# Hybrid Deep Learning For Cyclone Intensity Estimation Using Multisource Satellite Data

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***Abstract*—Accurate estimation of tropical cyclone (TC) intensity is crucial for disaster preparedness, especially in the Indian Ocean. This study introduces a hybrid deep learning framework that combines Vision Transformer (ViT)-based global spatial feature extraction with domain-specific features, including Cloud Anisotropy Index (CAI) and Cloud Top Temperature Variance (CCTV), to predict cyclone intensity from INSAT-3D infrared satellite imagery. The ViT model employs transfer learning and Principal Component Analysis (PCA) for compact feature embeddings, which are integrated with meteorological indicators in a dual-branch architecture. A regression model is trained using Huber loss and optimized with Adam, incorporating callbacks to mitigate overfitting. Results show that this hybrid approach achieves superior prediction consistency and a reduced Mean Absolute Error (MAE = 17.87), surpassing traditional CNN models like VGG16 (MAE = 22.50). The model is also accessible through a web interface for real-time cyclone intensity monitoring**

## I. INTRODUCTION

Tropical cyclones (TCs) are among the most devastating natural disasters, especially in regions such as the Indian Ocean, where these events frequently cause large-scale destruction. These storms bring intense winds, torrential rainfall, and storm surges, leading to extensive damage to infrastructure, agriculture, and human life. Accurate and timely estimation of cyclone intensity is critical for disaster preparedness, early warning systems, and minimizing human and economic losses [1], [2].

Forecasting cyclone intensity remains a significant challenge due to the complex spatiotemporal dynamics of these systems, which are influenced by interactions between atmospheric and oceanic processes. Traditional Forecasting techniques including statistical, dynamical, and hybrid statistical-dynamical models—have been widely applied. While statistical models offer quick inferences, their accuracy is often limited [3]. Dynamical models, such as the Global Forecast System (GFS), simulate atmospheric systems using physical laws but require substantial computational resources and are sensitive to initial condition inaccuracies [4]. Statistical-dynamical methods aim to balance physical modeling with empirical learning but face challenges in real-time operation due to their complexity [5].

In operational practice, agencies like the India Meteorological Department (IMD) employ satellite-based tools, such as the Advanced Dvorak Technique (ADT), in combination with numerical weather prediction (NWP) models for cyclone intensity estimation. While useful, these approaches often depend on expert interpretation and may yield suboptimal results under ambiguous or obscured satellite conditions [21], [22].

Recent advancements in deep learning, particularly the use of Convolutional Neural Networks (CNNs), have shown significant potential in learning spatial features directly from satellite imagery, enabling automated intensity estimation without manual preprocessing [6], [7]. More recently, Vision Transformers (ViTs) have demonstrated superior performance by capturing long-range spatial dependencies in image data, which CNNs may fail to fully capture [9], [10]. Studies have found that ViT-based models can outperform traditional machine learning and numerical methods, especially in handling raw satellite inputs for rapid cyclone intensification prediction [24], [27].

However, most existing approaches still rely heavily on pre-segmentation of cyclone structures or storm center detection, which introduces additional complexity and potential error propagation—especially in time-critical scenarios [14], [16].

Additionally, many models are limited to single-source data inputs, which can reduce generalization across different cyclone types or environmental settings [15], [25], [26]. To address these limitations, this study proposes a novel hybrid deep learning framework for cyclone intensity prediction that leverages transfer learning via a pretrained ViT model combined with image-derived structural features. The proposed system processes raw infrared satellite imagery and augments it with engineered features such as the Central Area Index (CAI), Cloud Top Coldness Variance (CCTV), and optical flow—features that represent cloud organization, thermal variation, and motion dynamics respectively. These features, derived directly from infrared imagery, enhance the model's ability to learn both spatial structure and physical behavior without the need for external data sources [17]–[19].

