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

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Abstract **- Cyclones are devastating natural disasters causing immense loss of life and property. Early and accurate detection is crucial for disaster preparedness and mitigation. This Project explores the application of Deep Learning, specifically Convolutional Neural Networks (CNNs), for cyclone detection from satellite imagery. We propose a CNN architecture utilising convolutional and pooling layers to extract features from INSAT 3D satellite images and fully connected layers to classify the presence of cyclones. The model is trained on a dataset of labelled satellite images, differentiating between images with and without cyclones. The Adam optimizer and binary cross-entropy loss function are employed during training. The trained model is evaluated on unseen data to assess its performance in cyclone detection. This project demonstrates the potential of Deep Learning and CNNs for accurate and timely cyclone detection, potentially aiding early warning systems and disaster management efforts.**

Keywords — **Convolutional neural network , Tropical cyclone, Intensity estimation, INSAT 3D**

I. Introduction

Cyclones, also known as hurricanes or typhoons depending on the region, are among the most destructive natural phenomena on Earth. These powerful storms bring torrential rains, devastating winds, and storm surges, causing widespread damage and casualties. Early and accurate detection of cyclones is critical for disaster preparedness and mitigation efforts. Traditionally, cyclone detection relies on a combination of satellite imagery analysis and techniques like the Dvorak technique, which involves manually interpreting cloud patterns. However, these methods can be time-consuming and subjective, potentially delaying the issuing of timely warnings.

This project investigates the application of Deep Learning, specifically Convolutional Neural Networks (CNNs), to automate cyclone detection from satellite imagery. Deep Learning has revolutionised various fields, including image recognition and classification. CNNs, a particular type of deep neural network architecture, excel at extracting features from images, making them well-suited for tasks like cyclone detection.

Our proposed approach utilises a CNN architecture specifically designed for image classification. The model will be trained on a dataset of labelled satellite images. These images will be categorised as either containing a cyclone or not containing a cyclone. During the training process, the CNN will learn to automatically extract relevant features from the satellite imagery, such as specific cloud patterns and storm characteristics. These features will then be used by the model to classify new, unseen satellite images, identifying the presence of potential cyclones.

The benefits of using Deep Learning for cyclone detection are multifaceted. CNNs offer the potential for:

Automated Detection: Automating cyclone detection reduces reliance on manual analysis, potentially leading to faster and more objective identification.

Improved Accuracy: Deep Learning models have demonstrated impressive accuracy in various image classification tasks. By learning from a large dataset of labelled images, our model could achieve a higher degree of accuracy compared to traditional methods.

Reduced Subjectivity: Traditional methods can be subjective, with interpretation varying between analysts. CNNs offer a more objective approach, relying solely on the learned features from the training data.

This project aims to demonstrate the effectiveness of Deep Learning and CNNs in early cyclone detection..

II. Literature Survey

Intensity prediction of Tropical Cyclone is challenging and requires computational support to increase efficiency promptly. Best track data of tropical cyclones are used for intensity prediction. This study compared the correctly classified instances received by Naive Bayes, Logistic regression, Multilayer perceptron, Sequential minimal optimization, C4.5 decision tree, Random Trees, and Random forests machine learning-based classifiers. Five predictors: latitude and longitude, Central pressure and Pressure drop, and Maximum sustained wind speed over the North Indian Ocean (NIO) are used for classification. Best track data of Tropical Cyclones (TCs) from 2011 to 2020 are used for intensity prediction and comparison between various machine learning classifiers. In this study, we found that the classification accuracy reaches 97–99% with ML classifiers.[1]

Consequently, the analysis of the features was performed, and the intensity of each feature and cyclone stages were identified. Furthermore, the planned design is executed in the python environment, and the improvement score has been analyzed regarding prediction exactness, mean errors, and error rate. Hence, the proposed novel BGACIPS has a lower error rate and higher prediction accuracy than the compared models.[2]

