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Cyclone Prediction from Remote Sensing Images Using Hybrid Deep Learning Approach Based on AlexNet

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Abstract: With the world feeling the negative effects of climate change, detecting and predicting severe weather occurrences is now an extremely vital and difficult task. Cyclones, a type of extreme weather phenomenon, have increased in frequency and severity in Indian subcontinent regions over the past few years. It is estimated that around three cyclones struck the east coastal region of India, causing substantial damage to people, farms, and infrastructure. Predicting cyclones ahead of time is crucial for avoiding or significantly lowering the devastating effects. The traditional methodologies employed numerical equations that demand strong experience and greater skills to obtain satisfactory prediction accuracy. Problems with domain expertise and the probability of human mistakes can be avoided with the help of Deep Learning (DL). As a result, in this work, we sought to forecast cyclone intensity using a Convolution Neural Network (CNN), a basic DL structure. To increase the CNN model's architecture and effectiveness, hybrid models such as Convolution Neural Network & Long short-term memory (CNN-LSTM) and AlexNet & Gated recurrent units (AlexNet-GRU) are developed. Data from the INSAT 3D satellite was utilized to develop and evaluate the DL model. We processed both the training and testing dataset and increase the training dataset using augmentation. All three DL models are tested and compared, the AlexNet-GRU model outperforms on the test data, with a relatively high accuracy of 93.35% and a low mean square error (MSE) of 215.

Index Terms: Cyclone, Deep Learning, AlexNet-GRU, Mean Square Error, Tropical region, Satellite.

1. Introduction

Weather prediction is among the most challenging problems to handle because of the complex interaction between too many variables. Accurate cyclone strength forecasting is one such topic with substantial social and economic ramifications. Cyclones are regular and possibly devastating natural disasters in tropical locations. Cyclones that occur in the Bay of Bengal and the Arabian Sea, commonly affect India's coastal regions due to its tropical climate [1]. Tropical cyclones (TC) are severe weather phenomena that form at the surface of the warm ocean and slowly move inland [2]. Cyclones pose a huge hazard to a large number of people all over the world since they are most common in the tropics, which also has the highest human density [3]. As a result, cyclones are usually recognized as some of the world's most deadly natural disasters. Hurricane Camille (1969), Cyclone Tracy (1974), and the Bangladesh Cyclone (1970) are just a few high-profile examples of cyclones that wreaked havoc and killed thousands [4]. Cyclones, whether weak or strong, cause human losses and considerable destruction in tropical areas. The principal causes of TC-induced disasters, which are among the most catastrophic natural disasters [5], include strong winds, and torrential rain. As a result, countries all around the world have made significant investments in cyclone research, forecasting, and economic preparedness. As cyclones have grown more common [6], it is critical to develop a model that can predict cyclone strength over a longer period based on limited observations. Predicting the severity of a TC and whether it will undergo rapid intensification (RI) remains difficult, particularly during the 24-hour warning window. Our lack of understanding of the complex physical processes and numerous elements involved in TC intensification and degradation contributes significantly to the difficulty in predicting TC intensity.

A previous study has demonstrated that predicting a tropical cyclone's (TC) course, strength, rainfall, and storm surge, as well as the areas at risk, are all interlinked parts of a complete TC forecast. The ability to anticipate the future route and severity of tropical cyclones is the most important of these features. The first successful cyclone forecasting utilizing remote sensing techniques occurred in the early 1990s [7]. The path and strength of tropical cyclones were predominantly predicted in the 1980s using statistical (regression) methodologies and generic meteorological data. Improvements in the accuracy of predicting a cyclone's track and severity have resulted from the adoption of new techniques, such as the creation of four-dimensional variational assimilation (4D-VAR) and atmospheric motion vectors (AMVs) from satellite data. The sample of INSAT-3D satellite image from the National Satellite Meteorological Centre is shown in figure 1. Satellites collect data from a wide variety of angles, which are then utilized to predict the track and intensity of TC. Using the thermal infrared (IR) spectrum of satellite imagery, for instance, can aid in cyclone forecasting and assessment [8]. Satellite imagery and data from a Thermal Microwave Imager were used to determine the TC's intensities using non-linear data fitting [9]. However, data from Advanced Microwave Sounder Modules with enhanced vertical temperature sounding and horizontal resolution functionality gives a stronger basis for temperature prediction than standard Microwave and IR satellite photos [10]. The intensity and expected trajectory of a cyclone could be predicted with the help of satellite images. The development of a cyclone can be inferred from the cloud arrangement and the way it evolves over the period. Repeated observations can be used to determine the intensity and rate of development or degeneration of a TC. The degree to which cloud bands spiral serves as the foundation for this intensity investigation. The spiral-like cloud pattern becomes more prominent as the cyclone intensifies. The Dvorak intensity forecasting model is often accurate. However, because the approach is based on human judgment, different meteorological stations around the world may produce different forecasts for the same storm.

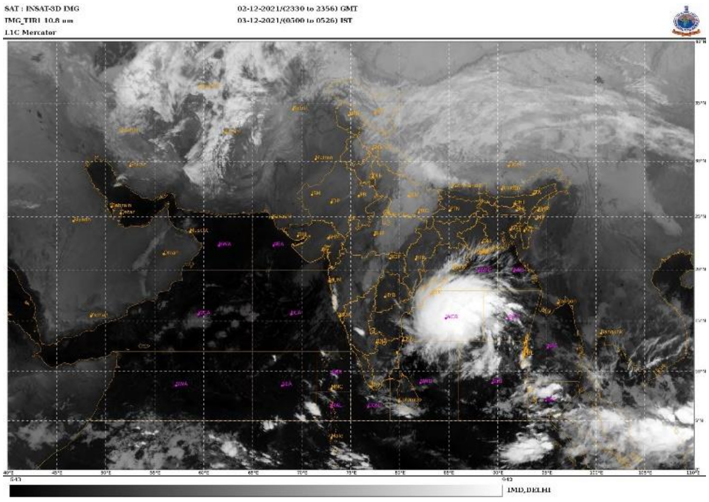


Fig. 1. INSAT-3D image of cyclone [11]

