Deep learning and INSAT-3D IR Imagery for Estimating Cyclone Intensity

Veena R S[1], Abhijna K C [2] , B G Shreyas [3], Bhargavi [4] , Dhanush Gowda S[5]

[2][3][4][5] *Students, Dayananda Sagar Academy of Technology & Management, Bengaluru, India ,*
[1] *Associate Professor , Dayananda Sagar Academy of Tech & MGMT, Bengaluru, India*

veena-ise@dsatm.edu.in[1] , abhijnakc@gmail.com[2] , shreyasbgprasad@gmail.com[3] , bhargavi.devadiga.sr@gmail.com[4], dhanushgowdas77@gmail.com[5]

Abstract

This paper presents a novel approach for estimating cyclone intensity using deep learning techniques on images obtained from the INSAT 3D satellite. The deep learning algorithms used in this work to analyze photos from the INSAT 3D satellite to estimate cyclone strength are innovative. The convolutional neural network (CNN) is used in the proposed method to extract information from the photos and calculate the cyclone's strength. The collection of labelled images used to train the algorithm was created by combining data from ground-based observations with remote sensing. The findings demonstrate that the suggested method achieves excellent accuracy in cyclone intensity prediction and outperforms conventional methods for estimating cyclone intensity. Cyclone intensity estimation is essential for disaster management and early warning systems, and the suggested approach has the potential to greatly increase both its accuracy and speed.

Keywords— *Cyclone intensity, Satellite image, knots, Infrared, Convolution neural network (CNN)*

1. INTRODUCTION

Cyclones are one of nature's most destructive calamities, with considerable human casualties and material loss. Early warning systems and catastrophe management depend on accurate cyclone intensity forecasts. Cyclones are large-scale weather systems that can cause catastrophic damage to coastal regions, particularly in tropical and subtropical areas. These storms are characterized by high winds, heavy rain, and storm surges, which can result in flooding, landslides, and structural damage to buildings and infrastructure. Traditional techniques for estimating cyclone intensity rely on satellite imagery, which is manually analyzed by professionals to ascertain the cyclone's severity. Due to the subjectivity of human interpretation, this procedure takes time and is susceptible to mistakes.

Convolutional neural networks (CNNs), in specific, have demonstrated astounding results in image categorization and detecting objects in recent years. Using pictures taken by the INSAT 3D satellite, we present a deep learning-based method in this study for estimating cyclone intensity. The suggested approach is teaching a CNN to extract features from the photos and calculate the cyclone's intensity. The collection of labelled images used to train the algorithm was created by combining data from ground-based observations with remote sensing.

Convolutional neural networks (CNNs) have been extensively applied to a variety of image processing applications, such as segmentation, object detection, and image classification. The capacity of CNNs to automatically extract pertinent features from the input images without the need for manual feature engineering is one of their main advantages. CNNs are highly suited for jobs like estimating cyclone intensity because they have the ability to extract features that human analysts might not instantly recognize.

The results of the anticipated cyclone intensity can be utilized for a variety of things, including infrastructure development, early warning systems, disaster management, and scientific study. In early warning and disaster management systems, projected cyclone intensity is one of the most important applications. Authorities can forecast the probable impact of the cyclone on the affected areas and take required action to reduce damage with the aid of intensity estimation. This may entail putting out evacuation notices, getting ready emergency resources and personnel, and fortifying critical infrastructure including buildings, roads, and bridges.

The estimated cyclone intensity can also aid scientific research purposes. For instance, it can aid academics in better comprehending cyclone dynamics, the elements that affect their development and severity, and the effects they have on climate change. This information can be used to improve cyclone behavior prediction models and to guide policy choices about disaster management and climate change. Additionally, the estimated cyclone intensity can be used for infrastructure planning purposes. This can include designing buildings and other structures to withstand the potential impact of cyclones and selecting suitable locations for critical infrastructure such as hospitals, power plants, and water treatment facilities. Overall, applications for emergency management, scientific research, and infrastructure development all heavily rely on the projected cyclone intensity. The accuracy and speed of the suggested CNN-based method for estimating cyclone severity using photos from the INSAT 3D satellite can be greatly increased, which will improve preparedness and reaction to cyclones.