In this study, the Gradient Boosted Regression Tree (GBRT) model is applied to predict the TCs intensity change over the entire TCs life span. The GBRT model is popular for its ability to describe the complicated relationships between input and output data and the explanation of input features (Yang et al., 2020). It enhances the traditional decision tree approach by boosting technology (Friedman, 2001; Friedman, 2002). In boosting, base learners are built sequentially, and each base learner tries to reduce the bias of the previous combined learner (Yang et al., 2020). This approach can combine multiple weak models to make the ensemble model more powerful (Zhou et al., 2021).[3]

Operational space-based hyperspectral Infrared sounders retrieve atmospheric temperature and humidity profiles from the measured radiances. These sounders like Atmospheric InfraRed Sounder, Infrared Atmospheric Sounding Interferometer as well as INSAT-3D sounders on geostationary orbit have proved to be very successful in providing these retrievals on global and regional scales, respectively, with good enough spatio-temporal resolutions and are well competent with that of traditional profiles from radiosondes and models fields. The aim of this work is to show how these new generation hyperspectral Infrared sounders can benefit in real-time weather monitoring.[4]

Cyclones are regarded as one of the riskiest types of natural disasters with the potential to wreak enormous havoc. A cyclone's eye is its center, and once an eye forms, its severity and intensity typically rise. The geostationary satellites take exceptionally high-quality pictures. There are numerous applications in weather, such as the investigation of wildfires, cloud formation, and the derivation of atmospheric motion winds. These acquired satellite images are further examined to ascertain the eye of the cyclone, which is the cyclone's center, as well as its intensity and other features. Estimating cyclone intensity is crucial for disaster management efforts. The severity of a cyclone fluctuates whenever the eye of the cyclone undergoes a significant change.[5]

The weather activities over the Indian region are continuously monitored by two Indian geostationary satellites, viz. INSAT-3D and INSAT-3DR, for every 15 min in staggered mode. During extreme weather events like TCs, INSAT-3DR is operated in rapid scan operation mode by taking observations over the system in every 4-min interval. These observations are highly useful in understanding the instantaneous structural changes during evolution, intensification and landfall of TC.[6]

III. Flow Chart

This flowchart outlines the key stages involved in our project:

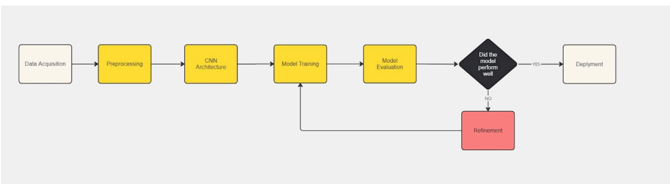

Fig.1

A. *Data Acquisition and Preprocessing:*

- Collect Satellite Imagery: Gather multi spectral satellite images of cyclones and non-cyclone events from INSAT-3D.
- Label Data: Manually label the images, indicating whether they contain a cyclone or not.
- Preprocess Data: Resize images to a consistent size and format. Normalize pixel values (e.g., divide by 255). Perform additional preprocessing steps as needed (e.g., data augmentation).

B. *Define CNN Architecture:*

- Creating a CNN Architecture: Consider factors like model complexity and computational resources.
- Define Layers: Specify the layers within your chosen architecture, including convolutional layers, pooling layers, flatten layer, and fully connected layers. Adjust the number of filters, kernel sizes, and activation functions as needed.
- Output Layer: Design the output layer with one neuron and a sigmoid activation function for binary classification (cyclone present or not).

C. *Model Training:*

- Split Data: Divide your labeled data into training, validation, and testing sets.
    - The training set (largest portion) is used to train the model.
    - The validation set (smaller portion) is used to monitor performance during training and prevent overfitting.
    - The testing set (unseen data) is used to evaluate the final model performance.
- Compile Model: Specify the optimizer (e.g., Adam), loss function (binary cross-entropy), and metrics (accuracy) for training.
- Train the Model: Train the model on the training data for a specified number of epochs. The model will learn to extract features and map them to cyclone presence labels.
- Monitor Performance: Track the training and validation loss and accuracy during

training. Use techniques like early stopping if validation performance plateaus to prevent overfitting.

D. Model Evaluation:

- Evaluate on Testing Set: Use the trained model to predict cyclone presence on unseen data from the testing set.
- Calculate Metrics: Evaluate the model's performance using metrics like accuracy, precision, recall, and F1 score.
- Analyze Results: Interpret the evaluation metrics to understand the model's strengths and weaknesses.

