count of cyclone images in the proposed INCYDE dataset. The cyclone images are categorized in various classes using the IMD cyclone classification scheme, here D stands for Depression, DD stands for Deep Depression, CS for Cyclonic Storm, VSCS for Very Severe Cyclonic Storm, SCS for Severe Cyclonic Storm, and SuCS for Super Cyclonic Storm. VSCS appears to be higher than SCS because the range of classification for VSCS is one of the largest in the IMD classification scheme, i.e., from 64 to 119 knots, cyclones are classified as VSCS.

Table 1 shows the size of the proposed INCYDE dataset in comparison to other SOTA cyclone intensity estimation

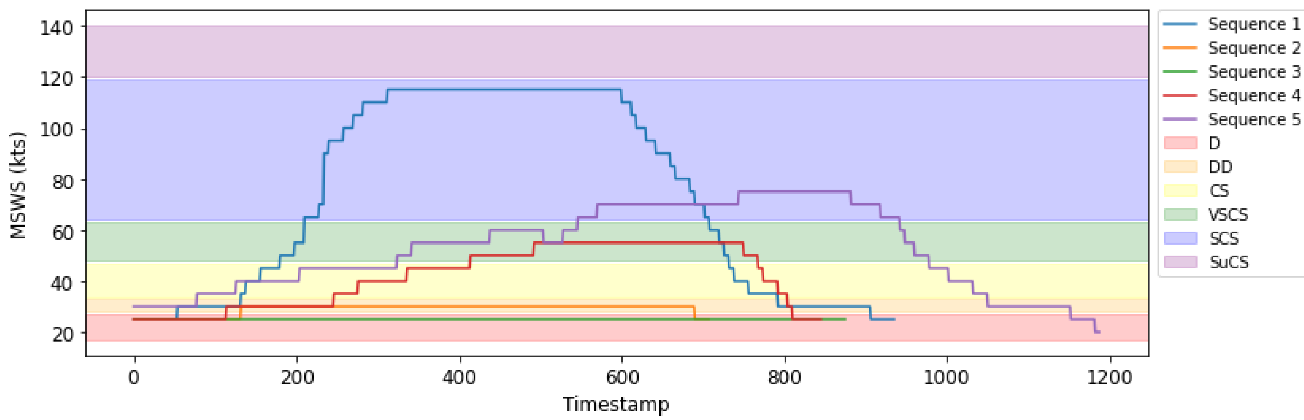


Figure 6. Temporal distribution of MSWS of 5 random cyclone sequences in the INCYDE dataset

datasets. It can be observed that our proposed INCYDE dataset has a higher number of images in the training dataset and the overall number of images are comparable to Maskey et al. In this table, we have also shown the number of images for the cyclone detection dataset. There is a slight difference between the number of images in cyclone detection and intensity estimation datasets as in some satellite images multiple cyclones have appeared at a single timestamp that resulted in 1 image for cyclone detection corresponding to multiple cropped images for cyclone intensity estimation. Table 2 shows some statistics about cyclone intensity estimation datasets. It can be observed that our proposed dataset has a higher image size as we did not downsample the original image to preserve the finer details that would help develop better models for cyclone detection and intensity estimation. All of the cyclone intensity estimation dataset use infrared (IR) satellite images.

Table 1. Cyclone intensity estimation dataset sizes

Dataset	Train	Test	Validation
Maskey et al [23]	70258	44378	–
TCIR [7]	70501	–	–
INCYDE (Intensity Estimation)	98466	2503	2399
INCYDE (Cyclone Detection)	96228	2503	2399

Table 2. Cyclone intensity estimation dataset statistics

Dataset	Image Size	Total Frames	IR Band
Maskey et al.	366 x 366	114636	IR
TCIR	201 x 201	70501	IR/PMW
INCYDE (Intensity Estimation)	380 x 400	103368	TIR
INCYDE (Cyclone Detection)	1618 x 1616	101130	TIR

5. Experiments

Along with the dataset, several baseline models have been trained on the proposed dataset for both cyclone detection and cyclone intensity estimation task. For object detection, YOLOv5[16], EfficientDet[32], Faster RCNN[26] have been trained as baselines. YOLOv5[16] is an efficient single-stage anchor-based object detector that uses a feature pyramid network PANet as the backbone. Faster-RCNN [26] is a two-stage object detector that uses a region proposal network in first stage to find the region of interest, and in the second stage, it performs object detection in order to be more accurate. EfficientDet [32] is another one-stage anchor-based object detector developed on top of efficient net [31] backbone. For cyclone intensity estimation, ResNet [12], Inception-V3 [29], EfficientNet [31], DenseNet-121 [15], MobileNet-V2 [27] with modified prediction heads to output a single value for intensity estimation are trained on the INCYDE dataset.

