DEEP LEARNING BASED CYCLONE INTENSITY ESTIMATION USING INSAT-3D IR IMAGERY

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ABSTRACT

Classifying the severity of a given cyclone is one of the key aspects of cyclone forecasting. The risk to human lives and the harm the storm does to the environment can both be decreased by projecting the strength of the cyclone. The Dvorak approach has traditionally been used to estimate cyclone intensity. The technique's highlights on the analysis of the cyclone's cloud patterns poses one of its biggest difficulties. By automating the intensity estimation procedure and eliminating the distinction involved with manual analysis, CNNs and INSAT 3D images significantly contribute to resolving these difficulties. It is a diagnostic model since it can properly predict the intensity of tropical cyclones. Estimating the disaster's intensity is a crucial step for staying updated on it. The primary goal of this research project is to estimate cyclone intensity in order to prevent damage from cyclones, which can be quite dangerous. The identification of previously unrecognized patterns in the existence of cyclone intensity and irregularities in earlier observations. This might make it easier for people to understand how tropical cyclone intensity changes. We used satellite photography to find the tropical cyclone because of the ideology. The technology uses deep learning research with hurricane satellite data to provide an automated way for cyclone estimation. The model is fine-tuned to take into account a range of environmental factors, such as the state of the air and sea surface temperatures, that have an impact on cyclone strength. In the research, the deep learning model outperformed more traditional approaches in terms of cyclone intensity forecast accuracy, which is encouraging. The current system needs more time complexity for accurate evaluations of tropical cyclone strength.

Keyword - *Deep learning research, Intensity, Estimation, and less timing complexity.*

1. INTRODUCTION

Tropical cyclones are rapidly rotating storms that have low pressure centers, limited low-level atmospheric wind motion, and heavy rainfall. This could lead to natural disasters, casualties, and property damage. When a tropical cyclone intensifies into a typhoon, it usually has extremely powerful winds that can result in significant harm to property and deaths in coastal areas. A developed cyclone has a central "eye" surrounded by a powerful wind ring. Studies show that high winds that cause seawater floods are to blame for almost 90% of the damage. The first crucial step in preventing significant losses from an active tropical storm is to estimate the cyclone's intensity in real-time, which indicates where it is in its development and how destructive it will be.

Following the estimation, actual downstream work can be done in order to prevent floods or landslides. This makes the study of Tropical cyclone Intensity Estimation (TIE) a crucial challenge in identifying tropical cyclone development and planning additional measures. The model given here has been implemented by Multilayer Perceptron (MLP) to train and test the feature values of Tropical Cyclone visuals, supervised learning is the method used in MLP. MLPs are subsets of feedforward artificial neural networks that includes input, and output layers as well as at least one hidden layer. Except for the input nodes, every node in the MLP is described as a neuron with a nonlinear activation function. A supervised learning technique for modeling training and testing is the backpropagation algorithm. INSAT (Indian National Satellite System) plays an important role in meteorological observation and disaster management. INSAT-3D is part of the Indian National Satellite System, which is a constellation of satellites that captures high-resolution thermal images of Earth's surface using an infrared imaging sensor. These IR images provide valuable information for monitoring cyclone evolution and monitoring cyclone movements. The creation of a cutting-edge, deep learning-based cyclone intensity estimation system employing INSAT 3D IR images is thoroughly outlined in this proposal. The goal of the proposed system is to use the power of CNNs and other deep learning algorithms to analyze the infrared images and estimate the cyclone intensity with high accuracy.

2. SCOPE

Even in their earliest stages, tropical cyclones represent one of the greatest threats to property and human life. Each of these risks has the potential to severely harm both people and property, and they all vary greatly. cyclones, flash floods, powerful winds, storm surges, and thunderstorms. When these risks are present together, the likelihood of deaths and property damage is significantly increased. People may find it simpler to figure out how tropical cyclone intensity fluctuates as a result. The technology uses deep learning research with tropical satellite data (INSAT) to provide an automated way for cyclone estimation.

3. LITERATURE REVIEW

Being a standard and essential task, the TIE has gone through extensive effort. Here, along with current methods that offer information on tropical cyclones in real time, some relevant research in observing wind speed from images obtained from satellites is discussed.