This hybrid model is trained and evaluated using a curated dataset of historical IR satellite images from the Indian Ocean region, with cyclone intensity (in knots) as the prediction target. The system achieves improved prediction accuracy and generalization, showing potential for real-time operational integration. Furthermore, the framework is designed to support an interactive, web-based visualization platform to assist meteorologists and disaster management agencies in monitoring and forecasting cyclone behavior more effectively [2], [30].

## II. RELATED WORK

This section reviews advancements in machine learning (ML) and deep learning (DL) for tropical cyclone intensity forecasting. Recent studies primarily utilize 2D CNNs or numerical weather prediction (NWP) models, which inadequately capture complex spatiotemporal dynamics. While ConvLSTM models enhance temporal modeling, they lack comprehensive 3D spatial representation. Some research employing atmospheric reanalysis data has not effectively integrated 3D convolutions or attention mechanisms, and data preprocessing has often been inadequate, neglecting noise and imbalance. The proposed TAM-CL model addresses these limitations through 3D ConvLSTM, temporal attention, and robust preprocessing [23].

A transformer model for short-term cyclone track and intensity prediction in the Northwest Pacific employs multi-head self-attention for time-series analysis of critical parameters, introducing a novel preprocessing technique that enhances model accuracy. Compared to traditional models like GRU and LSTM, the transformer shows significant performance improvements, indicating its potential in cyclone forecasting applications [24].

This study highlights the role of CNNs in spatial analysis of satellite imagery, noting their limitations in adaptability and data demands. Vision Transformers (ViTs) effectively capture long-range dependencies and salient features, addressing challenges faced by conventional methods like the Dvorak technique [25].

Additionally, a sophisticated deep learning model using infrared satellite data estimates cyclonic wind speeds with an RMSE of 13.24 knots. A CNN-based framework for real-time cyclone intensity assessment is developed, supported by a visualization portal for ongoing monitoring. Validation against Dvorak imagery emphasizes the need for interdisciplinary collaboration among ML engineers, meteorologists, and UI designers for successful predictive technology deployment [26].

Lastly, TC-Pred is a novel neural framework for cyclone intensity prediction, integrating multi-source environmental variables. It employs convolutional operations with a sequence-to-sequence architecture, addressing long-term dependencies through a convolutional transformer-inspired module. Empirical evaluations show TC-Pred outperforms baseline models, setting a new benchmark for spatio-temporal deep learning methodologies in cyclone forecasting [27].

The ConvLSTM model forecasts cyclone trajectories and intensities by capturing temporal and spatial correlations among meteorological parameters. It outperforms traditional LSTM and statistical methods, including the Advanced Dvorak Technique (ADT) and ECMWF models, in predictive accuracy and computational efficiency, making it valuable for cyclone risk assessment and disaster preparedness [28]. Additionally, a hybrid model combining LSTM networks with Cuckoo Search Optimization (CSO) effectively predicts cyclone intensity in the Bay of Bengal using data from 2003-2019. Key meteorological parameters are integrated to enhance forecast accuracy, with the LSTM-CSO model demonstrating superior performance metrics (RMSE, MAE, AUROC) compared to traditional methods [29].

Moreover, a novel architecture merging CNN and ConvLSTM analyzes cyclone intensity from INSAT-3D infrared images, categorizing intensity per the India Meteorological Department classification. This model achieves 93.47% accuracy, surpassing standalone CNN and Bi-LSTM models, representing a pioneering application of deep learning in the Indian Ocean context [30].

Finally, a deep learning framework classifies tropical cyclone intensity into weak, moderate, and strong categories using infrared satellite imagery. The hybrid CNN-LSTM architecture excels in both spatial and temporal learning, highlighting deep learning's potential for real-time cyclone intensity classification and enhancing meteorological predictive capabilities [31].

### A. Analysis of Deep Learning Architectures from Prior Work

In previous investigations, a variety of deep learning architectures have been systematically examined for the estimation of cyclone intensity utilizing satellite imagery as a primary data source.

