Cyclone Intensity Estimation Using Deep Learning

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Abstract
This study addresses the critical task of accurately estimating tropical cyclone intensity, vital for predicting severe weather events. The approach treats this as a classification problem, using intensity categories as classes. Unlike traditional supervised methods that demand abundant labeled data, real-world situations often provide only a handful of labeled samples. To overcome this, a novel semi-supervised deep learning framework is proposed. This framework, based on convolutional neural networks (CNNs), is tailored for FY-4 multispectral images. This model stands out by achieving precise classification and intensity estimation using a small initial set of labeled samples. It employs iterative training with a custom hybrid similarity measurement, enhancing classification performance throughout iterations. Experimental results highlight consistent performance improvement across iterations and demonstrate the superiority of the proposed method compared to existing approaches, even when working with small training sets. Overall, the study presents an efficient solution for cyclone intensity estimation, combining CNNs, semi-supervised learning, and iterative refinement.

Keywords: Convolutional Neural Network (CNN).

1. INTRODUCTION
High-intensity tropical cyclones can wreak havoc on coastal regions, underscoring the urgency of accurately analyzing remote sensing cyclone images and predicting their intensity in advance. Approaching cyclone intensity estimation as a classification challenge, machine learning techniques offer solutions. Various methods, including Multiple Logistic Regression (MLR), Support Vector Machine (SVM), and Back-Propagation Neural Network (BPNN), have been successfully applied to multispectral cyclone images, demonstrating favorable outcomes [1].Among these methods, the Convolutional Neural Network (CNN) stands out as a potent classifier, having undergone extensive exploration in recent years. A range of CNN variations, such as LeNet, GoogLeNet, and ResNet, have been proposed, achieving noteworthy advancements across diverse visual tasks. Notably, CNNs have been effectively employed for estimating cyclone intensity from infrared (IR) images [6].

However, both CNNs and many existing supervised techniques share a common challenge: their reliance on sizable training datasets. Unfortunately, the availability of accurately labeled samples remains limited, especially for cyclone intensity estimation using multispectral images from China's No. 4 meteorological satellite (FY-4), launched in December 2016. The intricate features within these multispectral images make it difficult for unsupervised methods to attain satisfactory classification accuracy since such methods are solely data-driven.The distinctiveness of the problem necessitates a nuanced approach. Neither purely supervised nor unsupervised methods are optimal for cyclone intensity estimation. Yet, amidst the scarcity of labeled data, the vast collection of unlabeled images holds immense potential due to their rich information. This establishes an opportunity for semisupervised classification to address these challenges. In this approach, both labelled and unlabeled data synergize to tackle the complexities of cyclone intensity estimation.[3]

2. LITERATURE REVIEW

[7] The CNN-TC employs adaptable CNN architecture to accurately gauge tropical cyclone intensity. It crafts specific CNN models for predicting cyclone formation based on diverse satellite factors. This innovative approach enhances prediction precision and adapts to varying conditions, revolutionizing cyclone forecasting. Reference [1] employs the Multilayer Perceptron (MLP) algorithm to predict cyclone intensity, using image-based geometric traits of tropical cyclones (TC). The Dvorak technique extracts significant features from satellite TC images. These features train the MLP model, enabling it to effectively estimate TC intensity based on learned patterns from the data. [4] This approach involves developing and deploying models for manufacturing after evaluating them against CAM-recognized functions and Dvorak T-wide variety images. The models are trained on local servers to minimize training costs. Once trained, they're integrated into the manufacturing system. The user interface for interacting with these models is built using React and Redux, known for their dynamic interface design and efficient state management. An analytical assessment and skill evaluation study is conducted over a thirty-minute timeframe, focusing on various levels of design and efficient state management. An analytical assessment and skill evaluation study is conducted over a thirty-minute timeframe, focusing on various levels ofcyclone attributes such as intensity and structure. This evaluation involves measuring the model's performance and its ability to make accurate predictions within this specific timeframe. Different aspects of cyclone behavior are taken into consideration during this analysis.[9] The model introduced in the context focuses on Very High-Resolution (VHR) remote sensing images. Its primary contribution lies in enhancing the precision of object detection and instance segmentation. Notably, this model incorporates a technique to compute the two-order integral, significantly elevating its accuracy levels .The Dvorak technique for calculating cyclone intensity has been used for a long time, but it relies on human judgment, which can be inconsistent and make it hard to use on big datasets. Convolutional Neural Networks (CNNs) combined with INSAT 3D images offer a solution to automate the process of cyclone intensity assessment. By leveraging these technologies, the system becomes proficient in autonomously recognizing patterns within the images that correspond to cyclone strength. This eliminates the necessity for human interpretation, ensuring a uniform approach across diverse datasets.

