North Indian Ocean Tropical Cyclone Detection Using YOLOv5

Manish Mawatwal[1]
DAASE
Indian Institute of Technology, Indore, India
ms2104121004@iiti.ac.in

Saurabh Das[1]
DAASE
Indian Institute of Technology, Indore, India
saurabh.das@iiti.ac.in

***Abstract*—This research paper focuses on the application of You Only Look Once version 5 (YOLOv5) Deep Learning (DL) architecture for cyclone detection and classification. Cyclones are one of the most devastating natural disasters that cause significant loss of lives and property damage. Accurate and timely detection and classification of cyclones can help in effective disaster management and mitigation. In this study, YOLOv5 is used for detecting and classifying cyclones in satellite images. The proposed method involves pre-processing the data, training the YOLOv5 model on the dataset, and evaluating the model's performance. The results demonstrate that the proposed method achieved high accuracy in both cyclone detection and classification tasks. This research paper provides insights into the potential of YOLOv5 in cyclone detection and classification, which can be beneficial in enhancing disaster management strategies.**

***Index Terms*—Cyclone, YOLOv5, Multiclass classification**

I. Introduction

Tropical cyclones (TCs) have become a major threat to human lives and the environment, with their frequency and intensity increasing due to climate change. Accurate detection and classification of TCs are crucial to prevent and mitigate their devastating effects. Deep Learning (DL) models have been incorporated in TC detection, including the application of neural networks in existing TC detection [1], precursor identification of TCs [2], detection of TC [3], TC track forecasting [4]. However, DL models typically demand a substantial number of training samples due to the challenge of achieving high accuracy with finite training data, as observed in computer vision and other domains [5], [6]. Transfer learning can effectively mitigate this issue, thereby enhancing the accuracy of DL models [7]–[9]. In recent years, DL techniques have shown promising results in image-based object detection, including TCs. Advancements in satellite imaging and computer vision have enabled accurate automatic weather prediction, including predicting cyclones.

Among other techniques, the You Only Look Once version 5 (YOLOv5) model has gained popularity due to its speed and accuracy. The economic losses associated with TCs are also significant, further highlighting the urgency of developing effective detection and mitigation strategies [10]. [11] introduce a novel detection framework, NDFTC, which utilizes deep transfer learning by merging DCGAN and YOLO v3 for identifying tropical cyclones in meteorological satellite images. [11] proposes a YOLOv5 algorithm for identifying TCs on GridSat dataset and China Meteorological Administration satellite data. The algorithm showed good identification ability, fast detection speed, and low missed detection rate. [12] proposes a cyclone detection technique with cyclone eye localization using satellite images. [13] evaluates convolutional neural network (CNN) models for object detection in aerial views of disaster affected areas. The CNN models are trained on a dataset containing annotated aerial videos collected during hurricanes in the US. Transfer learning is used to pre-train the models on the COCO/VOC dataset and then re-train them on the disaster dataset. [14] used YOLOv3 for cyclone detection and was trained to detect TCs using data from the Thermal InfraRed (TIR) Atmospheric Sounding Interferometer (IASI) onboard the Metop satellites. The proposed framework could be extended to other models and sensors like AIRS, MODIS, and SEVIRI. In this context, this paper aims to explore the application of the YOLOv5 model in TC detection and classification, with the goal of contributing to environmental sustainability and reducing economic losses.

II. Data and Pre-processing

Long wave infrared images are taken from CIMSS Tropical Data Archive [15] captured by Meteosat-5/7/8 for the period 2000-2022. The temporal resolution is 3hr/6hr and the image has a 10km spatial resolution. The dataset included images of various cyclones with different intensities, sizes, shapes, and from different perspectives. Best track data of North Indian Ocean (NIO) region is taken from the Indian Meteorology Department (IMD) [16] for labelling the intensity of the images. The best track cyclone intensity is provided at a resolution of 5 kt. The images are classified into Depression (D), Deep Depression (DD), Cyclonic Storm (CS), Severe Cyclonic Storm (SCS) and Very Severe Cyclonic Storm (VSCS). Fig. 1 shows the sample raw image from the CIMSS dataset, Fig. 2 shows a cyclone of D category, Fig. 3 shows a cyclone of VSCS category. Table 1 shows the category of cyclones with their frequency.