The AlexNet model, while historically significant as one of the first convolutional neural networks (CNNs), exhibited limitations in its ability to effectively capture the intricate and multifaceted features characteristic of cyclonic systems, primarily due to its relatively shallow architecture.

In contrast, DenseNet introduced an innovative approach through the implementation of dense connectivity, which facilitated enhanced gradient flow and more efficient featurereuse. However, this model was not without its drawbacks, as it resulted in elevated error rates in certain contexts.

The InceptionV3 architecture, with its multi-scale convolutional layers, provided a more comprehensive structural understanding of cyclones by enabling the model to process information at varying resolutions simultaneously.

Meanwhile, MobileNet was designed for lightweight efficiency, optimizing computational resources, albeit at the expense of fine-grained accuracy in feature extraction. The ResNet50 model, which employs residual connections to mitigate the vanishing gradient problem, and VGG16, characterized by its sequential arrangement of deep layers and utilization of small convolutional filters, demonstrated superior efficacy in extracting features that are specifically relevant to cyclone dynamics.

Among these models, VGG16 emerged as the most proficient, achieving performance metrics of Root Mean Squared Error (RMSE) of 19.34, Mean Squared Error (MSE) of 374, and Mean Absolute Error (MAE) of 24.23. These results indicate that VGG16 outperformed its counterparts in terms of precision and reliability for applications related to cyclone monitoring. To rigorously assess the performance of these models, several statistical metrics were employed, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). As summarized in Table I, VGG16 consistently exhibited the lowest error rates across these metrics, underscoring its effectiveness.

| Sr.No. | Algorithm | RMSE | MSE | MAE |
|---|---|---|---|---|
| 1 | Alex net | 22.93 | 525.14 | 28.73 |
| 2 | DenseNet | 31 | 961.00 | 38.84 |
| 3 | InceptionV3 | 61 | 3721.00 | 76.44 |
| 4 | Mobilenet | 61.96 | 3840.24 | 77.61 |
| 5 | Resnet50 | 58.66 | 3440.66 | 77.55 |
| 6 | Vgg16 | 19.34 | 374.00 | 24.23 |