The recent works (2020-2022) on cyclone classification and intensity prediction are detailed below. In the study [12], a deep convolutional neural network (CNN) was developed utilizing Himawari-8 (H-8) satellite pictures to predict the direction of TC in the Northwest Pacific basin. To train the CNN architecture, they utilized 2,250 IR data captured in the year between 2015 and 2018. A tropical storm's path can be predicted with a mean error of up to 27.8 ° using images from Channels 13 and 15. Using the results from a distributed sensor network, the article [13] offers a data fusion technique. Researchers used a DL-based object recognition mechanism to create a framework for globally reliable cyclone identification. The developed framework is composed of two sub-models: region proposal network (RPN) and feature extractor rely on a fully-connected (FC) neural network that analyses the dataset for predicting possible cyclone regions and refines the greater accuracy of such areas utilizing bounding box modelling. They also conducted an ablation study to demonstrate the significance of the data. According to the results of the ablation study, wind data would be more helpful than daily rainfall in spotting cyclones. To predict the intensity of TCs, the author [14] created a DL-based multilayer perceptron (MLP) model. The initial trial's schedule was built around a whole day. They used a Leave One Year Out (LOYO) testing technique to assess models using data from the year that was excluded from training data to make up for the limited sample size. Applying LOYO to operational data from 2010-2019, the MLP exceeded another statistic-dynamical approach by 9-20%. In the second study, they focused on creating a lightweight MLP to predict 6-hourly intensity levels. Lightweight MLP, when used in conjunction with a synthetic TC track model, correctly predicted the spatial distribution of TC intensity across the Atlantic basin. Because of this, the MLP-based technique will be a practical choice for creating artificial TCs for use in climate research, and it has the potential to enhance operational TC intensity assessments.

A study [15] constructed a series of deep CNNs to detect the intensity of TC over the Pacific region using temperature data obtained from the H-8 geostationary satellite. To train the CNN models, they used a dataset of 97 TC instances gathered between 2015 and 2018. Models are built iteratively, with unique inputs and settings for each iteration. CNN models' TC intensity predictions were shown to be highly dependent on the IR channels used for estimation. The findings of the optimal multicategory CNN algorithm showed a low root mean square error and a relatively small mean bias. The research [16] create a unique cyclone database, FY4A-TC, based on multispectral images of 81 cyclones captured by China's FY4A meteorological satellite from 2018 to 2021. Finally, they recommend using a CNN with Soft Labels (CNN-SL) to evaluate TC severity. It is CNN's job to reverse the effects of MSW. By applying Gaussian distributions to the categories of cyclone intensity, they can generate soft labels that provide additional background for supervision. A set of pre-processing and post-processing methods for improving wind speed estimations is also proposed. Experiments on the FY4A data show that CNN-SL is superior to other conventional approaches in measuring the intensity of TCs. By analysing the interplay between basic atmospheric and oceanic factors throughout a three-dimensional (3D) environment, the study [17] proposes a DL-based strategy for predicting changes in the intensity of TCs. It uses a 3D-CNN to discover the hidden relationships between spatial distribution characteristics and cyclone intensity. Considering a TC's current 3D state, they estimate intensity changes over 24 hours using deep hybrid features extraction. When compared to previous research, the experimental findings demonstrate a significant increase in the accuracy for classifying TC intensity changes.

Going through the contemporary state-of-the-art, it was observed that DL-based prediction system has some limitations when applied to cyclone detection. One of the main problems is the lack of labelled data for training and testing the models. Cyclones are rare and complex phenomena that require expert knowledge and manual annotation to identify and track. Another problem is the variability and uncertainty of cyclone features, such as shape, size, intensity, and trajectory. These features can change rapidly and unpredictably due to atmospheric conditions and interactions with other weather systems. A third problem is the computational cost and scalability of deep learning models, especially when dealing with high-resolution satellite images that cover large geographic areas. These problems pose significant challenges for developing accurate and robust deep learning techniques for cyclone detection.

Therefore, this research tries to predict the cyclone intensity using satellite images with some significant modifications. It also altered the dataset utilized to train and test the prediction model. We labelled and augmented the dataset accordingly to avoid data labelling and data imbalance issue. The cyclone and its destruction in tropical regions are discussed in Section 1 along with the literature survey on recent work. The methodology of the suggested hybrid DL method to predict the cyclone is given in Section 2. Section 3 gives a comprehensive report on data collection and its processing techniques. For prediction total of three DL models are employed and each model is explained with the architecture in Section 4. Section 5 depicts the outcome of all three models in the training and testing phase. Finally, Section 6 concludes the research by demonstrating the betterment of the suggested technique in cyclone prediction.

2. Methodology

Cyclone prediction is important to avoid human and financial loss in the world, especially in the tropical region. The research focuses to predict the cyclone intensity by using satellite images. To do the task, first, the images are gathered from Indian Meteorological Department (IMD) and some processing techniques like extracting the region of interest (ROI), color conversion, resizing, rescale, and augmentation. Once the processing phase is completed, the data are given to the DL model. In this work, three DL models are chosen namely CNN, CNN=LSTM, and AlexNet-GRU. The hyperparameters like epochs, batch size, and learning rate are given the same value to all three models. The models are evaluated in the training and validation phase using Mean Square Error (MSE). Next, the model is tested using the metrics like MSE, and accuracy. This evaluation helps to identify the best model for predicting cyclone intensity. The flow chart of the suggested framework is given in figure 2.