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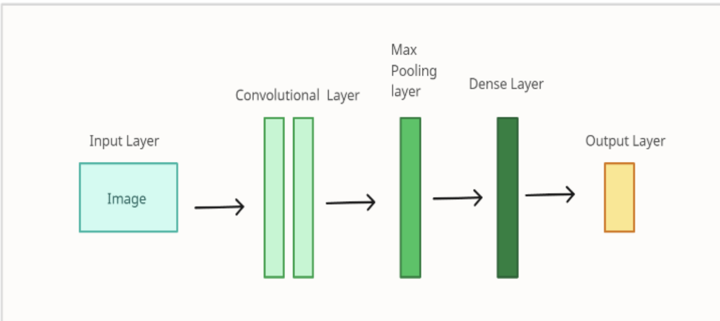


Fig 1. Methodology of Cyclone CNN model.

A COLLECTION AND CLASSES OF DATASETS

The INSAT 3D Infrared & Raw Cyclone Imagery dataset serves as a comprehensive collection of imagery covering the Indian Ocean region, spanning from 2012 to 2021. These images have been harnessed for training our model, INSAT3D, which is equipped with a CNN (Convolutional Neural Network) architecture. The dataset encompasses high-resolution infrared images captured by the IR Imager instrument onboard the INSAT 3D meteorological satellite.

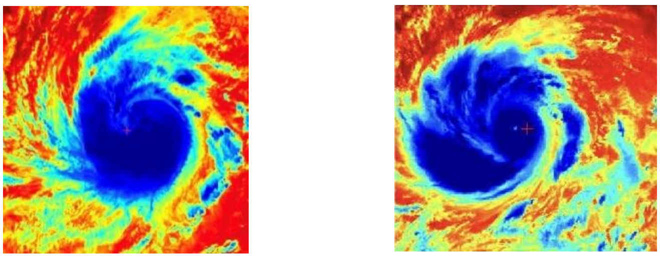


Fig. 2 Dataset of INSAT 3D IR Imagery

An accomplishment of ISRO (Indian Space Research Organisation).One of the pivotal aspects of this dataset is the pairing of each image with its corresponding timestamp and geographical coordinates. This integration allows for the creation of intensity graphs that reveal the fluctuations in temperature and cloud cover over time. Before being fed into the CNN, all images are standardized to a uniform size through resizing.In order to facilitate effective model training, the dataset is segregated into two subsets: the training set and the validation set. This separation enables the model to learn and generalize from a diverse range of imagery, enhancing its ability to accurately predict and analyze meteorological patterns.The INSAT 3D satellite itself is outfitted with an IR Imager instrument, capable of capturing intricate details of Earth's surface and atmosphere through infrared imagery This rich dataset offers valuable insights into the distribution of temperatures and cloud cover, thereby proving invaluable for an array of applications, including weather forecasting, climate monitoring, agricultural management, oceanography, and disaster response.The significance of this dataset lies in its consistent updates and open accessibility via ISRO's Meteorological Data Archive website. The platform provides an array of tools, such as maps, charts, and graphs, that empower meteorologists, researchers, and policymakers to scrutinize and interpret the data. This real-time resource has become a cornerstone for monitoring current weather conditions and predicting severe weather phenomena within the Indian subcontinent and its neighboring areas.Consequently, the INSAT 3D IR imagery dataset stands as an indispensable asset for those engaged in weather analysis and forecasting, research endeavors, and decision-making processes related to meteorological occurrences.