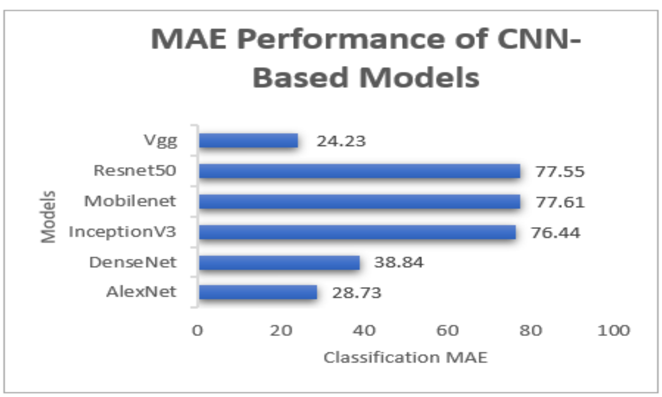



Fig 1 : Mean Absolute Error (MAE) Comparison

Of Deep Learning Models

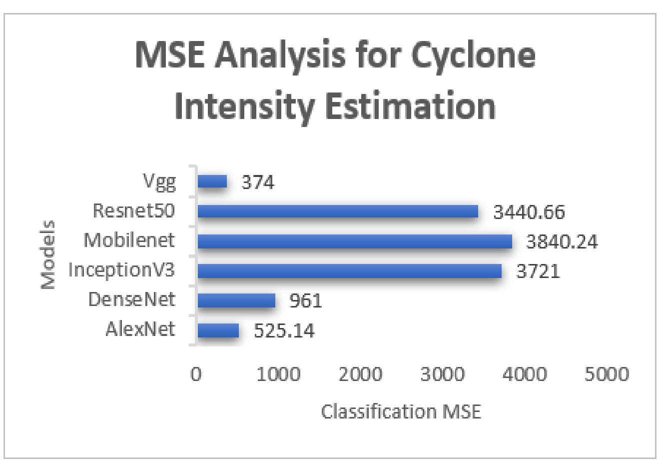



Fig 2 : Mean Squared Error (MSE) Analysis for Cyclone Intensity Estimation

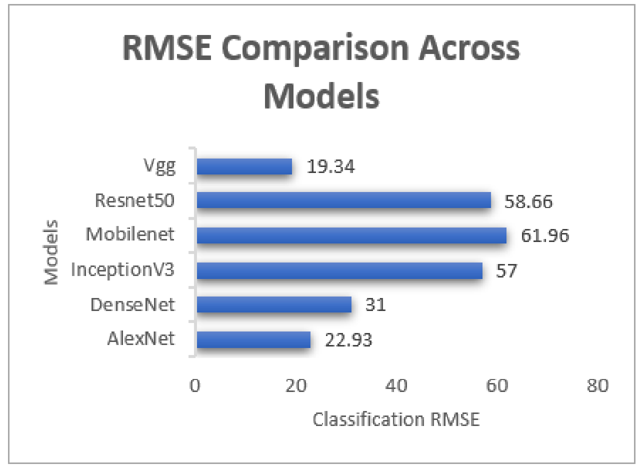



Fig 3 : Root Mean Squared Error (RMSE) Performance of Various CNN Models

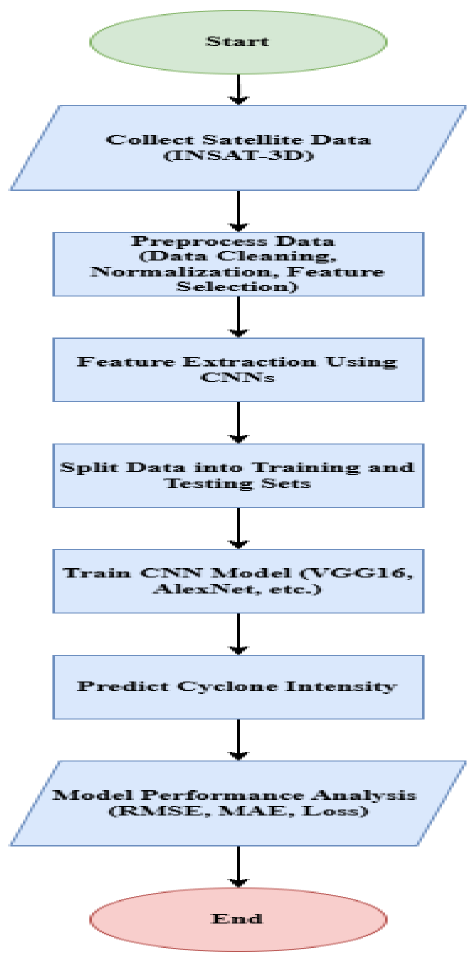



Fig 6: Proposed Methodology to Find Evolution Metrics value

TABLE I
Overview of Cyclone Intensity Estimation Methodologies and Gap finding

| SR.NO | TITLE | METHODOLOGY | DATASET | LIMITATIONS | GAP FINDING |
|---|---|---|---|---|---|
| 1 | Cyclone Intensity Estimation on INSAT 3D IR Imagery Using Deep Learning | CNN-based classification using TensorFlow/Keras. | INSAT-3D IR (2012–2021). | Limited resolution and image noise. | Lacks temporal modelling (e.g., LSTM). |
| 2 | Deep Learning Based Cyclone Intensity Estimation using INSAT-3D IR Imagery | CNN trained on IR images in 5 kt intervals. | INSAT-3D IR imagery with intensity labels. | No path prediction or temporal modelling. | Omits sequential modeling for dynamic changes. |
| 3 | A neural network framework for fine-grained tropical cyclone intensity prediction | Spatio-temporal model using transformer and feature aggregation. | Multi-source atmospheric, oceanic, precipitation data. | Poor fusion in prior methods, no fine-grained forecasts. | Enhances fine-scale prediction and data integration. |
| 4 | Transformer-based tropical cyclone track and intensity forecastin | Transformer with multi-head self-attention. | CMA data (1980–2021), 1257 TCs. | Assumes uniform data quality; sparse data. | Improves long-term dependency modeling. |
| 5 | Short-term prediction of the intensity and track of tropical cyclone via ConvLSTM model | ConvLSTM captures time and feature dependencies. | CMA, CIMSS, NOAA, ECMWF (1980–2021). | Cross-source data inconsistency. | Solves short-term and parameter correlation issues. |
| 6 | Tropical Cyclone Intensity and Track Prediction in the Bay of Bengal Using LSTM-CSO Method | LSTM optimized by Cat Swarm Optimization. | IBTrACS (2003–2019) with TC parameters. | Limited region and high computation cost. | Boosts speed and accuracy over traditional models. |