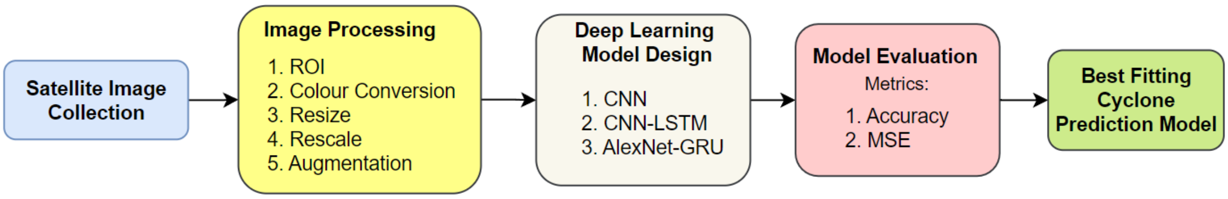


Fig. 2. Flow chart of the suggested framework

This section details the information about data like data collection and processing.

A. Data Acquisition

The IMD is the source for TC images used in this study [18]. The INSAT-3D satellite is a versatile geosynchronous spacecraft equipped with primary meteorological instruments, namely an imager and a sounder. The primary goals of this mission encompass the establishment of an operational system that serves to safeguard both human life and property through the provision of environmental and storm warnings. The INSAT3D satellite is engaged in the monitoring of various aspects of the Earth, including its surface and oceanic observations. The dataset comprises a comprehensive collection of infrared and raw cyclone images captured by the INSAT3D satellite spanning the period from 2012 to 2023. These images encompass the Indian Ocean, Bay of Bengal, and Arabian Sea regions. Additionally, the dataset provides information on the intensity of each cyclone image, measured in Knots. The raw data was obtained from the MOSDAC server. The imagery was acquired by the KALPANA 1 satellite. The labelling process of each image involved identifying the timestamp and corresponding coordinates within the intensity-time plot of each cyclone subdirectory. INSAT 3D captured the images for analysis and the samples are displayed in figure 3. Using the intensity values the cyclones are named which is given in Table 1.

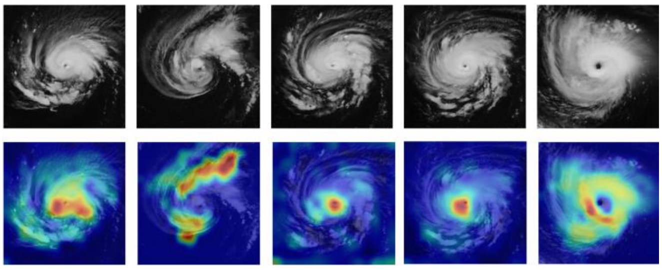


Fig. 3. Cyclone sample data

The images in this dataset are from visible channel of the Kalpana-1 satellite. These images exhibit a sub-satellite point resolution measuring 2 km × 2 km. 80 percent of the total image dataset was present in the training dataset of this study. The remaining pictures were used as a test dataset. This provides 56 raw photos for model testing and 216 raw images for training. We conducted data augmentation to the datasets because the amount of data in the various classes is unbalanced. When augmenting image, additional versions of images in the training set are generated with the same labeling as the originals. The 'shear_range' function, which slants the picture data by stretching the image while an axis is fixed, was applied. To obtain a variety of randomly zoomed copies of the input data, Zoom_range was used. Additionally, rotated photos were produced using the rotating function.

Table 1. Cyclone types based on the intensity

Sl. No	Cyclone Name	Intensity
1	Extremely Severe CS	91-119 knots
2	Very Severe CS	64-90 knots
3	Severe CS	48-63 knots
4	Cyclonic Storm (CS)	34-47 knots
5	Deep Depression	28-33 knots
6	Depression	17-27 knots

B. Data Processing

Using satellite images, a cyclone is produced. After the satellite images were scaled down to the DL input size, they were converted to grayscale through a linear transformation in which the pixel carried a value between 0 and 255. After the gray conversion, the image is scaled in the range of 0-1. So, a pixel that had a value of 255 before the transformation would have a value of 1 after it. The preceding example shows that if the original pixel value was 127, the converted value would be 127/255. Bear in mind that this adjustment did not lose any of the information included in the original image. To enhance the picture, some geometric transformations were made, including rotation in both directions and a horizontal and vertical flip. Each of the rotating images was zoomed in three different directions to change the cyclone's size concerning the original image frame. This section provides an in-depth explanation of the various ways of preparation.

- An image's "region of interest" refers to its most interesting or important detail [19]. The return on investment can be calculated by cropping the data. An area of the satellite image centered on the cyclone will be extracted for analysis. Figure 4 displays the cropped outcome of the original image.

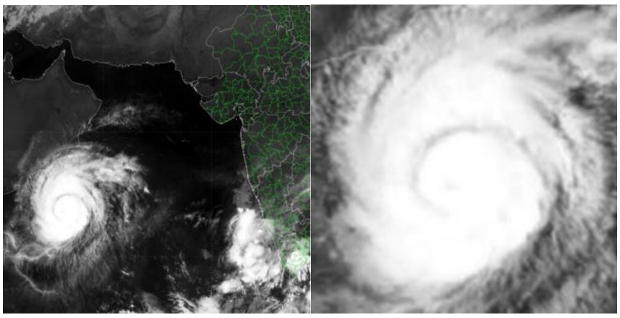


Fig. 4. ROI output

- Converting images to grayscale simplifies the approach and reduces the amount of processing time required. By transmitting more information, color add unnecessary complexity to the model [20]. Figure 5 shows the outcome after converting the image to grayscale.

