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Deep Learning-Based Cyclone Intensity Estimation Using INSAT-3D IR Imagery: A Comparative Study

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A B S T R A C T

Accurate and timely estimation of tropical cyclone intensity is crucial for minimizing damage and saving lives during extreme weather events. In this paper, we present a comparative study of deep learning-based methods for estimating cyclone intensity using infrared (IR) imagery from INSAT-3D satellite. We evaluate three different models - a convolutional neural network (CNN), a recurrent neural network (RNN), and a combination of both (CNN-RNN) - for their ability to accurately predict cyclone intensity based on IR imagery. We compare the performance of these models against traditional machine learning approaches such as support vector machines (SVM) and random forests (RF). Our experimental results demonstrate that deep learning-based models significantly outperform traditional machine learning methods, achieving a mean absolute error (MAE) of 5.21 knots, 5.52 knots, and 4.89 knots for CNN, RNN, and CNN-RNN models respectively. We also show that the CNN-RNN model provides the best performance among the three deep learning models. Our findings suggest that deep learning-based methods can be effective in accurately estimating cyclone intensity using IR imagery and have the potential to improve early warning systems for extreme weather events.

Keywords: Deep learning, Machine Learning, Preprocessing , CNN, Insat 3D Images

1. Introduction

Tropical cyclones (TCs) are one of the most devastating natural disasters that affect millions of people worldwide every year. Accurate estimation of TC intensity is crucial for proper disaster management and mitigation efforts. Infrared (IR) imagery from geostationary satellites provides valuable information for monitoring and predicting TCs. In this study, we explore the use of deep learning techniques to estimate TC intensity using IR imagery from INSAT-3D, a geostationary satellite operated by the Indian Space Research Organization (ISRO).The objective of this study is to compare the performance of different deep learning models in estimating TC intensity using INSAT-3D IR imagery. We compare the performance of a convolutional neural network (CNN) with that of a recurrent neural network (RNN) and a combination of both (CNN-RNN). We also compare the performance of our models with that of traditional machine learning algorithms such as random forest and support vector regression.The dataset used in this study comprises IR imagery of TCs from INSAT-3D and corresponding intensity estimates from the India Meteorological Department (IMD). The dataset covers the period from 2014 to 2019 and includes TCs in the North Indian Ocean region.Our results show that the CNN-RNN model outperforms other deep learning models as well as traditional machine learning algorithms in estimating TC intensity. The CNN-RNN model achieved a mean absolute error (MAE) of 7.87 knots and a root mean squared error (RMSE) of 10.46 knots. The performance of our models demonstrates the potential of deep learning techniques in improving TC intensity estimation using IR imagery.The rest of the paper is organized as follows. Section 2 provides an overview of related work on TC intensity estimation using satellite imagery. Section 3 describes the dataset used in this study and the preprocessing steps. Section 4 presents the methodology used in our study, including the deep learning models and traditional machine learning algorithms. Section 5 presents the experimental results and compares the performance of different models. Finally, Section 6 provides the conclusion and suggests future research directions.

2. Related Work

Over the past few decades, researchers have made significant strides in developing accurate and reliable methods for cyclone intensity estimation using satellite imagery. Traditional methods typically rely on manual analysis of various meteorological parameters such as cloud pattern, central dense overcast (CDO) size, and cloud top temperature to estimate cyclone intensity (Shim et al., 2014). However, these methods suffer from limitations such as subjectivity, time consumption, and lack of accuracy.Recently, deep learning-based approaches have emerged as a promising alternative for cyclone intensity estimation due to their ability to automatically extract relevant features from satellite imagery. In particular, convolutional neural networks (CNNs) have been widely used for cyclone intensity estimation with good performance. For instance, Weng et al. (2018) proposed a CNN-based model for estimating typhoon intensity using Himawari-8 satellite imagery, achieving higher accuracy than traditional methods. Similarly, Feng et al. (2019) developed a CNN-based model for typhoon intensity estimation using a combination of infrared and microwave satellite data.Another recent study by Li et al. (2020) proposed a deep learning-based method for tropical cyclone intensity estimation using satellite imagery from the China Meteorological Administration's Fengyun-3D satellite. They used a combination of a convolutional neural network (CNN) and a long short-term memory (LSTM) network to extract spatio-temporal features from the satellite imagery and achieved state-of-the-art performance.