| 7 | Tropical cyclone trajectory based on satellite remote sensing prediction and time attention mechanism ConvLSTM model | ConvLSTM with time attention mechanism. | NCEP/NCAR, HURSAT-B1 (1949–2022). | Needs preprocessing; limited data. | Improves 3D and long-term forecasting. |
| 8 | Cyclone Intensity Estimation Using INSAT-3D IR Imagery | Combines image processing, CNN, RNN, and meteorological models. | INSAT-3D IR imagery. | Accuracy limited by satellite quality. | Aims for real-time high-precision estimates. |
| 9 | Tropical Cyclone Intensity Prediction Using DeepLearning Techniques- A Survey | Review of CNNs and Transformers for TC intensity. | Satellite imagery (clouds, temp, structure). | Needs large, balanced data; low interpretability. | Calls for interpretable, sequence-aware models. |

Table 1 shows the evolution of tropical cyclone intensity prediction from traditional CNN-based models to advanced deep learning techniques like LSTM, ConvLSTM, and Transformers. While early models using INSAT-3D IR imagery captured spatial features, they lacked temporal modeling and struggled with data imbalance and image noise. Recent approaches address these gaps through spatio-temporal learning, attention mechanisms, and multi-source data integration. However, limitations remain, such as high computational cost, limited interpretability, and inconsistency across datasets. Overall, the findings highlight the need for interpretable, sequence-aware, and real-time capable models to enhance cyclone intensity prediction accuracy and reliability.

## III. METHODOLOGY

### *A. Collection and Preprocessing of Datasets*

The dataset we are discussing covers the period from 2012 to 2021 and offers essential information about temperature distribution and cloud cover. This data is crucial for weather forecasting and predicting cyclones. It includes timestamped coordinates, which enable us to observe changes in weather patterns over time and across different location