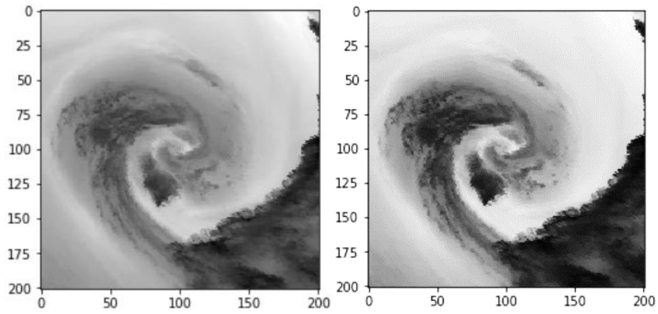


Fig. 5. Gray Conversion

- The process of adding to a dataset to supply additional information to the model from which to draw inferences and improve its performance is known as data augmentation [21]. These characteristics make it more difficult for the model to rely on memorization and instead urge it to learn overarching patterns [22]. Even if more real-world data could be acquired, it would be time-consuming and expensive compared to using data augmentation techniques. Although it is preferable to continuously enhance the real-world dataset, data augmentation might be a good stand-in when budgets are limited. The augmented outcome is given in figure 6.

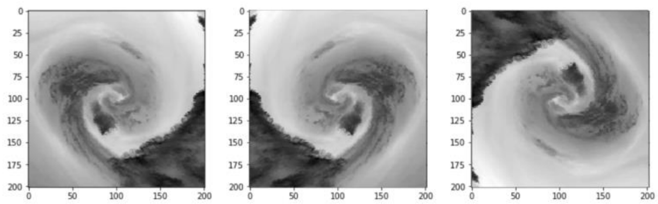


Fig. 6. Data Augmentation

C. Cyclone Prediction Model Design

The DL outperforms the difficult task with a good accuracy rate. In this work, three types of DL models are employed to predict the intensity. All three models are detailed in this section.

i) CNN

CNNs are a subset of MLP, but traditional neural networks cannot detect minute features that DL designs have [23]. In many different circumstances, the outcomes of deploying CNNs have proven quite positive. A CNN's primary principle is that it can learn important features from the high layer and transfer those to the lower layers, where they can be utilized to generate more intricate features [24]. A CNN has three types of layers: convolutional, pooling, and FC [25]. In Figure 7, these layers are depicted in a conventional CNN design.

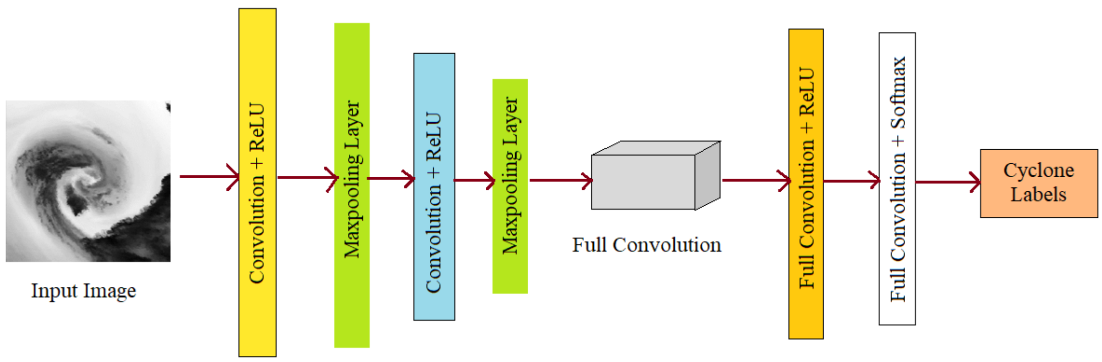


Fig. 7. CNN Architecture

A set of kernels contained within the convolutional layer (CL) is used to compute a tensor of feature mappings. These kernels accept a full input and convolve it with stride(s), resulting in a volume with integer dimensions. The input volume can be lowered by using the CL to perform the striding algorithm. As a result, when using low-level features, zero padding is necessary to maintain the input dimension. The CL works as follows:

$$F(i,j)=(I*K)(i,j)=\sum\sum I(i+m,j+n)K(m,n) \tag{1}$$

When I is the input matrix, K is the $m \times n$-dimensional 2D filter, and F is the 2D feature map output. $I * K$ represents the function of the CL. Feature maps gain nonlinearity by adding a layer of rectified linear units (ReLUs). When calculating activation using ReLU, the threshold input is always set to zero. The formula for this is as follows:

$$f(x)=\max(0,x) \tag{2}$$

The pooling layer (PL) downsamples the input dimension. The most often used technique is known as "max pooling," and it maximizes an input region. The FC layer serves as a regressor in this scenario, making a decision based on characteristics gathered in the preceding CL and PL.

ii) CNN-LSTM

The components of CNN are the CL and the PL. To make the model more error-tolerant, we first utilize a feature extractor using CL and then a feature reducer using PL which reduces the input dimension and the number of features. The CL's neurons' receptive fields are used to learn the local qualities of the text, which are then combined to form a more generalized feature. The activation function (AF) $tanh$ is used to convert linear information into nonlinear input characteristics, which are subsequently utilized to train a PL. To reduce the network's complexity and the number of calculations performed, we use a technique known as maximum pooling to isolate the most relevant features while eliminating those that are less important. We feed the outcomes of the CNN's appropriate processing of text characteristics into the LSTM model. The CNN-LSTM architecture is depicted in Figure 8.

