Deep Learning based Tropical Cyclone Intensity Estimation using INSAT-3D IR imagery

TEAM - In Convolution

ABSTRACT —

Cyclones cause mass-scale destruction, to the extent where they have changed land demography of the affected regions, bringing about tragic losses to life and infrastructure. By predicting the occurrence and intensity of a cyclone, we can build a progressive and efficient pre-warning system that helps in preventing/minimising the damage/losses by evacuating people and livestock to safer places.

There has been an endeavour to develop a pre-warn system in the past for predicting the occurrence of a cyclone and its intensity. One such technique, popularly known as the Dvorak Technique was used to predict the intensity of the cyclone using human interpretation while direct measurements were not available. Based on the cloud features such as length and the curvature of storm outer bands, the intensity is estimated by capturing the relationship between the features. In update to the existing Dvorak Technique there was the introduction to Advanced Dvorak Technique which included passive microwave data and measurements of the aircraft to estimate the intensity, however these techniques lacked performance. These techniques are manual and time consuming that heavily rely on human expertise and experience that may cause human bias and higher error margins.

From time to time, in Deep Learning research, different techniques have been invented in order to help human civilization. Modern ML/DL techniques are used for high impact weather forecasting to extract features from the weather data and are useful for real-time decision making. Observing the destruction caused by tropical cyclones, we have decided to develop a Deep CNN model.

The proposed model consists of two CNN network modules: a TC intensity classification module and a TC intensity estimation module. Initially the CNN classification model makes use of pre-processed images with **fish-eye effect** to classify the cyclone intensities (based on cyclone features like Cyclone eye, Eyewall and the brightness temperature). After the cyclone gets classified based on the intensity classes (i.e. Tropical Cyclone of Category - 1 to Category - 7 and for our model we added one more Category 0 for when no cyclone is detected for better understanding), an accurate estimation is made to find the cyclone intensity using CNN regression model with an expected error rate of 15 Knots in the intensity.

The resultant model is deployed in a web application, which will consist of 2 different interfaces for the public consumers and the organisations, ISRO and IMD. The web application shows the continuous output obtained from the CNN models in the form of **'three visually enhanced TIR1 images' (BD enhanced, NHC enhanced and BT curve enhancements), one raw image and predicted intensity** value to the organisation user. Public users can see and/or check the details of the active cyclones and/or cyclones that occurred in the past.

With the use of the latest open source technologies, our project becomes very flexible for the incorporation of additional features in the future.

IDEA DESCRIPTION—

ABOUT THE DATA COLLECTED —

The data used in the study were IR images from an advanced geostationary meteorological satellite called INSAT-3D which is positioned at 82º E, was launched by ISRO on 26 July 2013. INSAT-3D carries a multi-spectral six channels imager and a nineteen-channels sounder. The six imager channels are: i) Visible (VIS) covering [0.55 – 0.75 μm], ii) Short-Wave Infrared (SWIR) covering [1.55 – 1.70 μm], iii) Mid-wave Infrared (MIR) covering [3.8 – 4.0 μm], iv) Water Vapour (WV) covering [6.5 – 7.1 μm] and v) two split-window Thermal Infrared (TIR1 and TIR2) covering [10.2 – 11.3 μm] and [11.5 – 12.5 μm] ranges of spectrum, respectively. The spatial resolution of VIS and NIR channels is 1 km, for MIR, TIR1 and TIR2 channels is 4 km and for WV channels is 8 km. All half-hourly IR grayscale images were collected from the MOSDAC website with the research purpose authorization.

PREPROCESSING OF DATA —

The study area for the satellite image will be determined using the tool known as QGIS, using which we will perform the shapefile operation and only the Tropical cyclone centred study area will be cropped. For the cropped image that will be obtained we will implement the **fish-eye effect**, so as to make it more prominent for the CNN model to process it, similar to how a human eye would perceive it, making it easier to estimate the cyclone intensity during its initial phases when determination of accurate centre becomes difficult.

Every satellite image sample has a meta datafile in the HDF/GEOTIFF format, linked with it, which can be converted to CSV file format using Rasterio python library for easy access of the cyclone data. The processed image data would then be passed onto our CNN model for training.