B.IMPLEMENTATION OF THE MODEL

In the implementation of the model firstly it takes an image and after processing the input it is passed through the deep learning CNN architecture.

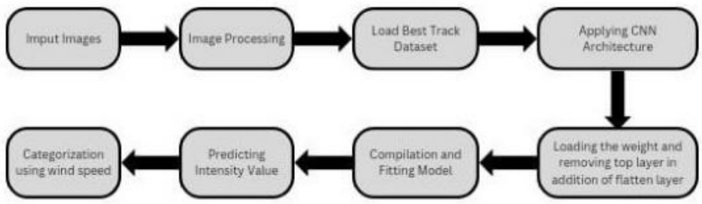


Fig. 3. Architecture For Intensity estimation and its classification.

In the case of intensity estimation, imagery data of satellite is often used, which consists of a series of images of the cyclone taken over time. Therefore, the problem can be viewed as an image classification task, where each image represents a different stage of the cyclone's development, and the goal is to accurately classify the cyclone based on these features and assign it to the appropriate intensity category, which can then be used for various purposes, such as predicting its potential impact on an area and informing emergency response efforts. CNNs are well-suited to this type of task because they are designed to extract features from images in ordered manner, using a series of convolutional layers that learn increasingly complex representations of the image data. This allows the CNN to capture the spatial relationships and patterns in the image data that are relevant to the task at hand.Therefore, CNNs are a suitable choice for tropical cyclone intensity estimation, as they can effectively handle the image data and learn the relevant features and patterns needed to classify the cyclone into different intensity categories based on the image data.The CNN architecture works as mentioned in the flowchart. Convolutional neural network (CNN) is used in image processing that is designed to process pixel data. After the images are passed, the images will be processed, and the datasets are loaded with a batch size of 16. A mean absolute error loss function is commonly used to calculate the difference between predicted and actual values. The activation function ReLU is often applied to the hidden layer, while a linear function is used for the final layer activation function. These techniques can help improve the accuracy of machine learning models. Rectified Linear Units (ReLU) function is given as

$$f(x) = \max(0,x) \quad (1)$$

x is input to the layer.

Loss function used here is Mean Squared Error:

$$MSE = 1/n \sum_{i=1}^{n} (\mathrm{y}i - \hat{\mathrm{y}}i) \quad (2)$$

Where, MSE: Mean Squared Error n: Number of data points yi: observed values ŷi: predicted values

Other formulas used for the comparison of CNN architectures are

Mean Absolute Error:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}| \quad (3)$$

MAE: Mean Absolute Error n: Number of data points yi: observed values ŷi: predicted values

|i=1 to n|: absolute value of the difference between actual and predicted values

Root Mean Squared Error:

$$RMSE = \sqrt{MSE} = \sqrt{1/n \sum_{i=1}^{n} (\mathrm{y}i - \hat{\mathrm{y}}i)} \quad (4)$$

RMSE: Root Mean Squared Error n: Number of data points yi: observed values ŷi: predicted values

R2 score:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \quad (5)$$

RMSE: Root Mean Squared Error n: Number of data points yi: observed values ŷi: predicted values Σ: sum of values

|i=1 to n|: absolute value of the difference between actual and predicted values.

1. InceptionV3:

Inception-v3 is a type of convolutional neural network that consists of 48 layers. The ImageNet consists of a trained variant network that was created in advance and trained on thousands of images. Several animals, a keyboard, a mouse, and a pencil are among the 1000 different item categories that the pretrained network can classify photographs into. As a result, the network now includes comprehensive feature representations for a range of photos. The input image for the network is 299 by 299 pixels in size [19].