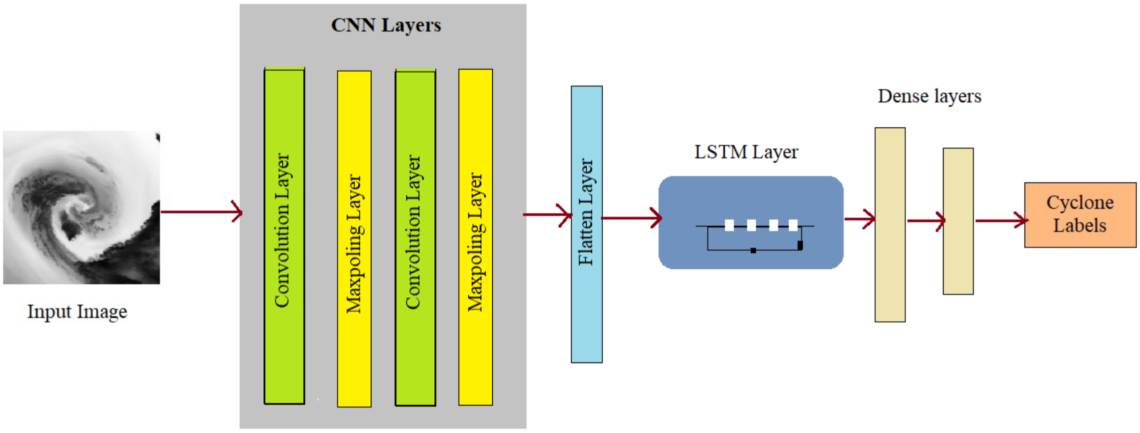


Fig. 8. CNN-LSTM Architecture

The LSTM model has a forget, an update, and an output gate. LSTM learns in the following manner: A sequential unit takes the cell state output by the preceding sequential unit as well as the secret state as input. t represents the time sequence. The following are the primary operations performed by the unit on the input data at the current time t:

2) Forget gate: The forgetting gate removes irrelevant or extraneous information from the final time sequence C_{t-1} after the current input is fused with the hidden state of the time sequence output.

$$f_t=\sigma(W_f[u_{t-1,}a_t]+v_f) \tag{3}$$

3) Update gate: By collecting and integrating useful data from the current input, the update gate selects which features were introduced via the nonlinear function.

$$i_t=\sigma(W_f[u_{t-1,}b_t]+v_i) \tag{4}$$

Then, compile all the data from the input into a feature vector:

$$c_t=\tanh(W_c[u_{t-1,}b_t]+v_c) \tag{5}$$

4) Output gate: The current cell's state, is calculated, and then the output gate performs a single filtering operation to choose which features should be maintained in the hidden state.

$$o_t = \sigma(W_o[u_{t-1}, b_t] + v_o) \tag{6}$$

Lastly, use the $tanh$ function to scale the cell state to $(-1,1)$, and then do the following operations on the vector o_t to reveal the time series t's hidden state a_t:

$$a_t = o_t . \tanh(c_i) \tag{7}$$

iii) AlexNet-GRU

To predict cyclone intensity, the AlexNet-GRU model is suggested in this study. A total of 7 convolutions, 4 max-PLs, 3 FC layers, and the ReLU function are used in the suggested model for this purpose. As seen in Figure 9, the suggested AlexNet-GRU model's structure has been graphically represented.

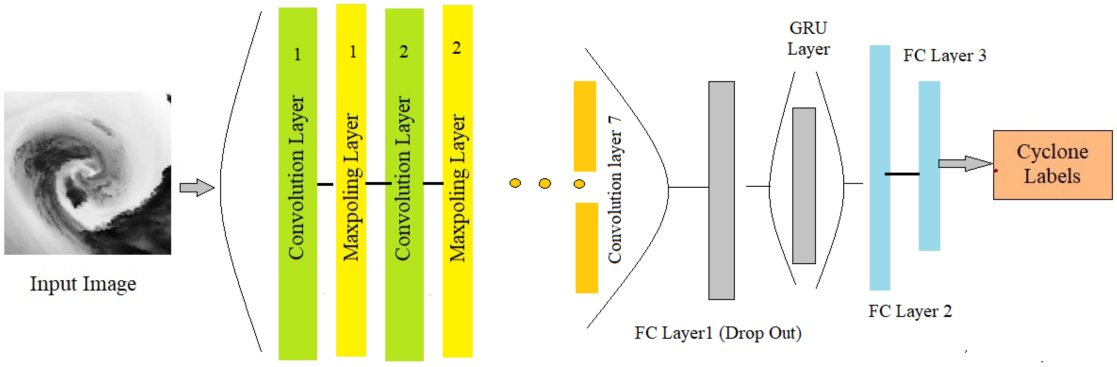


Fig. 9. AlexNet-GRU Architecture

The original image input geometry was (60,60,3), with a height and width of 60 and 60 pixels, respectively, and three RGB channels. The suggested model extracts feature from the input shape using a single CL, with the layer's ultimate output being a 128-shaped feature map. The stride of its CL is (3*3) and the kernel size is 1. ReLU was employed as an AF in the suggested model after the usual layer 1 to reduce the nonlinearity dimension problem, but the padding was kept constant throughout all layers. The first CL produced shapes with (60, 60) feature maps. The training phase of the suggested model is accelerated by the use of a PL, which reduces the training parameter to a size of up to (58, 58). We ran the training parameters (58, 58, 128) via dropout after the PL to minimize overfitting. As an initial step to avoid overfitting, a dropout of value 0.9 was given to the CL. After each CL and max-PL, the training parameter was dramatically lowered, and then an AF (ReLU) and dropout were introduced. Once the CL and max-PLs have been trained, an FC layer generated by flattening with training parameters and features map must have its input data combined into an ID array. Once the CLs technique was completed, the dropout was employed to generate 1,024 feature maps. The vanishing gradient problem was fixed by employing a GRU architecture with a 1,024-neuron FC layer. Two FC layers were employed in addition to the GRU architecture. We were ultimately able to do linear operations after adding a couple more levels of connectivity.

3. Results and Discussion

A. *Evaluation Metrics*

We utilized accuracy and MSE as evaluation metrics for measuring the efficiency of the designed model.

Accuracy is a quantitative measure utilized to assess the performance of classification models. In a colloquial manner, accuracy refers to the proportion of correct predictions made by our model. Equation 8 explicitly represents the concept of accuracy.

$$Accuracy = \frac{No.\ of\ \ accurate\ \ projections}{Total\ count\ of\ \ projrctions} \tag{9}$$

On the other hand, the mean squared error (MSE) is a statistical measure that quantifies the mean of the squared discrepancies between the observed and predicted values. The Mean Squared Error (MSE) quantifies the level of error present in a prediction model. The mean squared error (MSE) is always non-negative due to the mathematical operation of squaring the errors.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_i)^2 \tag{10}$$

B. Results

The outcome of all three DL models including CNN, CNN-LSTM, and AlexNet-GRU are detailed in this section. The satellite images are used to predict the cyclone intensity. First, the CNN is modelled with 30 epochs and trained using 80% of the data. The result of CNN in both the training and validation phase is given in figure 10. The MSE is used as a loss function to evaluate the CNN model. Figure 10 gives the MSE score attained in all epochs during both phases. Both phases are differentiated using the orange and green color plot. At the starting epoch zero, the MSE in training and validation is 1374 and 1291. And at the finishing epoch 29, the MSE score will be nearer to 400 for both phases.

