CNN Based Tropical Cyclone Intensity Estimation Using Satellite Images Around Indian Subcontinent

Parag Jha(✉), S. Sumam David, and Deepu Vijayasenan

Department of Electronics and Communication Engineering, National Institute of Technology Karnataka, Surathkal 575025, India
paragjha111@gmail.com

Abstract. In this work, we have used deep learning models for estimating tropical cyclone (TC) intensity using satellite images. This is an image to regression problem, where an image is given as input and intensity value is estimated as output. In the literature, various deep learning methods have been proposed for TC intensity estimation but their focus on cyclones around the Indian subcontinent is limited. We have implemented three models: regression model, classification model, and a multitask model having regression and classification output as two tasks. We have worked with two sets of input data. One set of data contains single channel input containing infrared (IR) brightness temperature satellite image. Another set of data contains two channel inputs having infrared (IR) brightness temperature satellite image as one of the channels, and rain rate derived from passive microwave (PMW) satellite image as another channel. We have used satellite images for cyclones occurring in the Atlantic, Northeast Pacific, and North Central Pacific regions from 2006 through 2016. For cyclones around the Indian subcontinent, we have used satellite images from 2005- 2016.

Keywords: Multi-task learning · CNN · Weather prediction · Cyclone prediction · Cyclone intensity estimation

1 Introduction

Tropical cyclones (TC) cause huge loss of lives and livelihood for people living around coastal areas. Thus, cyclones need to be predicted in advance to issue cyclone alerts and perform precautionary actions like evacuations. India has a coastline of around 7000 km. Thus, a large population is at risk of being affected by harsh weather events like cyclones.

Usually, TC intensity is defined in terms of maximum sustained wind speed (MSW) or minimum sea level pressure at the center of a cyclone, but the definition varies depending on the region and there is no standard definition. In intensity estimation, the goal is to estimate cyclone intensity using given features or parameters. In the literature, satellite image-based techniques have proven to be

H. Kaur et al. (Eds.): CVIP 2023, CCIS 2010, pp. 172–185, 2024.
https://doi.org/10.1007/978-3-031-58174-8_16

highly effective methods for real-time intensity estimation. With recent progress in deep learning models, there have been attempts to apply these techniques to TC intensity estimation.

Indian Meteorological Department uses Advanced Dvorak Technique for estimating intensity using satellite images [5]. There is large scope for improvement in intensity estimation as highlighted in the literature [2]. Hence, we attempt to use deep learning models for cyclone intensity estimation. Further, existing deep learning-based estimation literature does not focus on the estimation of cyclones around the Indian subcontinent.

Contributions. We have implemented three models: a regression model (TCRegNet), a classification model (TCClassNet), and a multitask model (TCMultiNet) having regression and classification output as two tasks. We trained the models on satellite images from HURSAT dataset [6] and labels from HURDAT2 dataset [7]. Further, we created two channel inputs by combining satellite images from HURSAT dataset and CMORPH Climate Data Record dataset [14], and used them to train the model. We used the model for the estimation of cyclones occurring around the Indian subcontinent.

This paper contains 6 sections. In Sect. 2, we discuss the background of the problem and explored existing methodologies present in the literature. In Sect. 3, we discuss model architectures in detail. In Sect. 4, we discuss the dataset used. In Sect. 5, we discuss experiments performed and the results obtained. In Sect. 6, we present the conclusion.

2 Literature Survey

With faster computing power availability, weather prediction problems are attempted by data-driven methods [12]. To solve weather prediction problems, the meteorology research community is trying to adopt deep learning technologies which has potential to solve such problems. In the literature, it is noted that machine learning methods may not be adequate for solving weather prediction problems having a complex statistical nature [11]. It encourages the use of deep learning methods that shows the potential to solve such problems.

The most popular technique for intensity estimation is Dvorak Technique [4]. The underlying principle of this technique is that pattern formed by the clouds is related to the cyclone's intensity - not the amount of cloud in the pattern as shown in Fig. 1. This techniques assigns a Tropical number(T-number) to the storm depending on the intensity. Features of the pattern used to estimate are the storm center and the overcast around the center. This is a subjective method and requires an expert forecaster to predict the intensity.