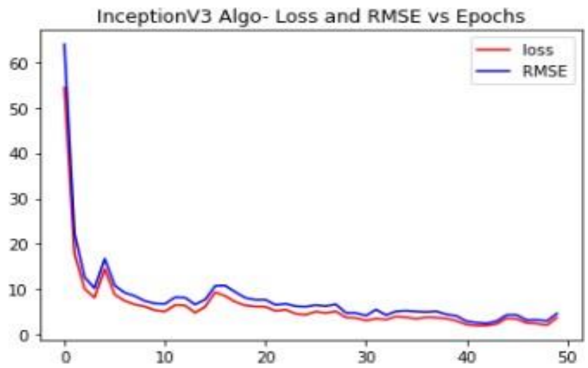


Fig. 4 Graph of Loss and RMSE vs epochs in InceptionV3

2. *VGG16:*

As a 16-layer transfer learning architecture with only CNN as its foundation, VGG16 is relatively comparable to earlier architectures, however the configuration is a little different. For this architecture, the input image with a standard dimension of 224 x 224 x 3, where 3 stands for the RGB channel has been used [20]. As a 16-layer transfer learning architecture with only CNN as its foundation, VGG16 is relatively comparable to earlier architectures, however the configuration is a little different. For this architecture, the input image with a standard dimension of 224 x 224 x 3, where 3 stands for the RGB channel has been used [20].

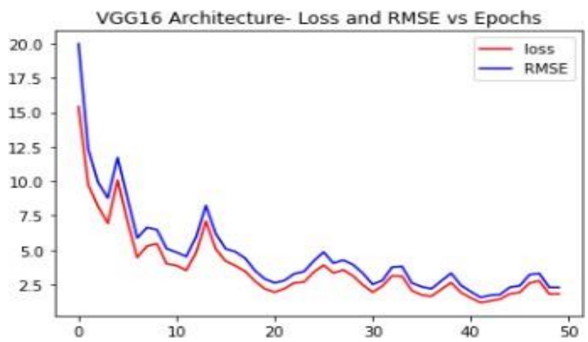


Fig. 5 Graph of Loss and RMSE vs epochs in

3 *Ensemble Learning:*
Ensemble learning is a popular technique used in computational intelligence to address various problems by creating and integrating multiple models, such as classifiers or experts. The main goal of ensemble learning is to enhance classification, prediction, function approximation, etc

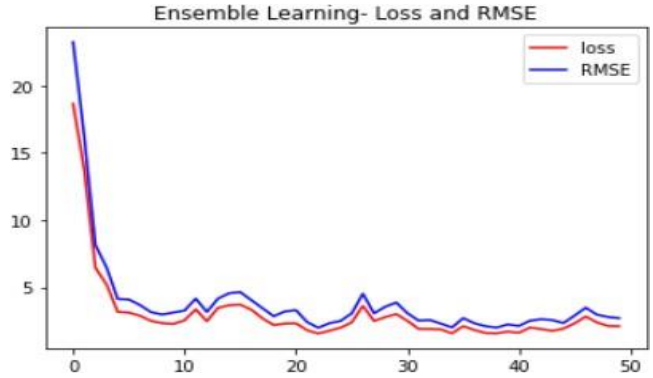


Fig. 6 Graph of Loss and RMSE in Ensemble Model

C.TRAINING AND TESTING MODELS

After the model is framed the training plays the major role. It is trained with the help of Keras and TensorFlow. We have run it on 50 epochs and saved the model. The system can effectively predict the wind speed for cyclone satellite IR imagery dataset. By minimizing the loss function (MSE), the model was trained. We have a single neuron in the last layer that is used to forecast a continuous value without any activation function being specified. The training was performed using the Adaptive Moment Estimation (Adam).