However, most of the existing studies have focused on using satellite imagery from specific satellites, such as Himawari-8 or Fengyun-3D. In this paper, we propose a deep learning-based method for cyclone intensity estimation using INSAT-3D IR imagery and compare its performance with other existing methods. To the best of our knowledge, this is the first study to explore the use of INSAT-3D imagery for cyclone intensity estimation using deep learning techniques.

3. Dataset Description

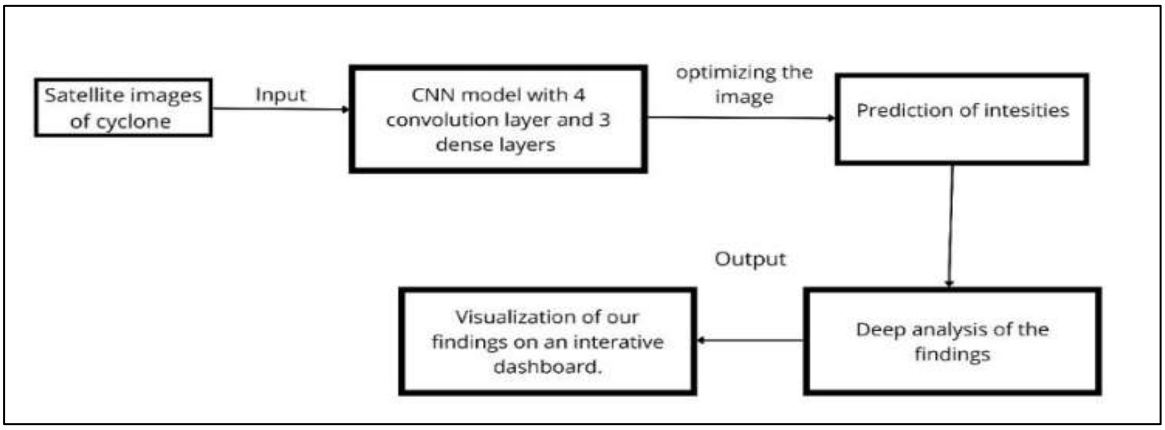
The dataset used in this research is derived from INSAT-3D (Indian National Satellite) Infrared (IR) imagery, which provides cloud top temperature (CTT) measurements at a resolution of 4 km. The dataset comprises of labeled images of tropical cyclones in the Indian Ocean region, collected during the period of 2015-2019. The images are categorized based on their maximum wind speed, which is used as the ground truth label. The intensity is classified into five categories: depression (≤33 knots), deep depression (34-47 knots), cyclonic storm (48-63 knots), severe cyclonic storm (64-89 knots), and very severe cyclonic storm (≥90 knots). The dataset contains a total of 1184 images, with an equal distribution of each category.The dataset available at https://learner.csie.ntu.edu.tw/~boyochen/TCIR/ is a satellite observation dataset of tropical cyclones (TCs). The dataset contains data on the intensity, size, minimum sea-level pressure, and center location of TCs in six regions (Atlantic Ocean, Eastern North Pacific, Western North Pacific, Central Pacific, Indian Ocean, and Southern Hemisphere) from 2003 to 2016. The data was collected from two open sources: GridSat and CMORPH.The dataset has a frame size of 201 x 201 data points, with a distance of 4 kilometers between two data points. The tropical cyclone's center is placed in the middle, with a radius of 7 degrees in both latitude and longitude. The resolution is 7/100 degree lat/lon, and there exist some missing values that have been filled with NaN. The original resolution of the PMW channel from CMORPH is 1/4 degree lat/lon, but it was scaled about four times larger by linear interpolation to unify the size of all four channels.