3.1 Dvorak Technique

The Dvorak method, a technique that detects cloud pattern, is based on a model of the growth and collapse of tropical cyclones. In order to track storms in the western North Pacific, it was first built and tested in 1969. Satellite images from polar satellites are used in this methodology. Orbits to describe the evolution of tropical storms . Observe the water with thermal photos during the day and night while using visible spectrum images. The technology aids in the discovery and measurement of the eye by using photographs taken by satellite to spot patterns in the observed storm structure. The primary disadvantage in this approach is that it significantly relies on expert knowledge or technique, which could lead to arbitrary conclusions. It acts as a reference for determining storm intensity and possible greater intensity rather than measuring or predicting wind, pressure, or other hurricane-related weather factors. Being near to the authorities is beneficial while making evacuation arrangements.

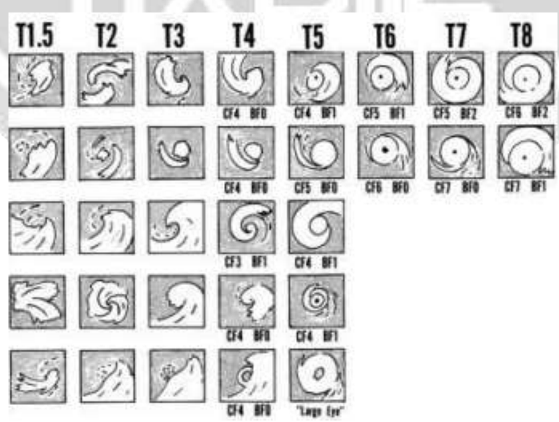

Fig -1: Dvorak's technique image of common development patterns and corresponding intensities.

3.2 Advanced Dvorak Technique

In the Advanced Dvorak Approach, a development of the manual Dvorak technique by Olander and Velden, satellite imagery is fed into an automated algorithm to produce a T-number. Passive microwave data, aircraft observations, and enhanced tropical cyclone concentrating have all been added to Advanced Dvorak Approach, which are all essential parts of the automated process. Although the manual Dvorak works better than the Advanced Dvorak Approach model performance worsens on smaller storms with unpredictable cloud distribution due to modeling technique. Thus, empirical thresholds are upheld to restrict how over time, cyclone strength fluctuates greatly.

3.3 Machine Learning based Techniques

The TIE challenge should be approached as a general regression, classification, or clustering problem when using machine learning-based techniques. Regarding regression issues, current research develops useful components from a satellite image to determine the precise wind speed. The algorithm used to solve classification problems is very similar to that used to solve regression issues, with the end estimation being the kind of tropical cyclone rather than a specific wind speed. Concerning clustering issues, current research often establishes parameters for clustering a group of tropical cyclones and then uses that information, such as the mean intensity of a cluster, to arrive at a final estimation.

4. METHODOLOGY

It has been popular to utilize the deep learning method to estimate tropical storm severity since it provides insight into a wide variety of diverse areas, including geoscience, brain emotion, etc. Deep learning methods also produce results that are competitive or better than the traditional methods.

4.1 Convolutional Neural Network

Convolutional neural networks, a kind of artificial neural networks, have completely changed the way that image processing and computer vision are researched. It is widely utilized in many different applications, including face identification, image segmentation, and object recognition. The biological framework of the human brain's visual cortex serves as the foundation for CNN's architectural design. Among the layers that make up this system are the input layer, convolutional layer, pooling layer, and fully connected layer. The raw data from the input layer, which is a picture, is subjected to a number of filters in the convolutional layer. A variety of elements in the image, including edges, corners, and forms, are detected using the filters. The pooling layer is used to lower the output's dimensionality and improve its computational efficiency after the convolution layer’s output. The classification process is then carried out using the identified features and the completely linked layer. Convolutional filters are used in CNN's operating system to extract information from an image. The input image is compressed with the filters, which are micro matrices, to create a feature map. A specific feature's activation at a certain spot in the image is represented by the feature map. The best combination of filters to utilize to identify different features in an image are learned by the CNN during the training phase.

5. PROPOSED WORK

In this research, a CNN model for the assessment of TC intensity is developed based on the analysis of the output distribution of various models. The model architecture is visible in the upper portion of the image, and the dotted line represents the regression network's structure. Each satellite image sample has a connected HDF/GEOTIFF meta data file for easy access to the cyclone data, which may be quickly converted to a CSV file format with the Rasterio Python program. The modified image would then be fed into our CNN model as input. The model is divided into two modules as Tropical Cyclone Intensity Classification module and Tropical Cyclone Intensity Estimation module.