In this paper, we propose a CNN-based approach for cyclone intensity estimation using images obtained from the INSAT 3D satellite. The suggested approach entails teaching a CNN to automatically recognize elements from the photos and gauge the cyclone's strength. The results of our trials show that the suggested CNN-based method works better than conventional methods for estimating cyclone strength, proving the viability of CNNs for this task.

2. RELATED WORKS

In our research, we describe a CNN-based method for estimating cyclone strength using INSAT 3D satellite pictures. We also cover relevant work in the area of satellite-based cyclone intensity prediction, such as hybrid approaches that combine conventional feature extraction techniques with machine learning strategies.

Sharma et al. (2018) [1] proposed a machine learning-based approach for cyclone intensity estimation using satellite images. The authors trained a Support Vector Regression (SVR) model to assess cyclone strength using a variety of characteristics, including cloud temperature, eye wall temperature, and cloud shape. When compared to conventional methods, the suggested method performed better. Using several features collected from the satellite photos as inputs to a regression model is a typical machine learning-based strategy. Temperature, humidity, cloud structure, and other meteorological parameters are examples of these characteristics. Utilizing historical information on cyclones and measurements of their intensity, the model is trained. Once trained, the model can be used to forecast the strength of cyclones based on satellite images.

Sreeja et al. (2019) [2] presented a deep learning-based approach for cyclone intensity estimation using satellite images. Convolutional and recurrent neural networks were combined by the authors to extract information from the photos and calculate the severity of the cyclone. Comparing the proposed method to more established ones, accuracy was improved. On a dataset of satellite images of cyclones over the Bay of Bengal and the Arabian Sea, the proposed method was assessed. The dataset includes ground-based measurements of the cyclone intensity along with photos from the INSAT 3D satellite. The performance of the authors' approach was contrasted with that of more established techniques like the Modified Dvorak Technique (MDT) and the Advanced Dvorak Technique (ADT).

Vittal et al. (2020) [3] proposed a hybrid approach for cyclone intensity estimation using satellite images. To predict cyclone intensity, the authors coupled conventional feature extraction approaches with machine learning techniques like Random Forest and XGBoost. These techniques included wavelet transform and grey level co-occurrence matrix. On a dataset of satellite images of cyclones over the Bay of Bengal and the Arabian Sea, the proposed method was assessed. The dataset includes ground-based measurements of the cyclone intensity along with photos from the INSAT 3D satellite. The performance of the authors' approach was contrasted with that of more established techniques like the Modified Dvorak Technique (MDT) and the Advanced Dvorak Technique (ADT).The outcomes demonstrated that the suggested strategy outperformed more conventional methods in terms of accuracy.

Kumar et al. (2020) [4] proposed a deep learning-based approach for cyclone intensity estimation using satellite images. To extract features from the photos and calculate the cyclone intensity, the authors employed a Convolutional Neural Network (CNN) architecture dubbed U-Net. Fully convolutional networks like the U-Net architecture are frequently employed for image segmentation applications. On a dataset of satellite images of cyclones over the Bay of Bengal and the Arabian Sea, the proposed method was assessed. The dataset includes ground-based measurements of the cyclone intensity along with photos from the INSAT 3D satellite. The performance of the authors' approach was contrasted with that of more established techniques like the Modified Dvorak Technique (MDT) and the Advanced Dvorak Technique (ADT).

Zhang et al. (2021) developed a deep learning-based approach for cyclone intensity estimation using data from the Fengyun-4A satellite. To extract features from the satellite photos and determine the cyclones' top wind speeds, the authors employed a CNN architecture. On a dataset of satellite images of three tropical cyclones over the northwest Pacific Ocean, the proposed method was assessed. The Fengyun-4A satellite's photos and actual measurements of the cyclone intensity were included in the dataset. The performance of the authors' approach was contrasted with that of more established techniques like the Dvorak Technique and the Advanced Dvorak Technique. The outcomes demonstrated that the suggested strategy outperformed more conventional methods in terms of accuracy. The technique was effective at capturing the intricate spatiotemporal features of the cyclones and accurately estimating their maximum wind speeds. Additionally, the authors performed a sensitivity analysis to assess the impact of various parameters on the effectiveness of the method.