The images of TCs in NIO are first cropped to an average dimension of 310 x 310 manually (average aspect ratio is maintained at 1) in a way that they contain cyclone eye in the off-centre, which makes the model more robust, as the region contains non-cyclonic parts as well. The reduction of image size is also done to reduce the processing time and to remove

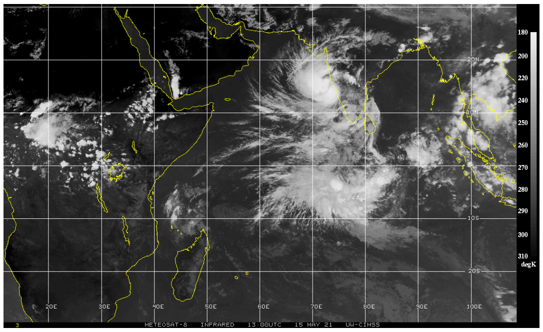

Fig. 1. Raw image from CIMSS dataset

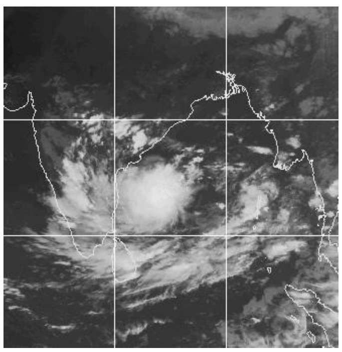

Fig. 2. Depression

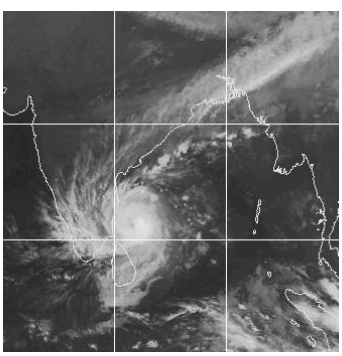

Fig. 3. Very Severe Cyclone

TABLE I
CATEGORY OF CYCLONES (MULTICLASS CLASSIFICATION)

Category	*Wind Speed*	*Actual number of images*
D	20-25 knots	352
DD	30-35 knots	534
CS	40-50 knots	396
SCS	55-65 knots	257
VSCS	70+ knots	305

the unwanted boundaries and excess noise in the data. The images are then converted into grayscale to improve detection. LabelImg annotation tool is used to create bounding box annotations of the TCs in the images. The images are labelled with bounding boxes around the cyclone, keeping the cyclone eye in the middle, indicating the location of the cyclone in the image. There are certain cases when multiple cyclones can be detected simultaneously in NIO. Some instances include, Kyaar and Maha cyclones in the year 2019, Pawan and 07A in 2019, Luban and Titli in 2018, Laila and Bandu in year 2010. Multiple cyclone detections in the image can also be done simultaneously. The images were then split into training and testing dataset. However, it should be noted that as the cyclone images in few hours doesn't change much, there is always a possibility of leakage of the data between training and testing samples. To avoid this, the evaluation is carried separately with a testing dataset of 2022 while keeping 2000-21 as training dataset. This, however, doesn't guarantee the proper representation of all the cyclone classes.

III. Methodology

YOLO is a popular DL algorithm used for object detection in images and videos. YOLO is known for its speed and accuracy in detecting and classifying multiple objects within an image or frame of a video in real-time. It achieves this by dividing the input image into a grid and predicting bounding boxes and probabilities for each grid cell simultaneously. YOLO has been widely used in various applications such as autonomous vehicles, surveillance, and augmented reality [17]. YOLOv5 is an improved version of YOLO DL model for object detection that uses a CNN architecture with anchor-based object detection. The algorithm consists of four modules: input, backbone, neck, and prediction. Input accepts images of various sizes and formats as input for object detection. Backbone utilizes a deep CNN to extract features from the input image. Neck enhances feature representation through additional layers such as convolutional and/or pooling layers. Prediction utilizes anchor-based object detection to generate bounding boxes and predict class probabilities for detected objects in the input image. Each bounding box prediction comes with a confidence score, which is a value between 0 and 1. A higher confidence score suggests that the model is more confident that the predicted bounding box contains an object of interest. [18].