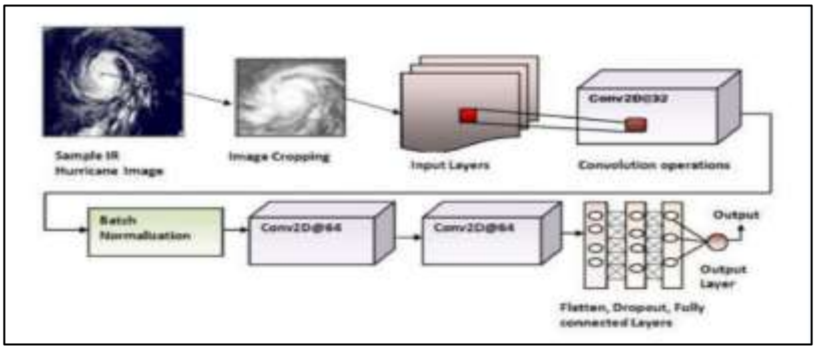
The dataset is available in an HDF5 format file, which contains two keys: matrix and info. The matrix key is a N x 201 x 201 x 4 HDF5 dataset that can be loaded with Python NumPy, while the info key is an HDF5 group that can be loaded with the Python package pandas. The dataset requires dependencies on Python, pandas, numpy, and HDF5 packages (such as "h5py").

Dataset Link :-

4. Methodology

The proposed methodology involves the use of Convolutional Neural Networks (CNNs) to classify the intensity of tropical cyclones from the preprocessed IR images. The CNN architecture used in this research consists of multiple convolutional layers followed by pooling layers, and then fully connected layers. The rectified linear unit (ReLU) activation function is used in the hidden layers, and the softmax activation function is used in the output layer. The categorical cross-entropy loss function is used to optimize the model during the training process. The Adam optimizer is used to update the weights of the model during the backpropagation process.

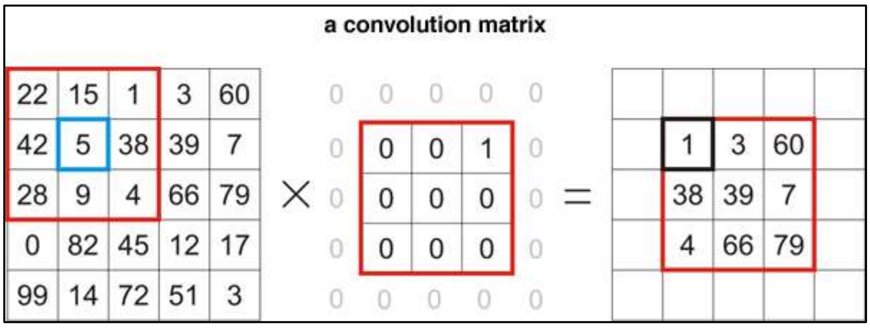




CNN

In past years, many applications of CNN for image recognition are producing high accuracy which inspired us to use deep CNN for tropical cyclone intensity predictions. Convolutional Neural Networks (CNNs) are most commonly used to show impressive results in processing two-dimensional visual data, such as images and videos. It takes images as inputs, learns the features of the image, and classifies them based on learned images. A convolutional neural network (or CNN) is a special type of multilayer neural network or deep learning architecture inspired by the visual system of living beings. CNN is useful to reduce human effort because it automatically detects the features. The applications are image and video recognition, image classification, computer vision, and natural language processing. CNN model aims to reduce the number of features that are present in the dataset and create a new feature that summarizes the original set of features. CNN model consists of three layers such as convolutional layers, pooling layers, and fully-connected layers. Each layer performs the task on input data and sends the result to the next layer. The first layers of a deep CNN learn low-level features, while the next layers learn more complex features. CNN contains fully connected layers. Deep learning can remove high-level abstractions of features and select necessary features for learning. It takes a time to train a deep CNN model, and the s classification task is complex and lengthy. Various deep learning architectures have produced state-of-the-art results on various computer vision tasks.Ex.CNN achieves a large decrease in error rate when applied to facial recognition

The heart of CNN is Convolutional operation which is used to detect the edges and features of images which gives a good performance.



The values of the resultant matrix can be obtained by superimposing a 3*3 image on a 5*5 image. we will multiply the values in each cell and then add all the values together. we will repeat this process by sliding this window until the end of the image. so this entire operation of getting this resultant matrix from this picture and filter is called convolutional operation. Any image with size(n*n) when convolved with an image of size (f*f) will generate the output (n-f+1)*(n-f+1).

CNN building block:

1. Padding:

Two problems arise with convolution:

1. Every time the original image size is reduced after the convolution operation, our original image is really reduced, but we don't want the image to be reduced every time.