The availability of computers in the 1980s gave rise to objective methods that can be run on computers [8]. The current state-of-the-art technique is Advanced Dvorak Technique (ADT) and is used by almost every meteorological department. ADT is a regression-based technique, where features are selected based on the region of the cyclone.

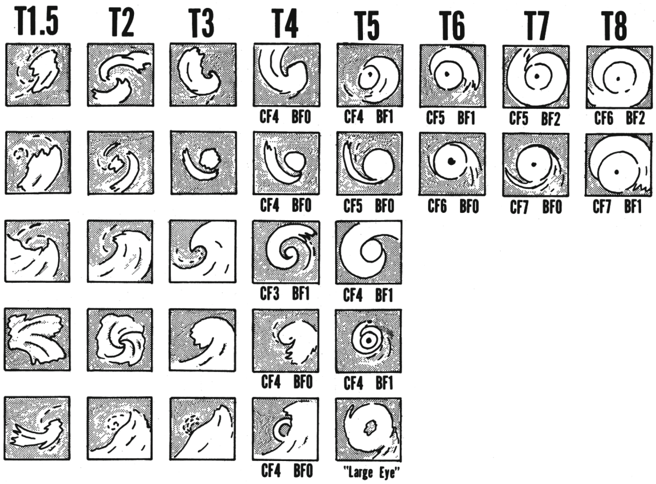

Fig. 1. Cloud pattern of cyclone at various stages during formation and development, and corresponding tropical number (T-number) [3]

Cyclone intensity estimation has been attempted using deep learning, both as a classification problem [9,13] and as a regression problem [1].

Pradhan el al. developed a eight-class classification model and these class predictions were converted to regression output by taking the weighted average of the two highest categories during inference [9]. They used satellite images from the tropical cyclone repository of the Marine Meteorology Division of U.S. Naval Research Laboratory, and labels from HURDAT2 dataset. Their model contained five convolution layers with max pooling followed by three fully connected layers. They reported root mean squared error (RMSE) value of 10.18 knot for the Atlantic region and Pacific region.

DeepMicroNet model based on AlexNet, developed by Wimmers et al., formulated the intensity estimation as classification problem [13]. Maximum sustained winds (MSW) value from 10 to 170 knot was divided in 33 classes by stepping up 5 knot in each class. For actual prediction task, only 29 out of 33 classes were used. They used passive microwave images in 37-GHz and 89-GHz band as their dataset. RMSE of 10.6 knot was reported on test dataset.

Chen et al. developed a regression deep learning model named CNN-TC based on AlexNet. They used GridSat dataset along with passive microwave image and RMSE of 10.59 knot was reported.

Zhang et al. proposed TCICENet model based on Inception-ResNet and AlexNet [15]. It divided the problem into two stages. First, it classified intensity into three broad categories using a classifier. Then, it estimated the intensity as a regression task. It used Infrared satellite images as dataset. RMSE of 8.60 knot and MAE of 6.67 knot was reported.

3 Methodology

We have implemented both classification and regression based models. We have implemented a multi-task model having two outputs, which are averaged to get a single output regression model. In this section, we discuss the implemented models.

3.1 Regression Model (TCRegNet)

We have implemented regression CNN model containing 11 individual layers, which can be grouped together in 7 blocks, as shown in Table 1. Figure 2 shows feature maps obtained at the output of each block. Input to model is $128 \times 128 \times 2$ image and maximum sustained wind speed is used as label. Block 1 contains convolution layer with ReLU activation function, followed by max pooling layer and batch normalization layer. Block 2, 3 and 4 contains convolution layer with ReLU activation function, followed by max pooling layer. Block 5, 6 and 7 contain fully connected layer. Block 5 and 6 is activated with ReLU function. No activation function is used on the last block. During training, we used Adam optimizer with a a learning rate of 0.0001. Mean squared error (MSE) is used as loss function. Root mean squared error (RMSE) is used to evaluate the model performance.