WHY CNN? —

Using shallow neural networks, the process of selecting the best features is challenging. Also, in the image classification using shallow neural networks, we will be losing the spatial information of a 2D or 3D image because we shall flatten it before passing on to the next layer. Hence, we will be utilising the CNN model to perform the cyclone intensity estimation. Also, the spatial information will be retained and the entire 2-D image will be passed as an input to the next layer. CNN is a set of layers, with each of them being responsible to detect a set of feature sets. These feature sets are automatically detected to find the best features and classify the images.

ABOUT OUR MODEL —

Our Model Architecture is defined as follows,

1. Our data consists of IR images and a convolution operation is applied on this input data in the convolutional layer and passes the result to the next layer.
2. We will have 2 different CNN models - Tropical cyclone intensity classification and Tropical cyclone intensity estimation.
3. The max pooling layer combines the outputs of a cluster of neurons in the previous layer into a single layer in the next layer.
4. Finally, the fully connected layer connects every neuron in the previous layer to every neuron in the next layer.
5. Additionally, L2 regularisation of 0.01 will be performed in the fully connected layers.
6. Also, to avoid overfitting of the model we will be using call-back techniques such as early stopping and dropout layers at a rate of 0.5

Description of the model being developed,

The model consists of 2 CNN modules:

- **a. Tropical Cyclone Intensity Classification**
- **b. Tropical Cyclone Intensity Estimation**

<u>Tropical Cyclone Intensity Classification:</u>

1. In India, the tropical cyclones can be divided into 7 categories:-
   - a. Depression (17-27 KT) - 1
   - b. Deep Depression (28-33 KT) - 2
   - c. Cyclonic Storm (34-47 KT) - 3
   - d. Severe Cyclonic Storm (48-63 KT) - 4
   - e. Very Severe Cyclonic Storm (64-89 KT) - 5
   - f. Extremely Severe Cyclonic Storm (90-119 KT) - 6
   - g. Super Cyclonic Storm (>120 KT) - 7

(*Note- Our model has an additional category labelled 0 - for when no cyclone has been detected or is it of extremely low intensity <17 KT*)

1. We pass in the preprocessed fish-eye IR images as data to the 1st layer i.e convolutional layer. The main purpose of this layer is to detect different patterns/features from the input images. So, to find these patterns/ features, we will define a filter also called a kernel. In this process, we basically will find the primitive features of the images, which are useful for initial layers of CNN.
2. Applying multiple kernels/filters on one image will result in multiple convolved images. Leveraging different kernels allows us to find different patterns in an image, such as edges, lines, curves and so on.
3. We will initialise the kernels with random values, and during the training phase, the values will be updated with optimum values, in such a way that the pattern will be recognised. We will be adding ReLu activation functions to the neurons on top of the nodes in the convolutional layer.
4. We will be using early stopping to stop training based on loss function on the validation data to avoid overfitting of the model. Also, we will add dropout layers - these are the layers that can be added to turn off neurons during training to prevent overfitting. Each dropout layer will drop a user-defined percentage of neuron units in the previous layer of every batch. Here in the model, we will specify the dropout rate to be 0.5 i.e 50% of neurons are going to be turned off randomly, which means each neuron has a 50% probability of turning off.
5. We will also specify the parameter patience in the EarlyStopping method. Here we will specify (patience=25) which means we will wait for 25 epochs, even after detecting a stopping point because of noise that could occur around the stopping point.
6. After the convolutional layer and adding a dropout layer to it, we will add another layer called max-pooling layer. This is done to downsample the output images from the ReLu function, to reduce the dimensionality of the activated neurons.
7. We will use max-pooling to perform downsampling as mentioned in the previous point, it is an operation that finds the maximum values and simplifies the inputs. In other words, it reduces the number of parameters within the model.
8. We will select the size of the window, based on which one of the maximum values is chosen. Here, in our model we have chosen the window size to be 2x2 and stride=2, so that the window will move 2 pixels everytime, by not overlapping each other.
9. After this we again add the dropout layers after each and every convolutional layer to prevent overfitting from the pooling layer.
10. The model was trained by minimising the loss function - multi class cross-entropy.
11. Then we add a fully connected layer, these layers take the high-level filtered images from the previous layers, and convert them into a vector.