The version of YOLOv5 used in this research is YOLOv5x. YOLOv5x model is a high-capacity variant of the popular YOLOv5 object detection framework. YOLOv5x is renowned for its superior performance in real-time object detection tasks, leveraging a deep CNN architecture. The model excels in accurately detecting and classifying objects within images or video frames, making it well-suited for applications such as surveillance, autonomous driving, and robotics. By utilizing YOLOv5x, we achieved precise object localization and classification results. YOLOv5x offers a compelling combination of speed, accuracy, scalability, and ease of use, making it a popular choice for a wide range of object detection applications. Once the dataset is collected and labelled, it is trained on YOLOv5 model using transfer learning. Transfer learning involves leveraging knowledge gained from training a model on one task or dataset to improve performance on a different but related task or dataset, typically by fine-tuning the pre-trained model's parameters on the new data [19].

Hyperparameters are parameters set prior to the training process that control the learning process of a machine learning (ML) model, influencing its performance, convergence, and generalization capabilities by adjusting aspects such as learning rate, batch size, or network architecture. They are used to optimize model performance and ensure effective training on specific tasks or datasets. Some of the hyperparameters that can be tuned in YOLOv5 in our research to improve its performance include:

- Input size: The size of the input images to the model can be adjusted to balance the trade-off between detection speed and accuracy. The cyclone images are resized to default of 640x640 adhering to the standard of YOLOv5 input.
- Number of anchors: The anchor boxes are used to predict the bounding boxes for the objects in the image by adjusting their width, height, and position relative to the anchor boxes. Confidence interval is a measure of how likely the predicted bounding box and class label are to be accurate. For this research, IoU threshold used for assigning ground truth boxes to anchor boxes is 0.2. Confidence threshold for cyclone detection is 0.25.
- Learning rate: The learning rate controls the step size during the training process and can be tuned to improve the convergence of the model. The initial learning rate is the starting value of the learning rate. The final learning rate is the target value towards which the learning rate decreases over the course of training according to the learning rate schedule. For this research, the initial learning rate is set to 0.01 and the final learning rate is set to 0.001.
- Batch size: The number of images processed in each batch during training can be adjusted to balance the trade-off between memory usage and training speed. For this research, the batch size is kept as 2.
- Number of epochs: The number of epochs determines the number of times the model will be trained on the entire dataset, and can be optimized to achieve the best performance. For this research, number of epochs are set to 70.

These hyperparameters are adjusted through experimentation and tuning to optimize the performance of the YOLOv5 model for cyclone detection. After training, the model is used to classify the cyclones based on their intensity, size, and other parameters, as well as detect the location of the cyclone in the image. The images can be detected individually or in a batch. Some of the metric used to evaluate the YOLOv5 detection over the testing dataset include

- Mean Average Precision (mAP) – Measures the average precision across all object categories, calculated as the mean of the average precision. Here, "c" represents the number of classes or categories being considered.

$$\text{mAP} = \frac{1}{c}\sum_{i=1}^{c} AP_i \tag{1}$$

- Intersection over Union (IoU) – Measures the overlap between the predicted bounding box and the ground truth bounding box of an object in an image, calculated as the ratio of the area of their intersection to the area of their union.

$$IoU = \frac{\text{Area of Intersection}}{\text{Area of Union}} \tag{2}$$

- Precision – Measures the proportion of detected objects that are actually true positives.

$$Precision = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{3}$$

- Recall – Measures the proportion of ground-truth objects that are correctly detected by the model.

$$Recall = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{4}$$

True Positives are the correctly detected objects, and False Negatives are the ground-truth objects that were not detected by the model.

IV. Results and Discussion

The YOLOv5 model utilised for detecting cyclone in images has shown promising results, with a precision of 60% and a recall rate of 96.9%. A high rate of recall suggests that it effectively captures a significant portion of actual cyclones. However, the precision score indicates that there is room for improvement in accurately identifying cyclones while minimizing false positives. mAP of 77% further suggests a relatively good balance between precision and recall. Additionally, the model's accuracy over the 2022 dataset stands at 89%, indicating its general effectiveness in correctly classifying images containing cyclones. This metric reflects the model's performance across the entire dataset and demonstrates its ability to handle various cyclone scenarios. The result of a case study on a cyclone and the output of the YOLOv5 model is shown. Fig. 4 shows the original image received from the CIMSS dataset, Fig. 5 shows the cropped version of the image, and Fig. 6 shows the bounding box around the actual cyclone in the Bay of Bengal Fig. 7 shows the enlarged view of the cyclone. Fig. 8, 9 shows the case where multiple cyclones are detected simultaneously in the NIO basin. This shows the versatility of YOLOv5 model. The model can detect multiple cyclone images accurately with correct labels (i.e., cyclone class) and confidence score.