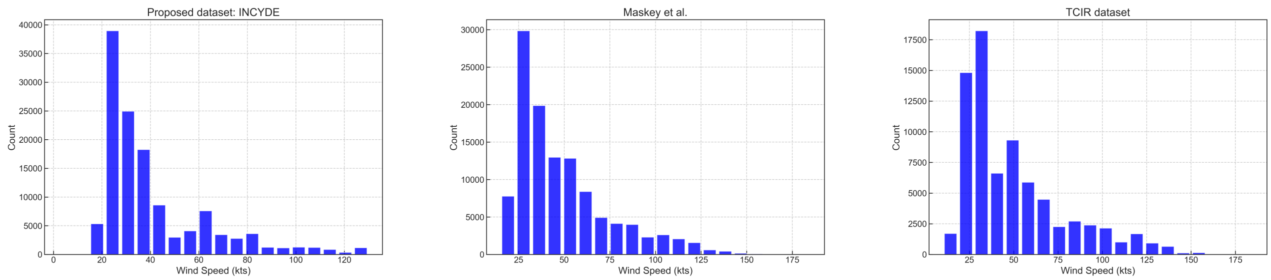
5.1. Evaluation metrics

In this work, the proposed dataset uses root mean square error (RMSE) as the evaluation metric for the cyclone intensity estimation task and mean average precision (mAP) as the evaluation metric for the cyclone detection task. RMSE as the name implies is calculated by taking the square root of the mean of the squared differences between the predicted values and the actual observed values. RMSE is calculated using the following formula:

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

where, pr = predicted value and, ob = observed value

Mean average precision (mAP) is a common metric used to evaluate the performance of object detection models. The mAP is calculated by first determining the precision and recall for each class in the dataset. Precision measures the accuracy of the model in identifying true positives, while



(a) Proposed INCYDE dataset (b) Maskey et al. (c) TCIR dataset

Figure 7. Histogram of mean sustained wind speeds in knots for various cyclone intensity estimation datasets

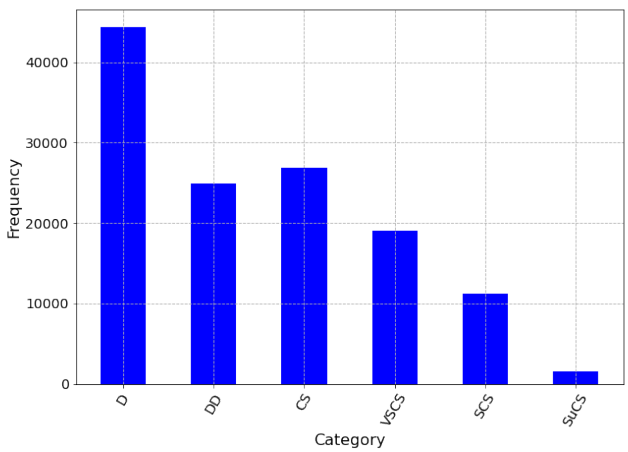


Figure 8. Bar graph showing the distribution of INCYDE dataset with respect to cyclone categories

recall measures the completeness of the model in identifying all positives. For object detection, the true positive is calculated using Intersection over Union (IoU) of bounding boxes of predicted and ground truth bounding boxes. The precision and recall values are then used to calculate the Average Precision (AP) for each class. AP is the area under the precision-recall curve for each class. The mAP is then calculated as the average of the AP values across all classes. This provides an overall measure of the model's performance.