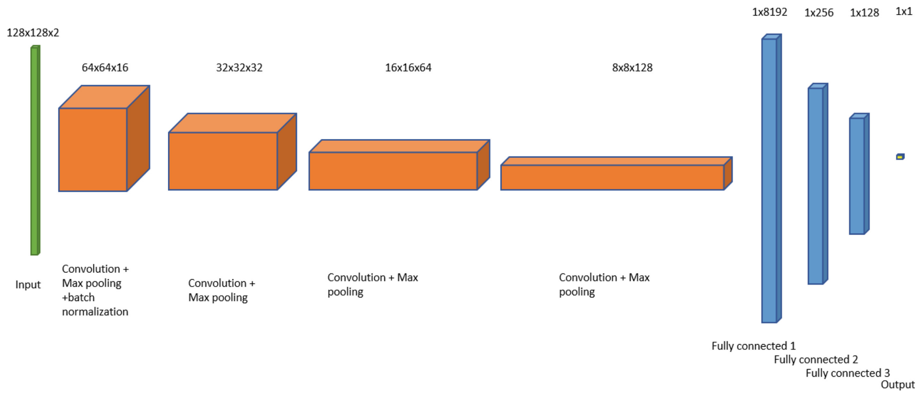

Fig. 2. TCRegNet feature maps

3.2 Classification Model (TCClassNet)

We have implemented a classification CNN model containing 11 individual layers, which can be grouped in 7 blocks, as shown in Table 2. We have divided output into steps of 5 knot from 15 to 185 giving 35 classes. We one-hot encoded the labels for the classification model. Figure 3 shows feature maps obtained at the output of each block. Input to model is $128 \times 128 \times 2$ image. Block 1 contains

Table 1. TCRegNet architecture

Layer	Type	Filter Size	Stride	Activation
In	Input			
C1	Convolution	4×4	1	ReLU
P1	Max pooling	-	2	-
BN1	Batch normalization	-	-	-
C2	Convolution	3×3	1	ReLU
P2	Max pooling	-	2	-
C3	Convolution	3×3	1	ReLU
P3	Max pooling	-	2	-
C4	Convolution	3×3	1	ReLU
P4	Max pooling	-	2	-
FC1	Fully connected	-	-	ReLU
FC2	Fully connected	-	-	ReLU
FC3	Fully conected	-	-	None

a convolution layer with ReLU activation function, followed by a max pooling layer and batch normalization layer. Block 2, 3 and 4 contains a convolution layer with ReLU activation function, followed by a max pooling layer. Blocks 5, 6, and 7 contain a fully connected layer. Layers 5 and 6 are activated with the ReLU activation function. Softmax activation is used on the last block. During training, we used Adam optimizer with a learning rate of 0.001. Categorical cross-entropy is used as loss function. Usually, classification models are evaluated based on prediction accuracy. As our problem is a regression one, we have computed RMSE to evaluate the model performance.

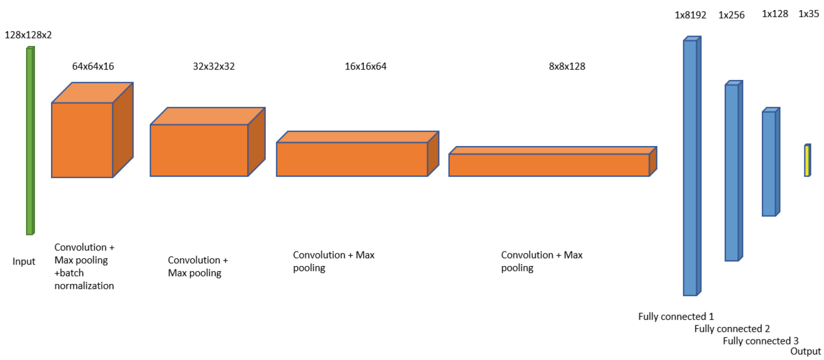

Fig. 3. TCClassNet feature maps

Table 2. TCClassNet architecture

Layer	Type	Filter Size	Stride	Activation
In	Input			
C1	Convolution	4×4	1	ReLU
P1	Max pooling	-	2	-
BN1	Batch normalization	-	-	-
C2	Convolution	3×3	1	ReLU
P2	Max pooling	-	2	-
C3	Convolution	3×3	1	ReLU
P3	Max pooling	-	2	-
C4	Convolution	3×3	1	ReLU
P4	Max pooling	-	2	-
FC1	Fully connected	-	-	ReLU
FC2	Fully connected	-	-	ReLU
FC3	Fully connected	-	-	Softmax

3.3 Multitask Model (TCMultiNet)

The idea behind multitask model is to train the model to perform multiple tasks simultaneously. In these models, some layers and parameters are shared between tasks. We have implemented two task model having a classification output and a regression output. Figure 4 shows implemented multitask model (TCMultiNet) with first four stages as shared convolution stage, followed by two separate fully connected branches (each branch has three fully connected layer), where upper branch is a regression branch, and lower branch is classification branch. During inference, outputs from both tasks are averaged together to give a single output model. Categorical cross-entropy is used as loss function in classification branch. Mean squared error (MSE) is used as loss function in the regression branch.