12. In the output layer, the activation function used is softmax activation function, the model prints out a categorical value (0-7) which is the classification of Tropical cyclone categories.

<u>Tropical Cyclone Intensity Estimation:</u>

1. The Tropical Cyclone Intensity Classification module is utilised to divide Tropical Cyclone intensity into (7+1) categories using infrared satellite images.
2. Similar steps from the Tropical Cyclone Intensity Classification model are carried out to build the initial layers of the Estimation model.
3. The training was performed using the Adaptive Moment Estimation (Adam) gradient descent. Final model weights were chosen at an epoch where the training and validation loss curves intersect.
4. The model was trained by minimising the loss function - mean squared error (MSE).
5. Here in the output layer, we have a single neuron and we do not specify any activation function as it is predicting the continuous value in the output neuron.

EXPECTED RESULTS —

1. The resultant model is deployed in a web application, which will consist of 2 different interfaces for the public consumers and the organisations, ISRO and IMD.
2. The public users can check the alerts and active cyclones if present.
3. Public users can see and/or check the details of the active cyclones and/or cyclones that occurred in the past.
4. Also, there is a login section for the members of the Indian Meteorological Department and Indian Space Research Organisation, for accessing the half-hourly real-time output obtained from the CNN models in the form of **'three visually enhanced TIR1 images' (BD enhanced, NHC enhanced and BT curve enhancements), one raw image and predicted intensity value**, along with various other important details about the cyclone.
5. The model predicts the intensity and other features such as the regions getting affected. And also shows to which category the cyclone belongs to as mentioned above in the category from 0 to 8.

REFERENCES —

1. Combinido, Jay Samuel, John Robert Mendoza and Jeffrey A. Aborot. “A Convolutional Neural Network Approach for Estimating Tropical Cyclone Intensity Using Satellite-based Infrared Images.” 2018 24th International Conference on Pattern Recognition (ICPR) (2018): 1474-1480.
2. Higa, Maiki & Tanahara, Shinya & Adachi, Yoshitaka & Ishiki, Natsumi & Nakama, Shin & Yamada, Hiroyuki & Ito, Kosuke & Kitamoto, Asanobu & Miyata, Ryota. (2021). Domain knowledge integration into deep learning for typhoon intensity classification. Scientific Reports. 11. 10.1038/s41598-021-92286-w.
3. Zhang, C. J., Wang, X. J., Ma, L. M., & Lu, X. Q. (2021). Tropical cyclone intensity classification and estimation using infrared satellite images with deep learning. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, 2070-2086.
4. M. Maskey et al., "Deepti: Deep-Learning-Based Tropical Cyclone Intensity Estimation System," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 4271-4281, 2020, doi: 10.1109/JSTARS.2020.3011907.
5. Kumar, Subodh & Panda, Jagabandhu & Singh, Kasturi & Guha, Bijay & Kant, Sunny. (2020). Structural characteristics of North Indian Ocean tropical cyclones during 1999-2017: a scatterometer observation-based analysis
6. Pradhan, R., Aygun, R. S., Maskey, M., Ramachandran, R., & Cecil, D. J. (2017). Tropical cyclone intensity estimation using a deep convolutional neural network. IEEE Transactions on Image Processing, 27(2), 692-702.
7. Chen, G., Chen, Z., Zhou, F., Yu, X., Zhang, H., & Zhu, L. (2019, August). A semi-supervised deep learning framework for tropical cyclone intensity estimation. In 2019 10th International Workshop on the Analysis of Multitemporal Remote Sensing Images (MultiTemp) (pp. 1-4). IEEE.
8. Tan, J., Yang, Q., Hu, J., Huang, Q., & Chen, S. (2022). Tropical Cyclone Intensity Estimation Using Himawari-8 Satellite Cloud Products and Deep Learning. Remote Sensing, 14(4), 812.
9. Lee, J., Im, J., Cha, D. H., Park, H., & Sim, S. (2019). Tropical cyclone intensity estimation using multi-dimensional convolutional neural networks from geostationary satellite data. Remote Sensing, 12(1), 108.