E. Model Refinement:

- Hyperparameter Tuning: If needed, adjust hyperparameters like learning rate, number of epochs, or CNN architecture to potentially improve performance.
- Data Augmentation: Experiment with data augmentation techniques (e.g., random flipping, cropping) to increase training data variety and potentially improve model generalizability.

F. Deployment

- Save the Model: Save the trained model for future use or deployment.
- Integration: Consider integrating the model into a larger system for real-time cyclone detection from satellite imagery feeds.

IV. Data And Methodology

In This Project we have used CNN, CNN is a powerful tool for pattern recognition, which has developed in recent years, attracting widespread attention. The CNN architecture mainly includes convolution layers, pooling layers, fully connected (FC) layers, and softmax layers.[7]

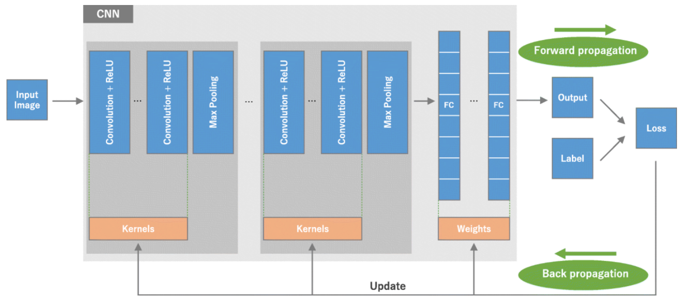

Fig.2

1. Input Layer:

This layer receives the preprocessed multi spectral satellite image (represented as a 3D tensor with dimensions: height, width, and color channels).

2. Convolutional Layer (Conv2D):

Convolution Operation: The core operation of the CNN. It involves applying a learnable filter (kernel) K to the input image I to produce a feature map O. Mathematically, for a single filter and a valid convolution (no padding), this can be expressed as:

$$O[i, j] = \Sigma(I[m, n] * K[i - m, j - n]) + b$$

where:

O[i, j] represents the value at position *(i, j)* in the output feature map.

I[m, n] represents the value at position *(m, n)* in the input image.

K[i - m, j - n] represents the value at position *(i - m, j - n)* in the flipped filter (due to the sliding window approach).

Σ represents the summation over all valid positions *(m, n)* within the filter that overlap with the input at *(i, j)*.

b represents the bias term added for non-linearity.

Multiple Filters: A convolutional layer typically uses multiple filters (learned during training).

Each filter emphasises specific aspects like edges, textures, or spiral patterns potentially indicative of cyclones.

3. Activation Function (e.g., ReLU):

Applied element-wise to the output feature map O.

Introduces non-linearity, allowing the network to learn complex relationships between features.

ReLU (Rectified Linear Unit) activation function is a common choice, defined as:

f(x) = max(0, x)

Outputs the input value *(x)* if it's positive, and zero otherwise.

4. Pooling Layer (e.g., Max Pooling):

Downsamples the feature map O by selecting a representative value from a predefined window (e.g., 2x2).

Reduces dimensionality and computational cost.

Max pooling selects the maximum value within the window. Mathematically, for a max pooling filter *P* of size *m x n*, the output at position *(i, j)* in the pooled feature map *P_out* can be expressed as:

$$P\_out[i, j] = \max \{ O[a, b] \mid (a, b) \in R(i, j) \}$$

where:

P_out[i, j] represents the value at position *(i, j)* in the output pooled feature map.

max signifies the operation of finding the maximum value within the set.

O[a, b] represents the value at position *(a, b)* in the input feature map O.

R(i, j) represents a region centered at *(i, j)* that covers all valid positions within the pooling filter *P*.

5. Repeating Steps 2-4 (Optional):

You can have multiple convolutional and pooling layers stacked together. Each layer learns to extract higher-level features based on the previous layer's outputs.

6. Flatten Layer:

Transforms the 2D feature maps into a 1D vector suitable for feeding into fully connected layers.