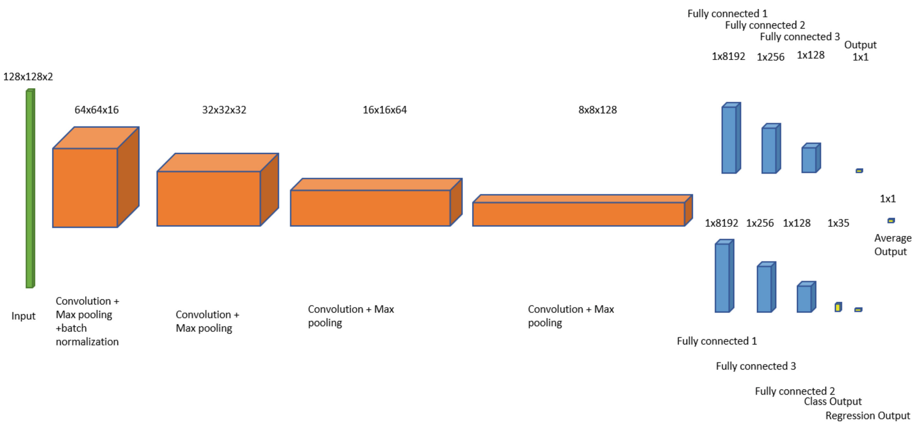

Fig. 4. TCMultiNet feature maps

4 Datasets

In this work, we have used dataset from four different sources, as listed below.

1. HURSAT dataset [6]
2. HURDAT2 dataset [7]
3. CMORPH Climate Data Record (CDR) [14]
4. Best track estimate data from Regional Specialized Meteorological Centre (RSMC), Delhi [10]

In this section, we will look at these datasets in detail.

4.1 HURSAT Dataset

Hurricane satellite (HURSAT) dataset [6] provides satellite images of tropical cyclones for the period of record from 1978 to 2016. The data is provided in netCDF format, and all the files for one cyclone are archived in zip format. These cyclones are organized as per their year of occurrence. The data is collected by geostationary satellites of Japan, Europe, and US, and is re-calibrated to minimize the differences due to the data acquisition instruments in the different satellites. Each file contains a 301×301 brightness temperature value (in kelvin) captured in infrared (IR) window channel and has a resolution of $0.07° \times 0.07°$ (latitude×longitude). Figure 5 shows some of the sample images from the dataset. We used images of tropical cyclones that occurred during 2006–2016 from HURSAT dataset for this work, cyclone images from 2006 was used as the validation dataset, 2011 images as the test dataset, and the remaining as the training dataset.

4.2 HURDAT2 Dataset

Hurricane database (HURDAT2) dataset [7] provides best track estimates, analyzed by National Hurricane Center (NHC). These estimates are calculated by hurricane specialists at NHC. It includes intensity (in knot), central pressure (in millibar), position, and size of tropical cyclones. It is divided into two parts based on the basin in which the cyclone occurs: Atlantic hurricane database spanning 1851–2022 and Northeast and North Central Pacific hurricane database spanning 1949–2022. It is provided as a single comma-delimited text file containing six-hourly information on the location (latitude and longitude), maximum wind speed (in knot), central pressure (in millibar), and (starting in 2004) size of all known tropical cyclones and subtropical cyclones. We converted these text files into CSV files and then merged both files (for two basins) into a single best track estimate file. We use intensity (given as maximum sustained wind speed) as the label for the models.