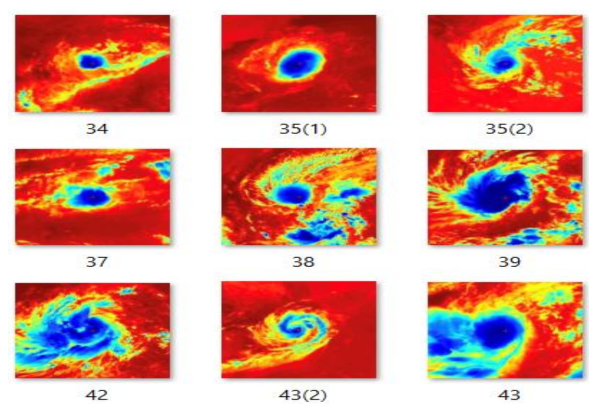


Fig 4: Insat3d IR Cyclone Images

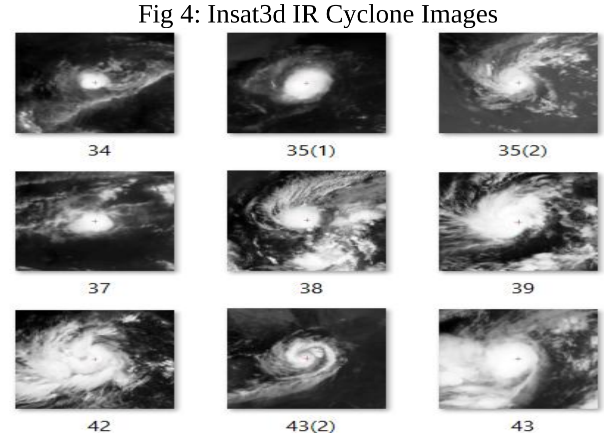


Fig 5: Insat3d Raw Cyclone Images

During the preprocessing phase, all images were resized to ensure they were uniform in size before being input into the Convolutional Neural Network (CNN). The dataset was then split into training and validation sets to enhance the model's performance and avoid overfitting. The INSAT 3D satellite is equipped with an infrared imager that captures detailed images of the Earth's surface and atmosphere. These images are vital for understanding temperature variations and cloud formations. They play a significant role in monitoring weather patterns, detecting severe weather events, and improving predictions of natural disasters, particularly cyclones in the Indian subcontinent and nearby regions. This dataset is regularly updated and is freely accessible through the ISRO Meteorological Data Archive, making it an invaluable resource for meteorologists, researchers, and policymakers.

*B. Proposed Model Architecture*

To improve the accuracy of estimating cyclone intensity from satellite imagery, we propose an advanced hybrid model. This model combines features extracted using a Vision Transformer (ViT) with carefully selected domain-specific features. This innovative approach blends deep learning and statistical techniques to capture both global context and local structural patterns found in cyclone imagery. The deep feature extraction component utilizes the ViT-base-patch16-224 architecture from the HuggingFace Transformers library. In this setup, we use the pooler_output, a compact 768-dimensional representation of the input image, as a feature embedding. To reduce the dimensionality of this output and eliminate redundant information, we apply Principal Component Analysis (PCA), ensuring that 95% of the original variance is preserved for a more efficient data representation. Simultaneously, we calculate seven handcrafted features from each satellite image, drawing on expert knowledge from meteorology and image analysis. The selected features include:

Cloud Anisotropy Index (CAI): This index measures the variability of cloud structure by comparing the standard deviation to the mean pixel intensity.

$$CAI=\sigma/\mu$$

Where,

$\sigma$ = Standard deviation of grayscale pixel intensities

$\mu$ = Mean of grayscale pixel intensities

Cloud Top Temperature Variance (CCTV): This feature quantifies the thermal characteristics of cloud tops by measuring the difference between the maximum and minimum pixel values.

$$CCTV=\max(I)-\min(I)$$

Where,

max(I) = Maximum pixel intensity

min(I) = Minimum pixel intensity

Optical Flow Magnitude: This feature captures the average motion of cloud patterns, using the Farneback algorithm to identify dynamic changes in cyclone formation.

Mean Intensity, Standard Deviation, and Maximum Intensity: These statistical measures provide insights into the overall brightness and variability of the cloud image. Symmetry Score: This metric assesses the structural symmetry by evaluating the average difference between the original image and its horizontally flipped version. The architecture of our proposed model consists of two parallel processing branches. The ViT branch processes its PCA-reduced features through a series of layers, including Dense(256), Dropout(0.3), and Batch Normalization, which enhance feature representation and mitigate overfitting. Meanwhile, the handcrafted feature branch undergoes a simpler transformation with Dense(64) and Dropout(0.2) to effectively utilize domain-specific knowledge. After both branches process their inputs independently, the outputs are concatenated and passed through a fusion network structured as Dense(128), Residual Add, and Dense(64). The model concludes with a single regression output from the final neuron, which quantitatively represents the intensity of the cyclone. This hybrid model effectively combines deep learning and domain expertise to provide a comprehensive approach to estimating cyclone intensity