While these results demonstrate the YOLOv5 model's competency in cyclone detection, there are still areas for enhancement, particularly in improving precision to minimize false positives. Moreover, ongoing evaluation and validation with diverse datasets could provide more robust insights into the model's capabilities and areas for improvement.

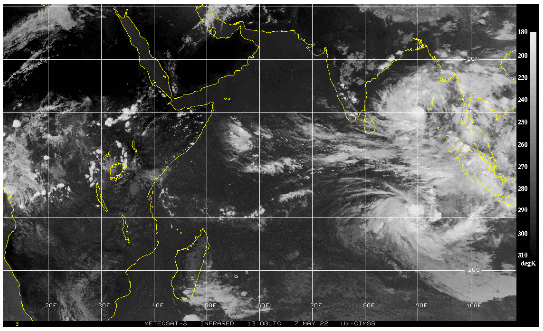

Fig. 4. Original image (2022-05-07, 12:00:00 hrs)

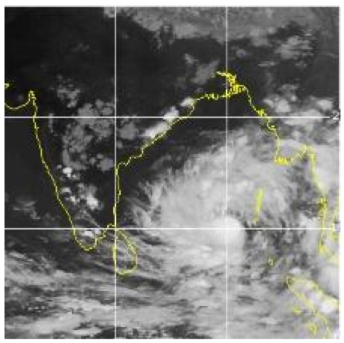

Fig. 5. Shows the pre-processed image.

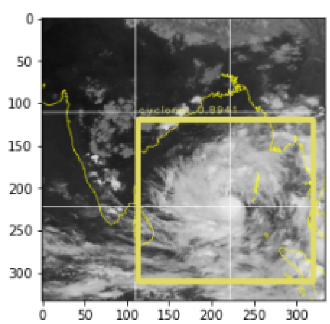

Fig. 6. Shows the detected cyclone

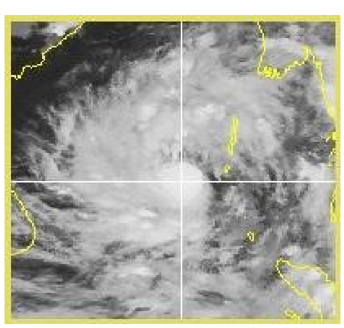

Fig. 7. Shows the enlarged view of the detected cyclone 'Asani'

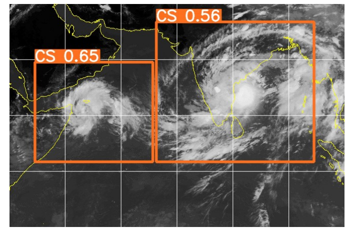

Fig. 8. Multiple cyclone detection

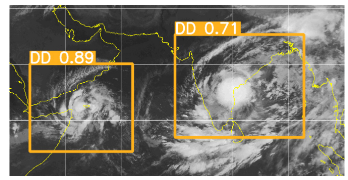

Fig. 9. Multiple cyclone detection

V. Conclusion and Future Scope

In conclusion, the YOLOv5 model has shown great promise in detecting TCs from satellite imagery. However, there are limitations to its accuracy due to a lack of sufficient data and the temporal resolution of 5 knots. This highlights the need for more research and data collection to further improve the model's performance. Future object detection models that take advantage of the latest advancements in DL techniques, such as attention mechanisms and graph neural networks, could potentially overcome these limitations and provide even more accurate cyclone detection. In addition, efforts should be made to expand the dataset and to cover a longer period of time. Such efforts would help to advance the field of cyclone detection and contribute to better management of the economic losses and environmental impact caused by these powerful storms. YOLOv5 can also be used for real-time TC detection's. YOLOv5 can be especially useful in mitigating the impact of natural disasters by providing advance warnings to those living in affected areas. By using this model, authorities can quickly identify and track the movements of TCs, thereby allowing for timely evacuation orders and other measures to be put in place.

References

[1] Liu, Y.; Racah, E.; Correa, J. Application of deep convolutional neural networks for detecting extreme weather in climate datasets. arXiv 2016, arXiv:1605.01156.