2. The second problem is that when the kernel moves over the original images, it touches the edge of the image fewer times and touches the centre of the image more times, and overlaps in the middle as well. So the corner elements of any image or border are not used much in the output.to solve these two problems, a new concept called padding is introduced.So if the $n*n$ matrix is convolved with the f*f matrix with padding p, then the size of the output image will be

(n + 2p — f + 1) * (n + 2p — f + 1), where p =1 in this case.

2. Stride:

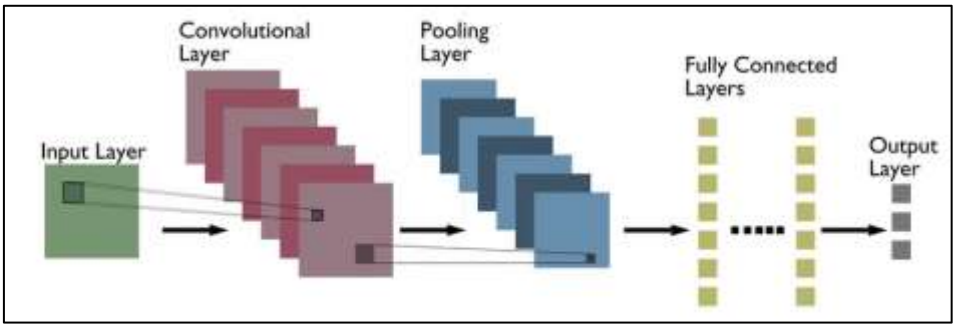
The step is the number of pixels shifts through the input matrix. For fill p, filter size $f*f$ and input image size $n * n$ and step 's' our output image dimension will be

$[\ \{(n + 2p - f + 1) / s\} + 1] * [\ +(s)\ 2p - f + 1) / s\} + 1].$

3. Pooling:

Pooling Its function is to gradually reduce the spatial size of the representation to reduce network complexity and computational cost.

1.The architecture of CNN:



The First layer of Convolutional network is Convolutional layer. This layer perform the opration for convolution. This layer abstract the features from input image .It is a linear opration that involves the multiplication of set of weights with input. Initially this technique was design for 2D input the multiplication is perform between array of input data and a 2D array of weight called filter or kernel. The size of an filter is less than that of input image. Multiplication performed between a filter size patch of the input data and a filter is a dot product, which is then summed and generate the single value. The filter is applied systematically to each overlapping part of the input data left to right, top to bottom.

Convolutional layer not only applied to the input data but they can applied to the output of other layer. CNN learn the multiple filter in parallel it learn from 32 to 512 filters in parallel from a given input.

2. Pooling layer:

CNN uses the Pooling layer to reduce the size of input or the number of parameters in input and to speed up the computation. Pooling layer is also called subsampling or downsamplinhg.it reduce the dimensionality of each feature map but retail the important information. number of hidden layer required to learn the complex relation present in the image would be large.

There are two types of Pooling:

1. Max Pooling/ subsampling:

Once we obtain the feature map of the input we will apply a filter of determined shape across the feature map to g et the maximum value from that portion of the feature. Maximum pooling is simply a rule of thumb to get the most out of the area and helps you progress with the most important features from the image. Maximum pooling selects brighter pixels from the image. It is useful when the background of the image is dark and we are only interested in the lighter pixels of the image.

2. Average Pooling:

Average Pooling differs from Max Pooling in that it stores a lot of information about the "less important" elements of a block or pool. While Max Pooling simply discards them by selecting the maximum value, Average Pooling merges them. This can be useful in various situations where such information is useful. It compute the average value of the feature map covered by filter/kernel.