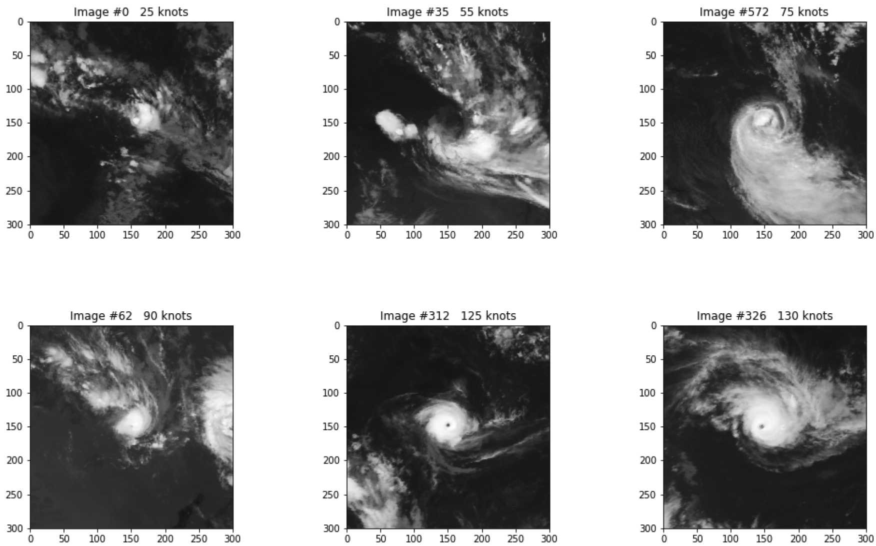

Fig. 5. IR satellite image samples from HURSAT dataset

4.3 CMORPH Climate Data Record (CDR)

CMORPH Climate Data Record (CDR) dateset [14] contains rain rate estimates, also known as precipitation estimates (rain rate in mm per unit time) provided by NOAA. Low-orbit satellites are used to capture microwave observations. These microwave observations are used to estimate the rain rate. Due to lower orbit, these data are available less frequently. Geostationary IR satellites can capture data more frequently compared to low-orbit satellites. Therefore, the CMORPH technique combines data from these two satellite sources [14]. Data is provided in 3 spatial-temporal resolutions. Full-resolution CMORPH data covers spatial resolution of $8km \times 8km$ with a temporal resolution of 30 min, giving rain rate in mm/hour. Hourly CMORPH covers spatial resolution of $0.25°$ lat/lon with a temporal resolution of 1 h, giving rain rate in mm/hour. Daily CMORPH covers spatial resolution of $0.25°$ lat/lon with a temporal resolution of 1 day, giving rain rate in mm/day. We have used hourly CMORPH data, cropped it to 128×128 image size, and upscaled it using linear interpolation to resolution of $0.07°$ lat/lon. Figure 6 shows some of the sample images from the dataset.

4.4 Best Track Estimate Data from RSMC, Delhi

Regional Specialized Meteorological Centre (RSMC), Delhi [10] publishes best track estimates for cyclones originating in the North Indian Ocean region. It contains intensity estimates, central pressure estimate (in hectopascal), pressure drop (in hectopascal), CI number (or T number), pressure drop, cyclone grade,

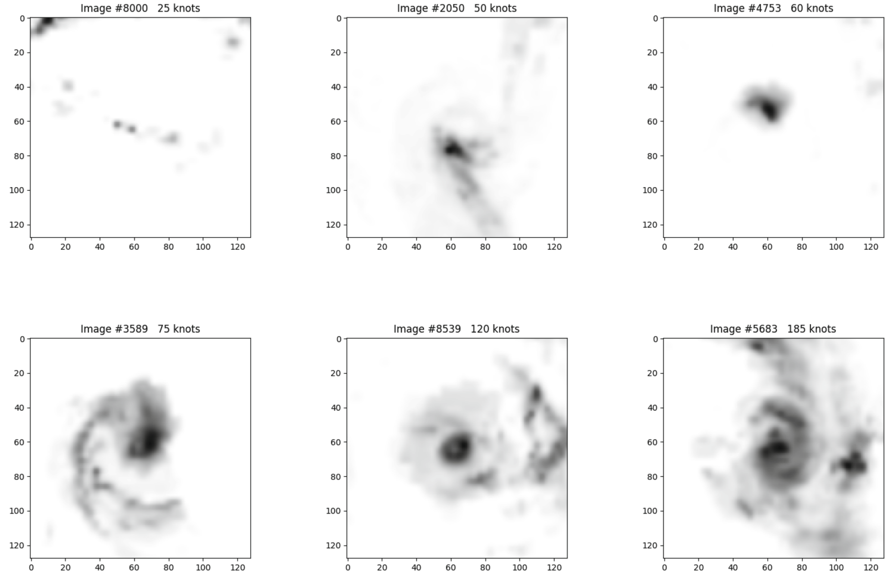

Fig. 6. Passive microwave derived rain rate samples from CMORPH Climate Data Record dataset

latitude, longitude, time and date of occurrence of cyclones over a period in 1982–2022, in Excel file format. We created a CSV file from the best track estimate file for our use.