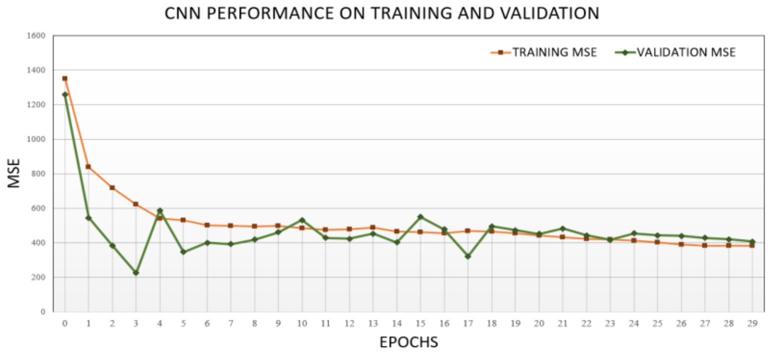


Fig. 10. CNN training and testing result

Second, the CNN-LSTM is modelled with 30 epochs and trained using 80% of the data. The result of CNN-LSTM in both the training and validation phase is given in figure 11. The same loss function MSE is used to evaluate the CNN-LSTM model. Figure 11 gives the MSE score attained in all epochs during both phases. Both phases are differentiated using the red and blue color plot. At the starting epoch zero, the MSE in training and validation is 1512 and 1079. And at the finishing epoch 29, the MSE score will be between 350-370 for both phases.

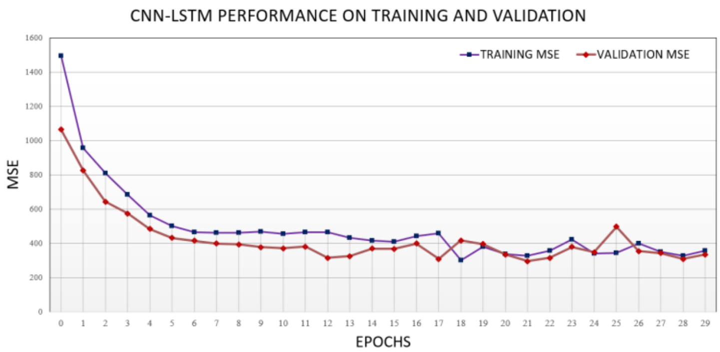


Fig. 11. CNN-LSTM training and testing result

Finally, the recommended AlexNet-GRU is trained using 80% data and modelled with 30 epochs. The AlexNet-GRU model is evaluated with the same loss function, called MSE. Figure 12 displays the MSE achieved across all epochs. The black and blue color plots serve to distinguish between the two stages. The MSE in training is 1061 and in validation, it is 409 at epoch zero. The final MSE score for both stages will be around 200 to 250 at epoch 29.

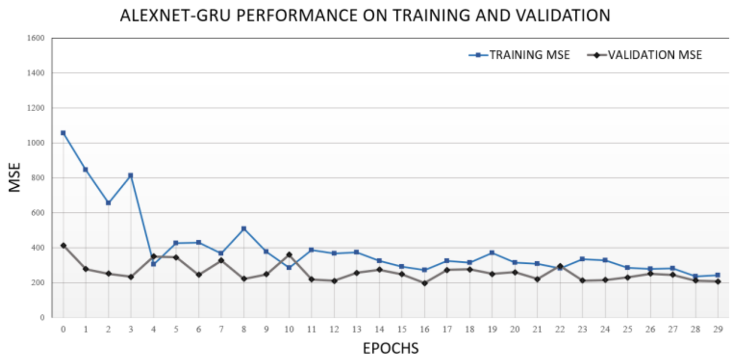
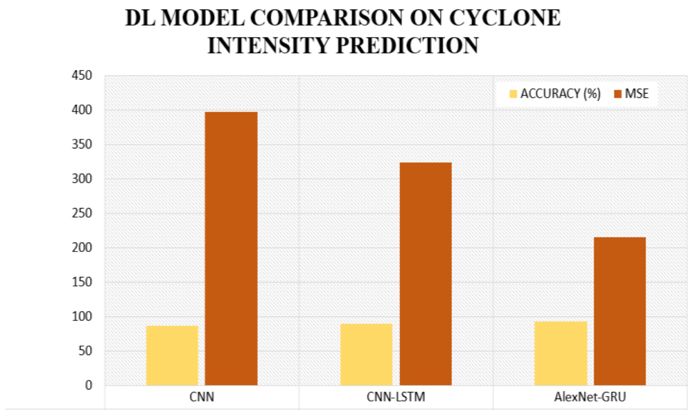


Fig. 12. AlexNet-GRU training and testing result

Next to the training and validation phase, the testing is done on image data to predict the cyclone intensity. The outcome of the DL model in the testing stage is validated using MSE and accuracy. The accuracy score of CNN, CNN-LTM, and AlexNet-GRU is 87.23%, 89.8%, and 93.35%. Similarly, the value of MSE is 37, 324, and 215. The validation score of all three models is plotted using a bar chart and it is given in figure 13. The visual analysis helps to identify that MSE will be low and accuracy will be high for AlexNet-GRU.