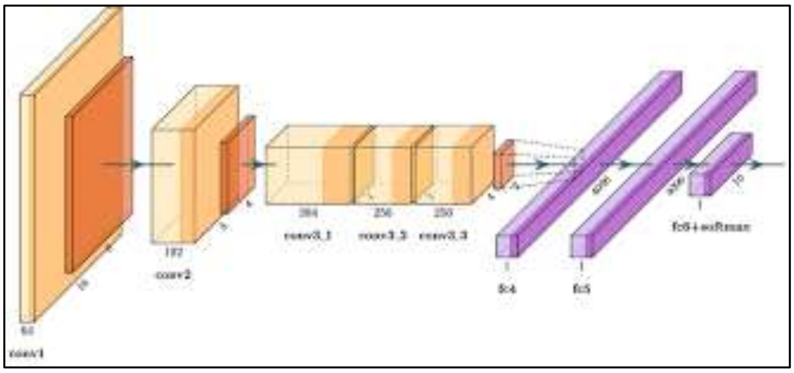
3. Fully Connected Layers:

Fully connected layers are dense networks of neurons. Every single neuron is connected to every other neuron from the previous layer and the next layer. Flatten output is fed as input to the fully connected layer. The aim of the Fully connected layer is to use the high-level features of the input image produced by the convolutional and pooling layer for classifying the input image into various classes based on the training dataset.

Flattening: After a series of Convolution and pooling operations on the feature representation of the image we will flatten the output of the final pooling layer into a single long continuous linear vector or array.

Alexnet

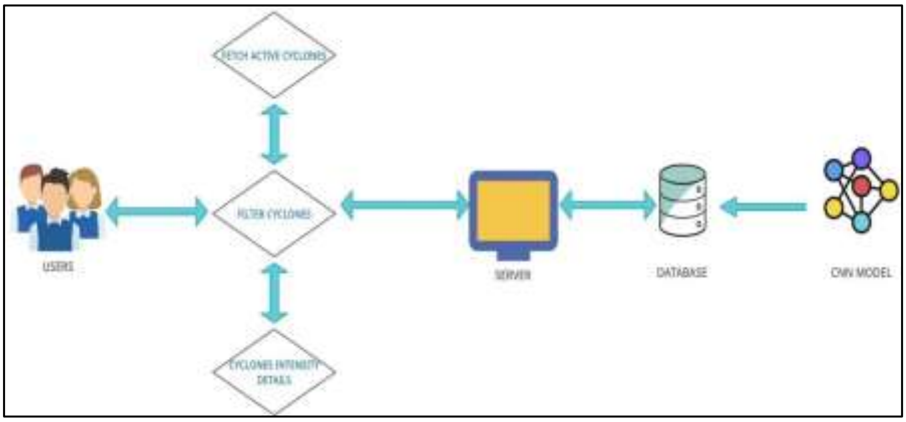
AlexNet is a deep convolutional neural network that was introduced by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in 2012. It is one of the earliest and most influential deep learning models, as it achieved state-of-the-art performance on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012.The architecture of AlexNet consists of eight layers: five convolutional layers followed by three fully connected layers. The first convolutional layer has 96 filters, and each subsequent convolutional layer has fewer filters, but a larger receptive field. The fully connected layers have 4096 neurons each. The activation function used throughout the network is the Rectified Linear Unit (ReLU), and the output layer uses softmax activation. AlexNet introduced several important techniques that are now standard in deep learning, such as the use of ReLU activation, local response normalization, and dropout regularization. The model was also trained on a large dataset (ImageNet) using data augmentation and stochastic gradient descent with momentum, which contributed to its success.in the research paper, we discuss how we incorporated AlexNet into deep learning-based cyclone intensity estimation model and how it compares to other architectures that we used. we also mention the impact of using pre-trained weights and transfer learning with AlexNet, if applicable We can discuss how we incorporated AlexNet into our deep learning-based cyclone intensity estimation model and how it compares to other architectures that we used in our research. We can also mention the impact of using pre-trained weights and transfer learning with AlexNet, if applicable. Additionally, we can discuss any modifications we made to the original AlexNet architecture to adapt it to our specific problem.



5. System Design

Tropical cyclones, also known as hurricanes or typhoons, are one of the most destructive natural disasters on the planet. Accurately predicting their intensity and path is critical for disaster preparedness and relief efforts. In this context, infrared (IR) images have emerged as a powerful tool for tracking tropical storms, due to their high resolution and accuracy.One common approach to using IR images is through convolutional neural networks (CNNs). These are deep learning models that are especially well-suited to image-based data. In the case of tropical storms, CNNs can be used to classify and estimate intensity based on features extracted from IR images.To achieve this, the IR images undergo a convolution process in the convolutional layer of the CNN. This process involves a set of filters that scan the image to identify patterns and features. The output of the convolution layer is then passed on to the next layer, often a max pooling layer that pools together the outputs of a group of neurons from the previous layer to form a single layer.