D.INTENSITY ESTIMATION / WIND SPEED

The wind speed is calculated in knots (KN). A knot is a measure of speed that is directly related to the world's coordinate systems for latitude and longitude. Because they are simpler to travel with than MPH and KPH, knots are frequently employed in the aviation and maritime industries. The intensity values are assigned to the images before the training of the dataset. Which is also known as supervised learning algorithms. On the basis of the eye or the center of the cyclone it checks how much the patch is spread in the image.In the case of estimating speed of wind from satellite images, the CNN can learn to identify spatial patterns that are indicative of wind speed. For example, the CNN might learn to identify the shapes and sizes of cloud formations, which can be used to infer wind speed. The CNN might also learn to identify the direction and speed of cloud movement, which can provide additional information about wind speed. During training, the CNN is presented with a dataset of labeled images, where each image is paired with a corresponding wind speed measurement. The CNN learns to adjust the weights ofits filters in order to minimize the difference between its predicted wind speed and the ground truth wind speed. By iteratively adjusting the filter weights and evaluating the model on a validation dataset, the CNN gradually learns to identify spatial patterns in the images that are strongly correlated with wind speed.Once trained, the CNN can be applied to new satellite images to estimate wind speed in real-time. The CNN is able to quickly and accurately analyze the spatial patterns in the image, producing a reliable estimate of wind speed.

E. CLASSIFICATION BASSED ON INTENSITY VALUES

Table 1. Classification based windspeed

Index	Category of Cyclone	Wind Speed
0	Depression	0-33KT
1	Storm	33-64KT
2	Category 1	64-83KT
3	Category 2	83-95KT
4	Category 3	95-113KT
5	Category 4	113-134KT
6	Category 5	<134KT

With the help of intensity or wind speed values the cyclonescan be classified into 8 categories. Here we have assigned the index value as 0 when the image detects no cyclone or extremely low intensity cyclone which is less than 17 KN.

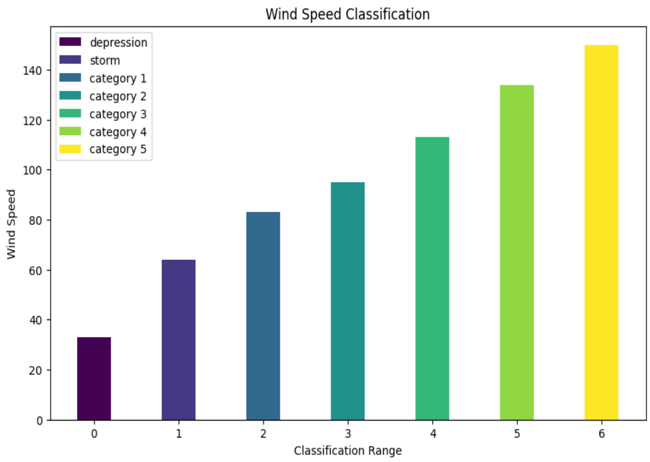


Fig.7 Cyclone Categories

F. SYSTEM WORKING

The first layer, a convolutional layer with an image size of 512 × 512, receives the preprocessed fish-eye IR pictures as input data. This layer's primary function is to identify various patterns and characteristics in the input pictures. Therefore, a filter is created also known as a kernel in order to discover these patterns/features. We identified the basic visual attributes in this method, which are helpful for CNN's initial layers. Multiple pictures will be convolved when different kernels or filters are applied to the same image. By utilizing numerous kernels, we may recognize different patterns in a picture, such as curves, lines, edges, and so on. After initializing the kernels with random values, the parameters will be updated with the ideal values during the training phase. The values will be changed with optimal values throughout the training phase, allowing the pattern to be detected.