5 Experiments and Results

We have performed two sets of experiments with three models. In one set of experiments, infrared brightness temperature satellite images were used as single channel input. In another set of experiments, the infrared brightness temperature satellite image and rain rate satellite image were stacked together as two-channel input. We have used satellite images from year 2006–2016 (11000 images), with the year 2011 images as the validation set (1000 images), and the year 2006 images as the test set (1000 images). As the number of images is less, we use data augmentation techniques to increase the number of images during training. Augmentation techniques used are image zooming (maximum scaling of 120%), horizontal and vertical shifting, image rotation (maximum rotation of 360°), vertical and horizontal flipping, and feature-wise normalization. We have used Keras deep learning library for implementation.

5.1 Single Channel Input Models

We have trained all models with a learning rate of 0.01 using Adam optimizer. We trained TCRegNet and TCClassNet models for 200 epoch, and TCMultiNet model for 300 epoch. Figure 7 shows RMSE curve of TCRegNet model. Figure 8 shows RMSE curve of TCClassNet model. Figure 9 and fig. 10 shows RMSE curve for regression and classification branches, respectively of TCMultiNet model. Table 3 shows results obtained for different models on test dataset. Comparing the result of three models, TCClassNet model performs worse than other two models.

Table 3. Result of models on single channel input

Model	RMSE (in knot)
TCRegNet model	11.0150
TCClassNet model	12.4552
TCMultiNet model	11.0322

5.2 Two Channel Input Models

As seen in the case of single channel experiments, TCClassNet model perform worse than other two models. Hence, we did not consider this model for further experiments and proceeded with TCRegNet and TCMultiNet models. We have trained both models with a learning rate of 0.0001 using Adam optimizer for 300 epoch. Then, we trained both the models for further 600 epoch with a learning rate of 0.00001. Figure 11 shows RMSE curve of TCRegNet model. Figure 12 and fig. 13 show RMSE curve of regression and classification branch, respectively of TCMultiNet model. Comparing results of single channel input and two channel input, we observe that two channel input performs better, showing that model is able to learn comparatively more features in two channel case. Figure 14 shows residual plot of TCMultiNet model. We observe that images that are underestimated have smaller error compared to images that are overestimated. In other words, model predicts with larger value of error when it overestimates.