[2] Nakano, D.M.; Sugiyama, D. Detecting Precursors of Tropical Cyclone using Deep Neural Networks. In Proceedings of the 7th International Workshop on Climate Informatics, Boulder, CO, USA, 20–22 September 2017.

[3] Kumler-Bonfanti, C.; Stewart, J.; Hall, D. Tropical and Extratropical Cyclone Detection Using Deep Learning. J. Appl. Meteorol. Climatol. 2020, 59, 1971–1985.

[4] Giffard-Roisin, S.; Yang, M.; Charpiat, G. Tropical cyclone track forecasting using fused deep learning from aligned reanalysis data. Front. Big Data 2020, 3, 1.

[5] Cao, J.; Chen, Z.; Wang, B. Deep Convolutional networks with superpixel segmentation for hyperspectral image classification. In Proceedings of the 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Beijing, China, 10–15 July 2016; pp. 3310–3313.

[6] Li, Z.; Guo, F.; Li, Q.; Ren, G.; Wang, L. An Encoder–Decoder Convolution Network with Fine-Grained Spatial Information for Hyperspectral Images Classification. IEEE Access 2020, 8, 33600.
[7] Pan, S.J.; Tsang, I.W.; Kwok, J.T.; Yang, Q. Domain Adaptation via Transfer Component Analysis. IEEE Trans. Neural Netw. 2011, 22, 199–210.
[8] Yang, J.; Zhao, Y.; Chan, J. Learning and transferring deep joint spectral–spatial features for hyperspectral classification. IEEE Trans. Geosci. Remote Sens. 2017, 55, 4729–4742.
[9] Liu, X.; Sun, Q.; Meng, Y.; Fu, M.; Bourennane, S. Hyperspectral image classification based on parameter-optimized 3D-CNNs combined with transfer learning and virtual samples. Remote Sens. 2018, 10, 1425.
[10] Li, L., Shuai, Z., Hu, J., Zhang, Y. (2022). Classification of Tropical Cyclone Intensity Based on Deep Learning and YOLO V5. In: Sun, X., Zhang, X., Xia, Z., Bertino, E. (eds) Advances in Artificial Intelligence and Security. ICAIS 2022. Communications in Computer and Information Science, vol 1586. Springer, Cham.
[11] Pang S, Xie P, Xu D, Meng F, Tao X, Li B, Li Y, Song T. NDFTC: A New Detection Framework of Tropical Cyclones from Meteorological Satellite Images with Deep Transfer Learning. Remote Sensing. 2021; 13(9):1860.
[12] Haque, M.N., Ashfaqul Adel, A.A.M., Alam, K.S. (2022). Deep Learning Techniques in Cyclone Detection with Cyclone Eye Localization Based on Satellite Images. In: Arefin, M.S., Kaiser, M.S., Bandyopadhyay, A., Ahad, M.A.R., Ray, K. (eds) Proceedings of the International Conference on Big Data, IoT, and Machine Learning. Lecture Notes on Data Engineering and Communications Technologies, vol 95. Springer, Singapore.
[13] Yalong Pi, Nipun D.Nath, Amir H. Behzadan, "Convolutional neural networks for object detection in aerial imagery for disaster response and recovery", Advanced Engineering Informatics, January 2020, vol 43.
[14] Lam L, George M, Gardoll S, Safieddine S, Whitburn S, Clerbaux C. Tropical Cyclone Detection from the Thermal Infrared Sensor IASI Data Using the Deep Learning Model YOLOv3. Atmosphere. 2023; 14(2):215.
[15] University of Wisconsin – CIMSS.
[16] IMD Cyclone Best Track Data.
[17] Redmon, J.; Farhadi, A. Yolov3: An incremental improvement. arXiv 2018, arXiv:1804.02767.
[18] Horvat, Marko & Jelečević, Ljudevit & Gledec, Gordan. (2022). A comparative study of YOLOv5 models performance for image localization and classification.
[19] Zehui Zhao, Laith Alzubaidi, Jinglan Zhang, Ye Duan, Yuantong Gu, A comparison review of transfer learning and self-supervised learning: Definitions, applications, advantages and limitations, Expert Systems with Applications, Volume 242, 2024, 122807, ISSN 0957-4174.