5.2. Results and Discussions

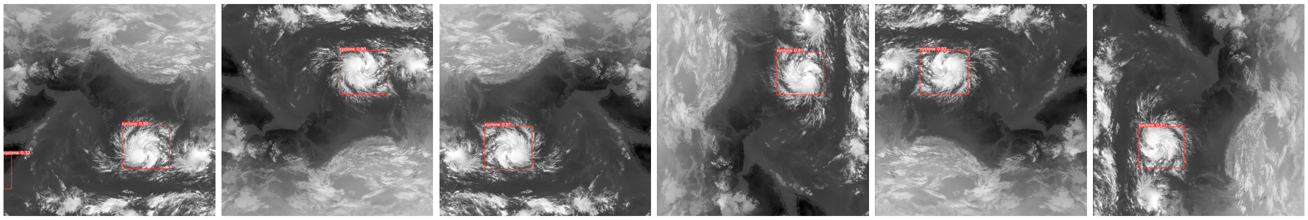
For baseline models, a few algorithms were trained on the proposed dataset for cyclone detection as well as intensity estimation tasks. The trained models with their respective accuracy metrics are shown below. The models were trained on a subset of the entire INCYDE, specifically, these models were trained only on the dataset without augmented images as the size of the augmented dataset makes it impossible to train the baseline models in reasonable time with limited resources, so we have kept the task of training the baseline models on an augmented dataset for future work. For cyclone detection, i.e., an object detection task, the mean average precision (mAP) metric is used while for intensity estimation, i.e., a regression task, root mean squared error (RMSE) is used to report the results.

Table 3 shows the mean average precision (mAP) of YOLOv5, Faster-RCNN, and EfficientDet on the proposed dataset along with a YOLOv5 model trained on the augmented INCYDE dataset. It can be observed that the mAP of SOTA object detectors hovers around 40-63 mAP on the validation set which acts as a solid baseline for future work. In our study, we found out that the models trained on the dataset without augmentation performed well on nonaugmented images but performed poorly on augmented images, while the YOLOv5 trained on augmented INCYDE dataset dropped in terms of mAP as compared to YOLOv5 trained on non-augmented INCYDE dataset but the YOLOv5-Aug, when used to inference on the augmented dataset, performed much better implying the use of augmentation in the proposed INCYDE dataset actually helped train a better generalizable model. Figure 9 shows the inference of YOLOv5 trained on the INCYDE dataset with augmentation, it can be observed that the model is able to detect cyclones anywhere in the image, implying better generalization ability.

Table 4 shows the RMSE of ResNet-18, Inception-v3, EfficientNet, DenseNet-121, and MobileNet V2 trained on the proposed dataset. In table 4, it can be observed that the best RMSE achieved was with MobileNet-V2 at 15.44 RMSE which acts as a solid baseline for future work. The RMSE of MobileNet-v2 on the proposed INCYDE dataset is comparable to baseline models on other related datasets.

Table 3. Summary of baseline models for object detection

Model Name	Validation mAP	Epochs
YOLOv5 [16]	63.35	20
Faster [26] RCNN	48.5	20
EfficientDet [32]	40.5	20
YOLOv5-Aug [16]	42.37	20



(a) Original (b) Horizontal Flip (c) Vertical Flip (d) Rotation 90 (e) Rotation 180 (f) Rotation 180

Figure 9. YOLOv5 trained on augmented INCYDE dataset inferred on satellite infrared images

Table 4. Summary of pre-trained baseline models for intensity estimation

Model Name	RMSE Test	Epoch
Resnet-18 [12]	18.78	60
Inception-v3 [28, 29]	18.28	60
EfficientNet [31]	15.28	13
DenseNet-121 [15]	15.55	60
MobileNet V2 [14, 27, 13]	15.44	60

6. Conclusion and Future Directions

In this work, a novel dataset has been presented for cyclone intensity estimation and cyclone detection. The dataset contains INSAT 3D/3DR thermal infrared satellite images since the year 2013 to 2021. The proposed INCYDE dataset is curated using a series of steps involving data collection, data cleaning, label interpolation, data augmentation, and data split. A few SOTA object detection algorithms are trained on the proposed INCYDE dataset to act as baselines. A few modified deep CNN models are also trained on the proposed INCYDE dataset for cyclone intensity estimation to act as baselines for cyclone intensity estimation. The INCYDE dataset contains over 100k images of cyclones with their annotations in bounding box configuration for object detection in COCO format as well as for single-valued intensity estimation tasks in a CSV format. The dataset is comparable to other cyclone intensity estimation datasets in the literature. The INCYDE dataset would help researchers develop state-of-the-art models for cyclone detection and intensity estimation using innovative techniques which in turn would be used as an early warning system for cyclones.

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