5.1 Tropical Cyclone Intensity Classification

The convolutional layer uses data from the preprocessed fish-eye IR pictures. This layer's primary function is to identify various patterns and features in the input images. Therefore, we will define a filter also known as a kernel in order to find these patterns/features. Multiple images will be convolved when different kernels or filters are applied to the same image. The kernels will be initialized with random values, and during the training phase, the values will be updated with optimal values, allowing us to recognize the pattern.. We will be using early stopping to stop training based on loss function on the validation data to avoid overfitting of the model. We will also specify the parameter patience in the Early Stopping method. After the convolutional layer, a dropout layer is added to it and we will add another layer called max-pooling layer. This lowers the dimensionality of the activated neurons by downsampling the pictures produced by the ReLu function, max-pooling to perform downsampling and it reduces the number of parameters within the model. The size of the window is selected based on which one of the maximum values is chosen. In our model we have chosen the window size to be 2x2 and stride=2 by not overlapping each other. After this we again add the dropout layers after each and every convolutional layer to prevent overfitting from the pooling layer. The model was trained by minimizing the loss function - multi class cross-entropy. Then we add a fully connected layer, these layers take high-level filtered images from the previous layers, and convert them into a vector. In the output layer, an activation function used is softmax activation function, the model prints out a categorical value (0-7) which is the classification of Tropical cyclone categories.

5.2 Tropical Cyclone Intensity Estimation

The Tropical Cyclone Intensity Classification module is utilized to divide Tropical Cyclone intensity into (7+1) categories using infrared satellite images. Similar steps from the Tropical Cyclone Intensity Classification model are carried out to build the initial layers of the Estimation model. Adaptive Moment Estimation (Adam) gradient descent was used for the training. At an epoch where the training and validation loss curves meet, the final model weights have been determined. The model was trained by minimizing the loss function - mean squared error (MSE). 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.

6. ADVANTAGES

In estimating cyclone intensity, CNNs can automatically pick up spatial elements from gridded weather data or satellite imagery, capturing structures and patterns vital for forecasting cyclone intensity. Learning hierarchical features is made possible by the numerous layers of convolutional and pooling procedures that make up CNNs. As a result, they are able to automatically recognize basic elements (like edges) at lower layers and eventually combine that information to learn more complicated properties (like cyclone shapes or cloud patterns) at higher layers. CNNs are capable of learning characteristics that are independent of translations in the input data, which is known as translation invariance. As cyclones can travel and change positions over time, this can be helpful for estimating cyclone intensity because CNNs can be trained to recognize important traits regardless of the cyclone's location in the input data. By pooling layers, CNNs can efficiently reduce the dimensionality of the input data, capturing the most crucial spatial properties while minimizing computing complexity. CNN models that have already been trained, such as those trained on huge picture datasets like ImageNet, can be tailored for estimating cyclone strength. CNN designs can be modified to accommodate a variety of input data formats, such as multi-channel data or images with varied resolutions. They can be used for a variety of cyclone strength assessment tasks using satellite images, weather radar data, or other sources because of their flexibility. CNNs have attained cutting edge results in a variety of computer vision applications, and when correctly set up and trained, they can also be quite successful for estimating cyclone strength. Frameworks like TensorFlow and PyTorch, offer pre-implemented CNN layers and topologies, making it simpler to create and test CNN-based models for estimating cyclone intensity.

7. CONCLUSION

There are various benefits of using Convolutional Neural Networks (CNNs) to estimate cyclone intensity. CNNs are excellent for automatically extracting spatial properties from data that resembles a grid, such as gridded meteorological data or satellite photos. They are useful for precisely assessing cyclone strength because they can capture complicated patterns, learn hierarchical representations, and give translation-invariant features. Because CNN designs are adaptable to diverse data formats and resolutions, they can be used for various cyclone intensity estimation tasks. Additionally, the construction and optimization process is made simpler by the availability of pre-trained models and deep learning frameworks. From this model the accuracy of the TC will be increased. As we use two modules for classification and estimation the time complexity will be reduced and we will attain a more accurate result on the intensity of the cyclone. The combination of modules will result in a more precise result than compared to the existing model.

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