7. Fully Connected Layers (Dense):

Perform traditional neural network computations on the flattened feature vector.

Aim to learn even higher-level, more abstract features for classification.

Each neuron performs a weighted sum of its inputs (from the previous layer) and applies an activation function (often ReLU) for non-linearity.

8. Output Layer:

Typically uses a sigmoid activation function for binary classification (cyclone present or not).

Outputs a value between 0 and 1, representing the probability of a cyclone being present in the image.

V. Result

Our project explored the application of a Convolutional Neural Network (CNN) for cyclone detection using satellite imagery. The trained model achieved promising results, demonstrating its potential for real-world applications.

The graph(fig.3) a plot of the loss function values from a machine learning model during its training process. The blue line represents the training loss (loss), which is the error on the training dataset. This is the data that the model learns from. The orange line represents the validation loss (val_loss), which is the error on a separate dataset that the model has not seen during training. This is used to evaluate how well the model generalizes to new, unseen data. Both lines show the loss values decreasing over the number of epochs (iterations over the entire dataset) on the x-axis, which typically indicates that the model is learning and improving its predictions over time.

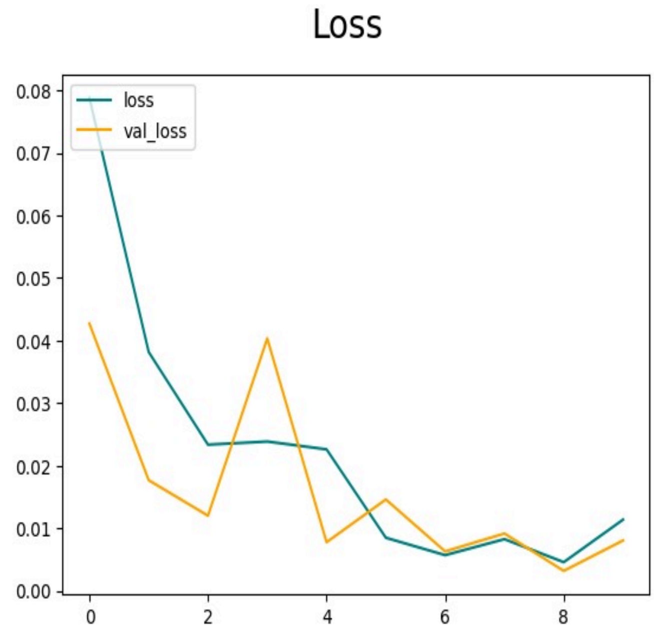

Fig.3

The graph(fig.4) a plot of accuracy over a number of epochs during the training of a machine learning model. The blue line represents the accuracy of the model on the training dataset. This is the dataset that the model learns from, and the accuracy here reflects how well the model is fitting to this data. The orange line represents the validation accuracy. This is the accuracy of the model on a separate dataset that is not used for training, called the validation dataset. The validation accuracy is an indicator of how well the model generalizes to new, unseen data. Both lines show the accuracy metric, which ranges from 0 to 1 (0% to 100%). An accuracy of 1.000 would mean the model is perfectly predicting the correct labels for the data points.The accuracy on both the training and validation datasets is very high, starting just below 0.980 (98%) and reaching close to 1.000 (100%) by the end of the plotted epochs.