Table 4. Result of models on two channel input

Model	RMSE (in knot)
TCRegNet model	10.8431
TCMultiNet model	10.8664

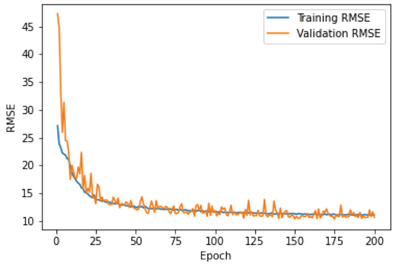

Fig. 7. RMSE of single channel TCRegNet model

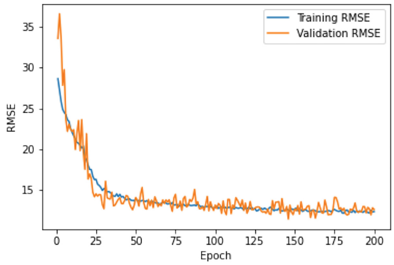

Fig. 8. RMSE of single channel TCClassNet model

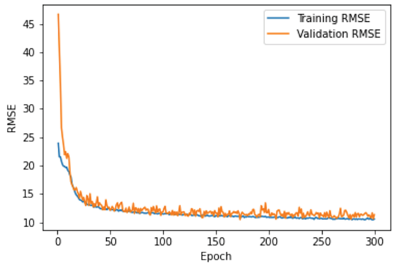

Fig. 9. RMSE of regression branch of single channel TCMultiNet model

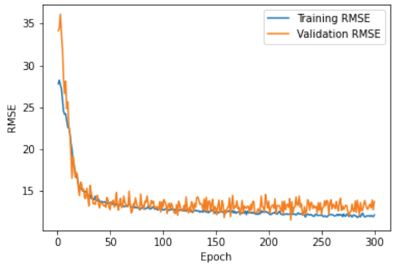

Fig. 10. RMSE of classification branch of single channel TCMultiNet model

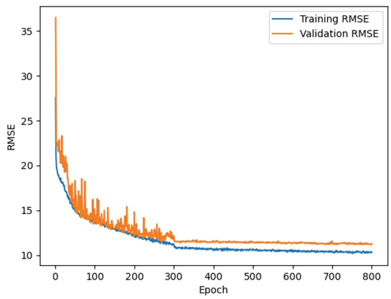

Fig. 11. RMSE of two-channel TCRegNet model

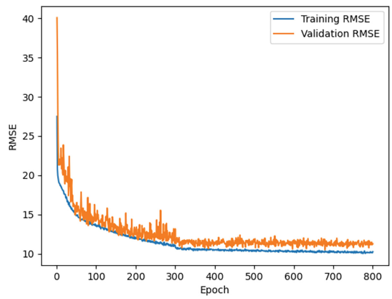

Fig. 12. RMSE of regression branch of two-channel TCMultiNet model

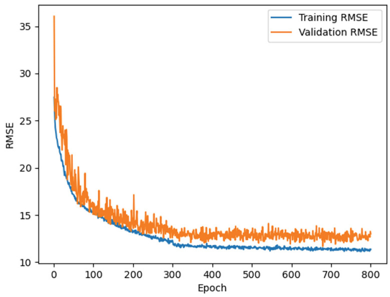

Fig. 13. RMSE of classification branch of two-channel TCMultiNet model

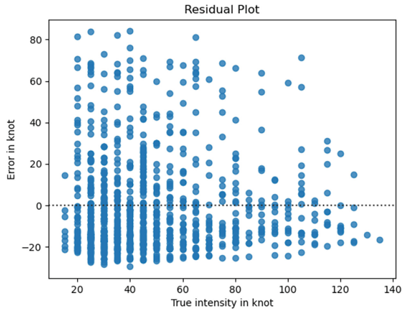

Fig. 14. Residual plot of two-channel TCMultiNet model

5.3 Improvement in TCMultiNet Model

As observerd earlier, TCClassNet performs worse than the other two models. Prediction strategy for TCClassNet is to predict the class with highest possibility. This prediction approach is used in classification branch of TCMultiNet. It was expected that changing the prediction strategy for classification branch may help in improving the model performance. We modified the prediction strategy of classification branch of TCMultiNet to include the weighted average of top six classes with weights being 0.3, 0.2, 0.2, 0.1, 0.1 and 0.1. RMSE of 10.3847 was reported on test dataset. As seen in Table 5, our model (TCMultiNet) performance is very close to state-of-art single stage deep learning based estimation methods.

Table 5. Performance comparison with state-of-art intensity estimation models

Model	RMSE (in knot)
TCMultiNet	**10.3**
DeepMicroNet [13]	10.6
CNN-TC [1]	10.6
Pradhan et al. [9]	10.2

5.4 Result for Cyclones Around Indian Subcontinent

We have divided cyclone images into two time periods, 2005–2010 (600 images) and 2011–2016 (800 images). We used images for 2011–2016 to test our model, and results without fine-tuning are shown in table 6. We fine-tuned the model by using images from the year 2005–2010 at a learning rate of 0.000001 for 150 epochs, and tested our model on images from 2011–2016. The final results after fine-tuning are shown in table 6. Without fine-tuning, the result of cyclones around the Indian subcontinent is relatively poor compared to the Atlantic and

Pacific region. This is because different satellites are used to capture images in different regions. We observe that fine-tuning helps in improving model performance.