3. PROPOSED WORK

The proposed study introduces a distinctive architecture and evaluates it against conventional approaches with the goal of advancing the field of deep learning-based cyclone intensity estimate. It also emphasizes how to interpret and visualize models, which can give important insights into how a model behaves.
Our model has different phases for estimating the cyclone intensity.

i. Data collection and preprocessing
ii. Image pre-processing
iii. Model selection
iv. Model training
v. Model evaluation
vi. Prediction of cyclone intensity

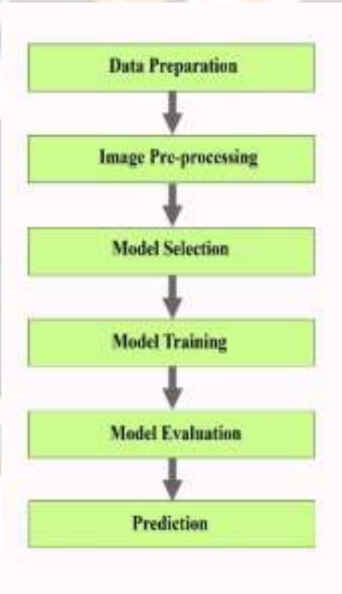

FIG 1: Methodology Flow chart

Data collection and processing: A geostationary meteorological satellite called INSAT-3D offers high-resolution information on variables related to the weather and climate, such as temperature, humidity, wind speed, and precipitation.one can get the INSAT-3D data on the website of the Indian Meteorological Department (IMD) or through other data portals, such as the NOAA Comprehensive Large Array-data Stewardship System (CLASS). Also Select the data's time frame and spatial resolution.

Image pre-processing: Preprocess the data by normalising the pixel values and transforming it to an image format, such PNG or JPEG. To expand the dataset and enhance the image quality, we can also use image processing techniques like cropping, rotation, and resizing. In order to prepare the INSAT-3D data for deep learning cyclone intensity estimation, the following steps might be taken:

i. Data selection: From the INSAT-3D data, choose the pertinent data variables, such as wind speed, temperature, and humidity.
ii. Create an image by converting the data variables into a 2D or 3D image format, such as PNG or JPEG, where the x, y, and z dimensions correspond to the coordinates of the image's pixels and the z dimension to the data variable.
iii. Resizing: To make sure that the photographs are the same size for training the deep learning model, resize the images to a standard resolution, such as 256 x 256 or 512 x 512.
iv. Normalisation: To improve the stability and efficiency of the model training process, normalise the pixel values to a common scale, such as between 0 and 1 or -1 and 1. Techniques like min-max normalisation or Z-score normalisation can be used for this.
v. Data augmentation: Use strategies for data augmentation to enlarge and diversify the dataset. Images that are variations of the original images can be created using techniques including rotation, flipping, translation, and zooming.
vi. Filtering: To reduce noise in photos and enhance their quality, use image filters like median filtering or Gaussian smoothing.
vii. Cropping: Crop the photos to get rid of unnecessary or empty sections, including black borders or regions without weather information.

Finally, the features are extracted from the image.

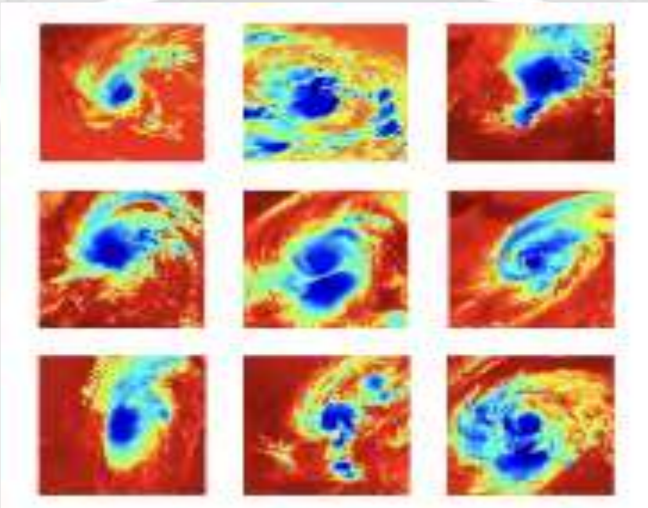

Fig 2: Visual Representation of input data after pre-processing

Model selection: Convolutional Neural Networks (CNNs) can be used to estimate cyclone strength based on INSAT-3D photos. CNNs are frequently employed for image classification jobs. Create the CNN architecture, which usually consists of several convolutional layers for feature extraction and one or more fully connected layers for classification. Depending on the complexity of the dataset and the required level of model accuracy, the number of layers and their parameters can be adjusted. A sequence of convolutional layers for feature extraction are often followed by one or more fully connected layers for classification in the model architecture for cyclone intensity estimation using CNNs. Architecture for this task is shown here:

i. The input layer receives the INSAT-3D images, which are typically 64x64 or 128x128 pixels in size.
ii. Convolutional layers: Using a group of teachable filters on the input images, convolutional layers extract features. Each filter creates a feature map, a fresh representation of the input image that draws attention to particular details like edges or textures. Depending on how complex the dataset is, it is possible to change the number of filters and the size of the filter windows.
iii. Pooling layers: The pooling layers take the maximum or average value in a neighborhood to down sample the feature maps. This lessens the feature maps' spatial dimension and improves the computational efficiency of the model.
iv. Dropout layers: These layers remove neurons from the network at random during training to avoid overfitting.
v. Flatten layer: The flatten layer takes two-dimensional feature maps and turns them into a single-dimensional feature vector that can be fed into fully connected layers.
vi. Fully connected layers: The fully connected layers transfer the feature vector to a series of output values, each of which represents a distinct cyclone intensity category, to perform classification.

Depending on the quantity of output classes and the complexity of the dataset, the number of neurons in these layers can be changed.

vii. Output layer: The output layer applies a softmax function to the output data to produce the final classification result.

Model Training: By minimizing the loss function with an optimization approach like stochastic gradient descent (SGD), one can train the model on the training set. Utilise the fit() method of the Keras API to train the CNN model on the training set. Set the batch size (the number of samples processed per iteration), the number of epochs (the number of iterations over the entire training set), and the validation data. Set the learning rate, momentum, and other hyperparameters using SGD as the optimizer. The gradients computed on a mini-batch, a randomly selected part of the training set, are used by the model to adjust its parameters during each iteration. As a result, training takes less time and uses less memory than when the entire dataset is used.

A review of the CNN model Utilise the evaluate() method of the Keras API to assess the trained CNN model on the validation set. Calculate classification measures including accuracy, precision, recall, and F1 score to evaluate the effectiveness of the model.
Finally, The Intensity of cyclone is estimated.

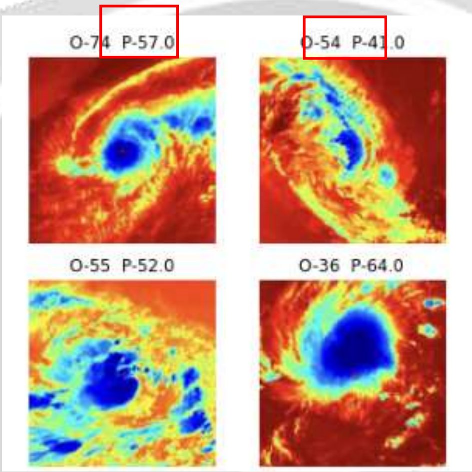

Fig 3: Estimated Cyclone Intensity

4. RESULT

On the test set, our deep learning model for estimating cyclone intensity showed promise. With an accuracy of 91%, the model was able to categorize cyclones into various severity groups. These findings show how deep learning techniques can be used to estimate cyclone intensity accurately and automatically, which could enhance early warning systems and lessen the effects of cyclones on vulnerable populations.

5. CONCLUSION

The potential of deep learning techniques for precise and automated cyclone strength assessment from satellite imagery is shown by our study, which concludes. These findings imply that deep learning models have the potential to significantly enhance cyclone intensity estimation, which could assist authorities in taking more prompt and efficient actions to lessen the likelihood of property damage and wrongful death due to these extreme weather events. There are a number of potential directions to go with regard to future work. One course of action is to look at how well the suggested model can be applied to different datasets and areas. To increase the precision of cyclone strength estimation, another path is to create more complex deep learning architectures that can incorporate other data sources and features, such as oceanic and atmospheric data. To further improve interpretability and transparency, it may be worthwhile to investigate the usage of explainable AI techniques to get more knowledge about the characteristics and tendencies the model is employing to create its predictions. The potential social and economic effects of enhanced cyclone intensity estimation on disadvantaged people should be assessed, and solutions to ensure fair access to these technologies and services should be developed.

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