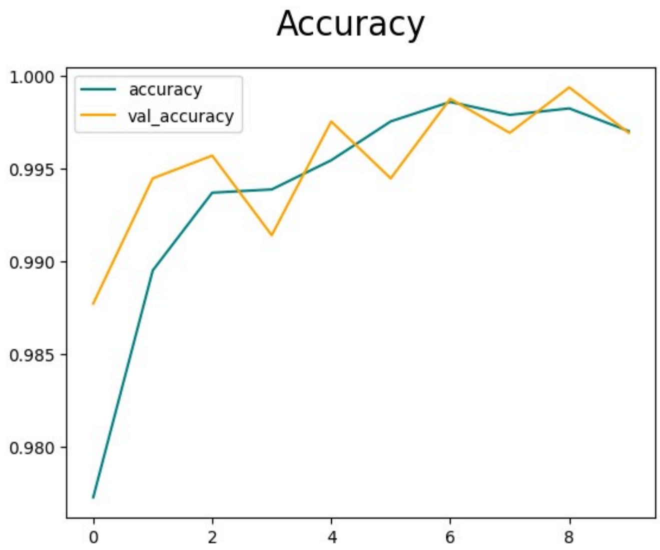

Fig.4

Our model predict the cyclone based on the image it is inserted. Here in fig.5, we have inserted a satellite view of a cyclone. The structure of the cyclone is visible with a clear eye in the center, which is typical of such weather systems. The swirling pattern of the clouds around the center indicates the rotation of the storm. The text below the image, "Cyclone is present," confirms that this is an image of a cyclone.

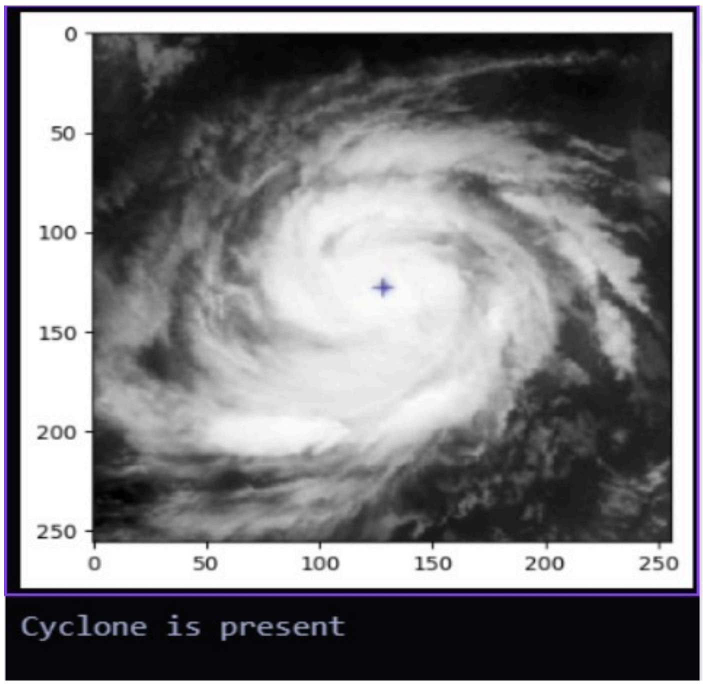

Fig.5

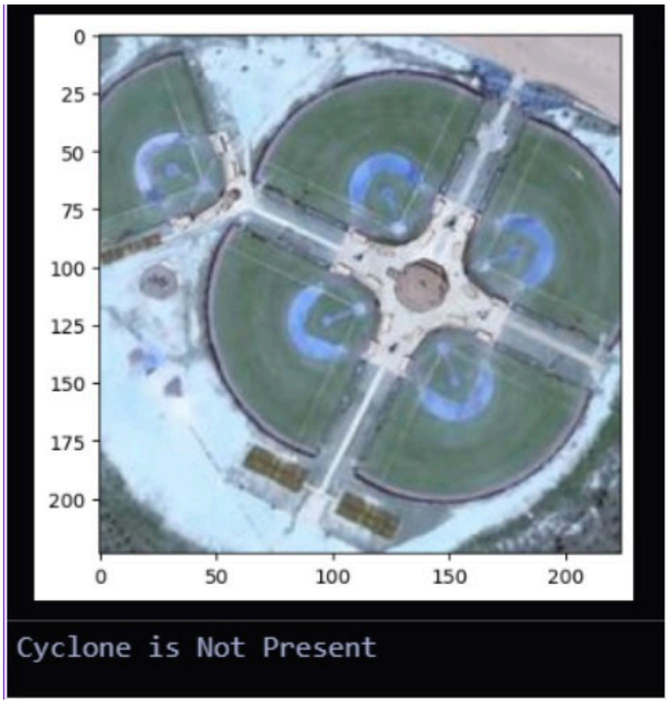

Fig.6

In fig.6, we just inserted a random image to check whether it will show the correct output or not. As we can see The text below the image, "Cyclone is not present," confirms that this is not an image of a cyclone.