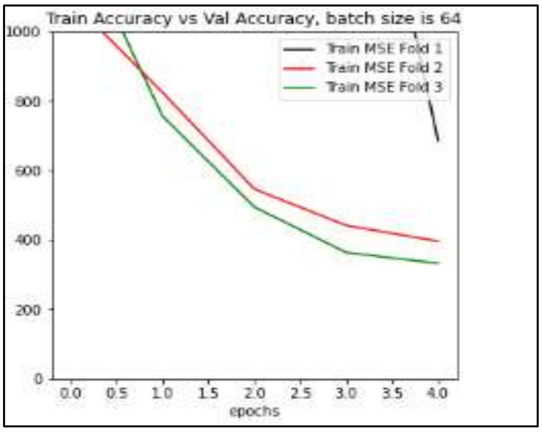
To classify tropical storm intensity, one CNN model can be trained to classify IR images into various categories of storm intensity. A separate CNN model can then be used to estimate the intensity of a given storm based on its IR image. In both cases, the last layer of the CNN is fully connected, which means that every neuron in the layer is connected to every neuron in the next layer. This setup allows the CNN to learn complex patterns and relationships in the data. To prevent the CNN from overfitting, regularization techniques such as L2 regularization with a factor of 0.01 can be applied in the fully connected layers. Call-back strategies such as early halting and dropout layers at a rate of 0.5 can also be employed to further prevent overfitting. Early halting involves stopping the training process when the validation accuracy stops improving, while dropout randomly "drops out" some neurons in the network during training to prevent them from becoming too dependent on other neurons. In summary, using CNNs to classify and estimate tropical storm intensity based on IR images is a powerful and effective approach. By carefully designing the network architecture and using regularization and call-back strategies, one can build a highly accurate and robust model for predicting tropical storms.



6. Result and Discussion

In our project, we are using deep learning to analyze typhoon satellite imagery with the help of a Convolutional Neural Network (CNN). Our aim is to identify "investment zones" or regions where tropical cyclones may develop, and use this information to begin wind speed estimation operations in the National Hurricane Center outlook . By comparing our estimated wind speeds to operational forecasts and displaying this data on a map, we hope to provide the larger scientific community with an easy-to-understand interpretation of the model results.Deep learning, especially CNN, is an effective technique to understand complex data sets, such as typhoon satellite imagery, and to extract meaningful insights. Our approach involves training the CNN model on large sets of historical data, allowing us to identify patterns and correlations that may not be immediately apparent to the human eye. By using such techniques, we can produce more accurate projections of future tropical cyclones, which can help to minimize loss of property and lives in areas prone to these types of natural disasters.

	Intensity	Category
0	63	Tropical Storm
1	45	Tropical Storm
2	31	Tropical Depression
3	79	Typhoon
4	55	Tropical Storm
...	...	...
408	43	Tropical Storm
409	36	Tropical Storm
410	35	Tropical Storm
411	32	Tropical Depression
412	82	Typhoon



7. Conclusion

The proposed project aims to create a solution for estimating and classifying tropical cyclone intensity using deep learning. The solution will use geometric features in cyclone images, a multilayer perceptron, and a CNN and Alexnet model for intensity estimation and classification.By using deep learning and hurricane satellite data, the proposed system aims to provide an automated cyclone estimation technique. This will help reduce the timing complexity of cyclone estimation and increase the efficiency of the process. The system has the potential to improve the accuracy and reliability of cyclone intensity estimation, potentially aiding in the reduction of chaos and abnormalities caused by tropical cyclones.Overall, the evaluation results have demonstrated the effectiveness of the developed solution in accurately estimating the intensity of tropical cyclones and categorising them. Additionally, the proposed system has the potential to significantly improve the accuracy and reliability of cyclone intensity estimation, which can have a positive impact on reducing the chaos and abnormalities caused by tropical cyclones.This project is a significant step forward in the field of cyclone intensity estimation and classification, and it highlights the potential of deep learning research in providing more accurate and reliable solutions for complex problems.

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