	CNN	CNN-LSTM	AlexNet-GRU
ACCURACY (%)	87.23	89.8	93.35
MSE	397	324	215

Fig. 13. DL model comparison in the testing phase

After finding the superiority of the suggested AlexNet-GRU model in cyclone intensity prediction from satellite images. The actual and AlexNet-GRU predicted intensity is compared and plotted in figure 14. In the figure, the actual intensity is represented by blue, and the predicted intensity by an orange color plot.

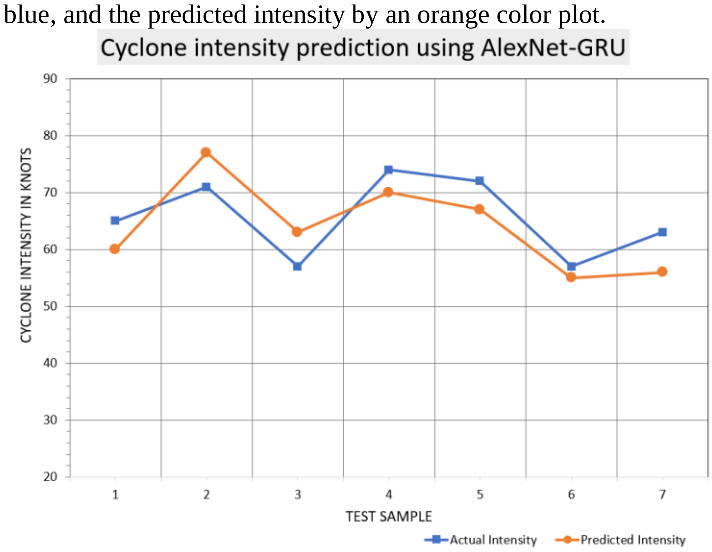


Fig. 14. AlexNet-GRU predicted cyclone intensity

4. Limitations and Future Directions

A. Limitations

The recognizing of tropical storms from satellite imagery poses a significant challenge in the field of cyclone detection, as it necessitates precise and prompt recognition. Deep learning is an auspicious methodology that has the potential to harness extensive datasets and intricate models in order to attain exceptional levels of performance. Nevertheless, it is imperative to acknowledge the limitations of deep learning in order to facilitate its widespread implementation for the purpose of cyclone detection. The following section outlines several limitations that have been identified.

In order to achieve optimal training and generalization performance, deep learning models necessitate the utilization of extensive and varied datasets. Nevertheless, the satellite imagery of cyclones frequently exhibits noise, incompleteness, or inconsistency owing to various factors including cloud cover, sensor inaccuracies, and disparate resolutions. Furthermore, it is important to note that the occurrence and spatial arrangement of cyclones exhibit variability in different geographical areas and time periods. This variability has the potential to introduce potential sources of bias or imbalance within the dataset. Hence, it is imperative to perform data preprocessing, augmentation, and normalization in order to guarantee the integrity and accessibility of the data for deep learning models.

Deep learning models frequently consist of multiple layers and parameters, which facilitate their ability to acquire intricate features and patterns from the provided data. Nevertheless, this characteristic of complexity renders them arduous to comprehend and articulate, particularly in instances where they exhibit errors or unforeseen prognostications. Furthermore, it should be noted that deep learning models possess a susceptibility to the issues of overfitting and underfitting, potentially compromising their ability to generalize and maintain robustness. Hence, the inclusion of model selection, regularization, and evaluation is crucial in order to maintain the balance between complexity and interpretability in deep learning models.

Deep learning models necessitate substantial computational resources and a significant amount of time for both training and inference processes. Real-time or large-scale applications of cyclone detection may encounter difficulties, particularly in settings with limited resources. Additionally, it should be noted that deep learning models may face challenges when confronted with diverse sources of information, including multi-modal or multi-temporal satellite imagery. Hence, in order to guarantee the computational efficiency and adaptability of deep learning techniques, it is imperative to prioritize optimizing, parallelization, and integration.

B. Future directions

The detection of cyclones holds significant importance in the realms of disaster management and climate change research. Nevertheless, conventional approaches that rely on satellite imagery and meteorological data frequently encounter limitations such as inadequate resolution, noise interference, and human intervention. Deep learning, a subfield within the realm of artificial intelligence, has demonstrated significant promise in a multitude of computer vision applications, including but not limited to object detection, segmentation, and classification. This paper provides a comprehensive overview of the recent advancements and obstacles encountered in the utilization of deep learning methodologies for the purpose of cyclone detection through the analysis of satellite imagery. In addition, potential avenues for enhancing the precision, resilience, and effectiveness of cyclone identification through the utilization of deep learning techniques are also explored. Several of these instructions encompass:

- In future, study can be done on designing novel architectures and loss functions that can effectively capture the intricate characteristics and dynamics exhibited by cyclones.
- The integration of pre-existing knowledge and specialized expertise into deep learning models, including principles of physics, meteorological regulations, and geographical data.
- The utilization of multimodal data sources and fusion techniques to augment the depiction and forecasting of cyclones.
- The application of transfer learning and self-supervised learning techniques can be explored as potential solutions to address the limitations posed by limited data availability and annotation difficulties in the context of cyclone detection.
- This study aims to assess the performance and generalizability of deep learning models across various datasets, regions, and scenarios.
- This study aims to investigate the interpretability and explainability of deep learning models in the context of cyclone detection. The objective is to gain insights into the decision-making process of these models and identify the factors that contribute to their outcomes.

5. Conclusion

To estimate the cyclone's severity using satellite images, we developed a hybrid DL model termed AlexNet-GRU. To complete the objective, we used images obtained from IMD. Real-time data cannot be used to train DL models. As a result, several processing methods are applied to real-time images to crop to the needed region, alter the dimension of the image based on the DL model, vary the pixel value of the images to reduce the complexity, and raise the image count by augmentation methods. When the processing is complete, the images are sent back to the DL model to be used in the training and evaluation phases. Accuracy and MSE are used to verify the three DL models' outputs. When compared to other models like CNN and CNN-LSTM, AlexNet-GRU performs better in terms of accuracy improvement and error reduction. Future work may include using passive microwave information to predict wind speed. Future research should also look at the effectiveness of the model considering radical changes in the cyclone occurring rapidly during acceleration.