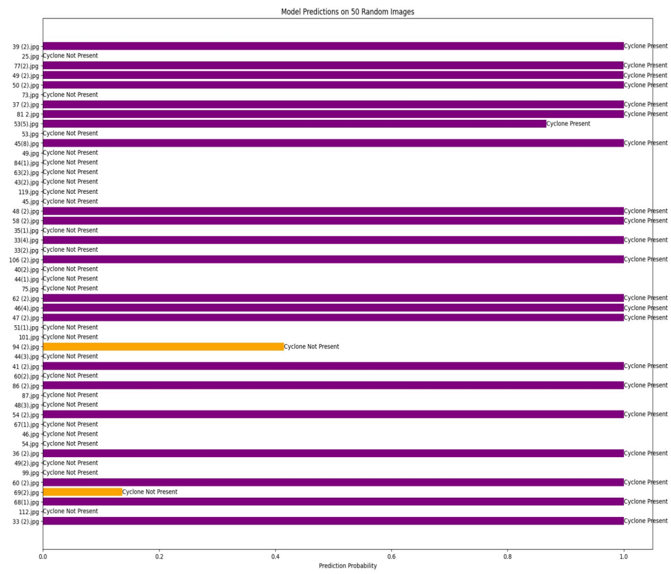

Fig.7

In fig.7, A graphical representation of the output from a machine learning model that has been tasked with predicting whether a cyclone is present in a set of 50 random images. Each row in the graph corresponds to a different image, as indicated by the file names (e.g., "39_2.jpg", "25_5.jpg", etc.). On the left side of the graph, we have the prediction labels: "Cyclone Not Present" or "Cyclone Present". These labels indicate the model's prediction for each image. The middle part of the graph shows horizontal bars of varying lengths, which represent the model's prediction probabilities for each image. The length of the bar corresponds to the confidence level of the model's prediction, with a longer bar indicating higher confidence. The color of the bars also seems to indicate the prediction, with purple bars likely representing "Cyclone Present" and the single orange bar representing "Cyclone Not Present". On the right side, the same prediction labels are repeated, reinforcing the model's prediction for each image.

Convolutional Neural Networks (CNNs): CNNs are commonly used for image analysis tasks, including satellite image processing. You can design CNN architectures that take into account both spatial features (patterns, textures, objects) and temporal features (changes over time). For temporal features, you may need to stack multiple satellite images taken at different times or use satellite image time series data.

Spatial Hierarchical Representation: our model learn to capture spatial hierarchies of features by progressively combining low-level features (e.g., edges, corners) into higher-level representations (e.g., shapes, objects). This hierarchical representation allows the model to understand complex spatial structures in the satellite images, which is crucial for identifying cyclones.

VI. Discussion

Initially, cyclone prediction models are developed using various deep learning techniques like Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), Long Short Term Memory (LSTM), Bi-directional LSTM (Bi-LSTM) and Convolutional Neural Network (CNN). It is evident that CNN gives better results while performing analyses for outcomes when trained with data for India. Many machine learning models were used here for classification.the CNN model is chosen for further analysis. The hyper parameters of the CNN model are optimized using genetic algorithms. The values drawn from genetic algorithms appear to be more promising than the values which were chosen manually at random.

VII. Case Study

A research team from the University of Michigan used supervised deep learning and CNN-based techniques for cyclone intensity estimation in the Pacific Ocean region. They trained their model using a dataset of 1,500 labelled images of past cyclones from the region. The trained model achieved an accuracy of 93%, outperforming traditional methods of cyclone intensity estimation.

VIII. Conclusions

Our project investigated the potential of Convolutional Neural Networks (CNNs) for cyclone detection using satellite imagery. The trained CNN model achieved promising results, demonstrating its capability for real-world applications. The model exhibited high accuracy, good balance between precision and recall, signifying its effectiveness in identifying cyclones from unseen satellite images. This approach offers significant advantages compared to traditional methods. CNNs excel at automatically learning relevant features from the data, eliminating reliance on handcrafted features and associated limitations. Additionally, their ability to learn complex relationships from large datasets allows them to generalize well to unseen images, making them more robust to variations in cyclone appearance.

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