Table 6. Result of model on Indian cyclone data

	Model	RMSE (in knot)
Before fine tuning	TCRegNet model	19.7080
	TCMultiNet model	18.8020
After fine tuning	TCRegNet model	14.4513
	TCMultiNet model	14.0190

6 Conclusion

In this work, we have used three CNN models to estimate cyclone intensity using satellite images: TCRegNet model, TCClassNet model, and TCMultiNet model. We used 9000 IR brightness temperature images of cyclones occurring in the Atlantic and Pacific region to train the model. We observed that the TCClassNet model performs worse than the other two models. We modified the input to a two-channel image containing an IR image and a rain rate image. We observe that two-channel input performs better showing that the model can learn comparatively more features in two-channel cases. We improved TCMultiNet model performance by changing the prediction strategy. On comparison, we noted that TCMultiNet performs as good as any state-of-art single stage estimation model. Further, We conclude that images that are underestimated have smaller errors compared to images that are overestimated. For cyclones around the Indian subcontinent, results have improved after fine-tuning the model.

References

1. Chen, B., Chen, B.F., Lin, H.T.: Rotation-blended CNNs on a new open dataset for tropical cyclone image-to-intensity regression. In: Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 90-99 (2018). https://doi.org/10.1145/3219819.3219926
2. Chen, R., Zhang, W., Wang, X.: Machine learning in tropical cyclone forecast modeling: a review. Atmosphere **11**(7) (2020)
3. Dvorak, V.F.: Tropical cyclone intensity analysis and forecasting from satellite imagery. Mon. Weather Rev. **103**(5), 420–430 (1975)
4. Dvorak, V.F.: Tropical cyclone intensity analysis using satellite data. NOAA Technical Report (1984)
5. Goyal, S., Mohapatra, M., Kumari, P., Dube, S.K., Rajendra, K.: Validation of advanced Dvorak technique (ADT) over north Indian ocean. MAUSAM **68**(4), 689-698 (2017). https://doi.org/10.54302/mausam.v68i4.768, https://mausamjournal.imd.gov.in/index.php/MAUSAM/article/view/768 https://doi.org/10.54302/mausam.v68i4.768https://mausamjournal.imd.gov.in/index.php/MAUSAM/article/view/768

6. Knapp, K.R., Kossin, J.P.: New global tropical cyclone data set from ISCCP B1 geostationary satellite observations. J. Appl. Remote Sens. **1**(1), 013505 (2007). https://doi.org/10.1117/1.2712816
7. Landsea, C.W., Franklin, J.L.: Atlantic hurricane database uncertainty and presentation of a new database format. Mon. Weather Rev. **141**(10), 3576–3592 (2013). https://doi.org/10.1175/MWR-D-12-00254.1
8. Olander, T.L., Velden, C.S.: The advanced Dvorak technique: continued development of an objective scheme to estimate tropical cyclone intensity using geostationary infrared satellite imagery. Weather Forecast. **22**(2), 287–298 (2007). https://doi.org/10.1175/WAF975.1
9. Pradhan, R., Aygun, R.S., Maskey, M., Ramachandran, R., Cecil, D.J.: Tropical cyclone intensity estimation using a deep convolutional neural network. IEEE Trans. Image Process. **27**(2), 692–702 (2018). https://doi.org/10.1109/TIP.2017.2766358
10. Regional Specialised Meteorological Centre (RSMC) Tropical Cyclones, N.D.: Best track data of tropical cyclonic disturbances over the north Indian ocean. https://rsmcnewdelhi.imd.gov.in
11. Reichstein, M., et al.: Deep learning and process understanding for data-driven earth system science. Nature **566**(7743), 195–204 (2019)
12. Schultz, M.G., et al.: Can deep learning beat numerical weather prediction? Philos. Trans. Royal Soc. A Math. Phys. Eng. Sci. **379**(2194), 20200097 (2021). https://doi.org/10.1098/rsta.2020.0097
13. Wimmers, A., Velden, C., Cossuth, J.H.: Using deep learning to estimate tropical cyclone intensity from satellite passive microwave imagery. Mon. Weather Rev. **147**(6), 2261–2282 (2019). https://doi.org/10.1175/MWR-D-18-0391.1
14. Xie, P., et al.: NOAA climate data record (CDR) of CPC morphing technique (CMORPH) high resolution global precipitation estimates (2019). https://www.ncei.noaa.gov/data/cmorph-high-resolution-global-precipitation-estimates/access/
15. Zhang, C.J., Wang, X.J., Ma, L.M., Lu, X.Q.: Tropical cyclone intensity classification and estimation using infrared satellite images with deep learning. IEEE J. Select. Top. Appl. Earth Observ. Remote Sens. **14**, 2070–2086 (2021). https://doi.org/10.1109/JSTARS.2021.3050767