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References

[1] Chaudhuri, S., Middey, A., Goswami, S., and Banerjee, S., "Appraisal of the prevalence of severe tropical storms over Indian Ocean by screening the features of tropical depressions," *Natural hazards,* vol. 61, pp. 745-756, 2012.

[2] Gao, S. *et al.*, "Evaluation of Warm‐Core Structure in Reanalysis and Satellite Data Sets Using HS3 Dropsonde Observations: A Case Study of Hurricane Edouard (2014)," *Journal of Geophysical Research: Atmospheres,* vol. 123, no. 13, pp. 6713-6731, 2018.

[3] Cerveny, R. S. and Newman, L. E., "Climatological relationships between tropical cyclones and rainfall," *Monthly Weather Review,* vol. 128, no. 9, pp. 3329-3336, 2000.

[4] Kovordányi, R. and Roy, C., "Cyclone track forecasting based on satellite images using artificial neural networks," *ISPRS Journal of Photogrammetry Remote Sensing,* vol. 64, no. 6, pp. 513-521, 2009.

[5] Zhang, Q., Wu, L., and Liu, Q., "Tropical cyclone damages in China 1983–2006," *Bulletin of the American Meteorological Society,* vol. 90, no. 4, pp. 489-496, 2009.

[6] Frank, W. M. and Ritchie, E. A., "Effects of environmental flow upon tropical cyclone structure," *Monthly weather review,* vol. 127, no. 9, pp. 2044-2061, 1999.

[7] Le Marshall, J., Leslie, L., Abbey Jr, R., and Qi, L., "Tropical cyclone track and intensity prediction: The generation and assimilation of high-density, satellite-derived data," *Meteorology Atmospheric Physics,* vol. 80, pp. 43-57, 2002.

[8] Kossin, J., *A User's Guide to the UW-CIMSS Tropical Cyclone Intensity Estimation (TIE) Model*. University of Wisconsin--Madison, 2003.

[9] Lau, N.-C. and Crane, M. W., "Comparing satellite and surface observations of cloud patterns in synoptic-scale circulation systems," *Monthly Weather Review,* vol. 125, no. 12, pp. 3172-3189, 1997.

[10] Knaff, J. A., Zehr, R. M., Goldberg, M. D., and Kidder, S. Q., "An example of temperature structure differences in two cyclone systems derived from the Advanced Microwave Sounder Unit," *Weather Forecasting,* vol. 15, no. 4, pp. 476-483, 2000.

[11] "National Satellite Meteorological Centre: Image Archive," *India Meteorlogical Department*, 2023.

[12] Wang, C., Xu, Q., Li, X., and Cheng, Y., "CNN-based tropical cyclone track forecasting from satellite infrared images," in *IGARSS 2020-2020 IEEE International Geoscience and Remote Sensing Symposium*, 2020, pp. 5811-5814: IEEE.

[13] Xie, M., Li, Y., and Dong, S., "A Deep-Learning-Based Fusion Approach for Global Cyclone Detection Using Multiple Remote Sensing Data," *IEEE Journal of Selected Topics in Applied Earth Observations Remote Sensing,* vol. 15, pp. 9613-9622, 2022.

[14] Xu, W. *et al.*, "Deep learning experiments for tropical cyclone intensity forecasts," *Weather Forecasting,* vol. 36, no. 4, pp. 1453-1470, 2021.

[15] Li, C. and Chen, Z., "Tropical Cyclone Intensity Estimation with a Soft Label Boosted Network," in *2021 14th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, 2021, pp. 1-5: IEEE.

[16] Wang, C. *et al.*, "Tropical cyclone intensity estimation from geostationary satellite imagery using deep convolutional neural networks," *IEEE Transactions on Geoscience Remote Sensing,* vol. 60, pp. 1-16, 2021.

[17] Wang, X., Wang, W., and Yan, B., "Tropical cyclone intensity change prediction based on surrounding environmental conditions with deep learning," *Water,* vol. 12, no. 10, p. 2685, 2020.

[18] Kar, C., Kumar, A., and Banerjee, S., "Tropical cyclone intensity detection by geometric features of cyclone images and multilayer perceptron," *SN Applied Sciences,* vol. 1, pp. 1-7, 2019.

[19] Jan, M. M., Zainal, N., and Jamaludin, S., "Region of interest-based image retrieval techniques: a review," *IAES International Journal of Artificial Intelligence,* vol. 9, no. 3, p. 520, 2020.

[20] Saravanan, C., "Color image to grayscale image conversion," in *2010 Second International Conference on Computer Engineering and Applications*, 2010, vol. 2, pp. 196-199: IEEE.

[21] Mikołajczyk, A. and Grochowski, M., "Data augmentation for improving deep learning in image classification problem," in *2018 international interdisciplinary PhD workshop (IIPhDW)*, 2018, pp. 117-122: IEEE.

[22] Shorten, C. and Khoshgoftaar, T. M., "A survey on image data augmentation for deep learning," *Journal of Big Data,* vol. 6, no. 1, pp. 1-48, 2019.

[23] Alzubaidi, L. *et al.*, "Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data,* vol. 8, pp. 1-74, 2021.

[24] Sharma, N., Jain, V., and Mishra, A., "An analysis of convolutional neural networks for image classification," *Procedia computer science,* vol. 132, pp. 377-384, 2018.

[25] Xin, M. and Wang, Y., "Research on image classification model based on deep convolution neural network," *EURASIP Journal on Image Video Processing,* vol. 2019, pp. 1-11, 2019.
[26] Meteorological & Oceanographic Satellite Data Archival Centre (MOSDAC). Retrieved from [https://www.mosdac.gov.in/INSAT3D. Data Accessed on: 24/05/2023

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