The convolutional layer's nodes get ReLu and linear activation functions that are applied to the neurons on top of them. Also included were dropout layers, which may be used to switch off neurons during training in order to avoid overfitting.
We added a layer named max-pooling layer, dense layer, flatten layer, and batch normalization after the convolutional layer and adding a dropout layer to it. By down sampling the images created by the ReLu function, this reduces the dimensionality of the active neurons As was noted in the preceding paragraph, down sampling is carried out via the operation of max-pooling, which also discovers the maximum values and streamlines the inputs. In other words, the model's parameter count is decreased. To avoid overfitting from the pooling layer, we then add the dropout layers once again after each convolutional layer. Then we add a completely linked layer; this layer creates a vector representation of the high-level filtered pictures from the preceding layers. The transfer learning algorithms were used where they are pretrained with millions of images, and on last layer the input images are validated. The model predicts the intensity and classifies the value (0-7) which is the categorization of Tropical cyclone categories in the output layer using a linear activation function.

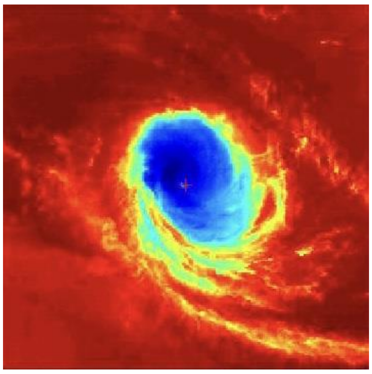
3...RESULTS AND DISCUSSIONS

The VGG16 Algorithm Model correctly analyzes and predicts the wind speed with the mean squared error of 1.8935 and the loss is 1.2124. The intensity and other characteristics, such as the regions affected, are predicted by the model. Additionally, it indicates which of the previously mentioned categories, from 0 to 7, the cyclone falls within. It becomes helpful for the public if there are any active cyclones whether it may be too harsh or too low on the basis of which they can take necessary action. After applying various algorithms using transfer learning and ensembling all them and comparing the values from above table the minimum loss of 1.1173 comes for VGG16 and after that Xception come out to be 1.3408 of loss. After integrating all the algorithms ensemble learning shows the loss 1.5124 and RMSE 1.8236 provided To distinguish between the header and body text in a document, users can utilize the options available in a dropdown menu.

From below figure, the various images are shown with their true output and predicted values by the model. The model is then further integrated with the android app where the cyclone intensity and its category is predicted.

Table 2:Classification based on wind speed

Sr no.	Algorithm	Loss	RMSE	MAE	MSE	R2 Score
1	Inception V3	1.7421	2.1434	1.7802	5.0453	0.6345
2	VGG16	1.2124	1.4320	1.2985	1.8935	0.8567
3	Ensemble Learning	1.6156	1.7846	1.2984	3.4985	0.8469



Output Intensity Value :79
Predicted intensity Value: 85 KN
Fig.8 :Category 2

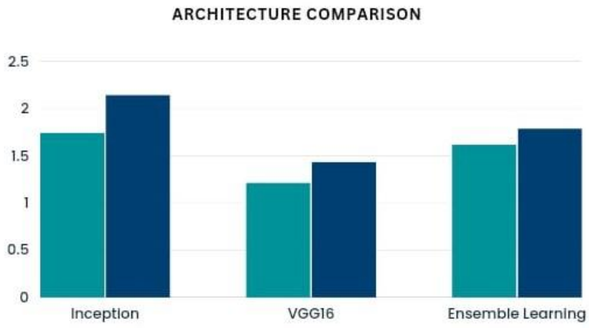


Fig.9. Comparison of Loss and RMSE in different CNN architectures

4. SCOPE OF PROJECT

This model can be trained on hurricanes and different types of natural disasters. On that basis, a larger integrated platform can be developed. An alert system can be made beforehand for the citizens if there is a chance of the cyclone or any other disasters

5. CONCLUSION

The suggested system aims to identify cyclone intensity by analyzing wind speeds and categorizing cyclone types within specific ranges. This is achieved through the application of CNN architectures, enhanced by ensemble learning techniques. The goal is to achieve heightened accuracy in results, updating on a half-hourly basis. This rapid and precise monitoring enables better awareness of potential hazards, prompting timely adjustments to mitigate risks and safeguard lives. Additionally, it aids in minimizing financial losses associated with cyclone-induced damages.

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