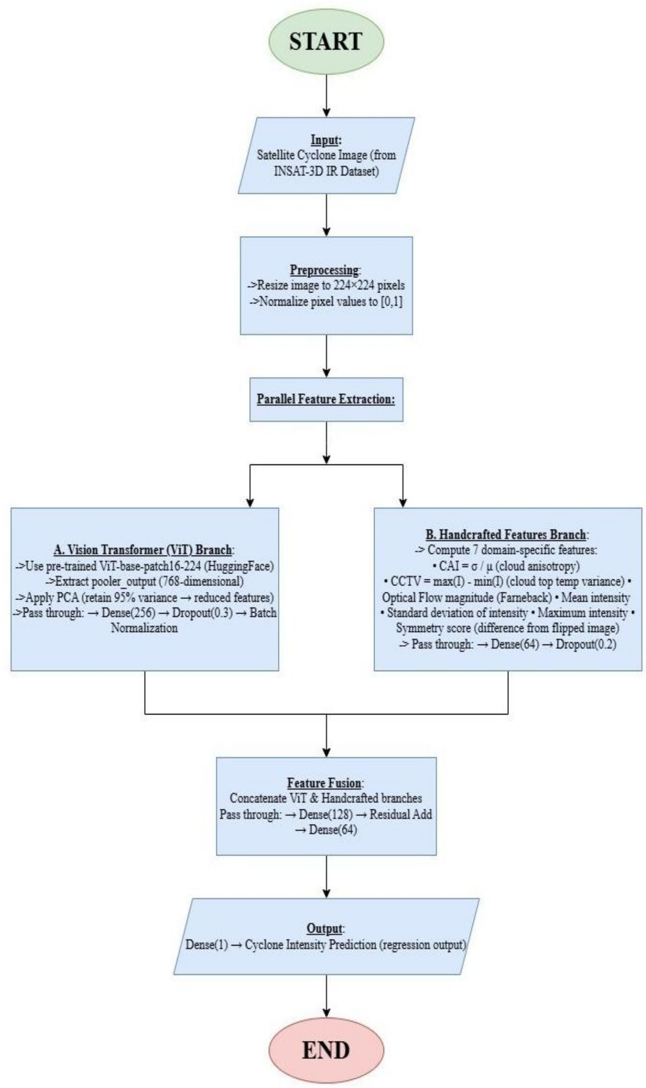



Fig 7: Proposed Methodology for Cyclone Intensity Prediction

*C. Model Training and Implementation*

We developed a hybrid model to predict cyclone intensity values using a method called regression. To achieve this, we employed the Huber loss function, which is effective in managing prediction errors while also being resistant to outliers. This is particularly important due to the natural variability found in real-world satellite data. For model training, we used the Adam optimizer with a learning rate set at 0.0001. To prevent the model from overfitting and to encourage adaptive learning, we implemented two strategies: 1. EarlyStopping: This stops training if the model's performance doesn't improve for 5 epochs. 2. ReduceLROnPlateau: This reduces the learning rate by a factor of 0.1 when the model's performance plateaus. The training process runs for 30 epochs with a batch size of 16, using an 80-20 split for training and testing datasets. Before training begins, we standardize the intensity labels using StandardScaler to ensure the regression target is normalized.

D. Web Interface for Model Deployment

To improve user interaction and visualize model predictions effectively, we created a web-based interface for real-time cyclone intensity estimation using React.js. This application allows users to upload satellite images of cyclones, which are then processed by a hybrid model based on Vision Transformer (ViT) technology running in the background. The interface is designed for ease of use, featuring a simple drag-and-drop upload option and a clearly labeled "Predict" button. Once an image is submitted, the system carries out several preprocessing steps to prepare the data for analysis. The processed image is then fed into the trained model, which provides a numerical estimate of cyclone intensity. This predicted intensity is displayed prominently on the user interface for easy visibility. Additionally, if the predicted intensity exceeds a certain high-risk threshold, the application will display a warning message to alert users about the potential severity of the cyclone, aiding in informed decision-making and risk assessment.

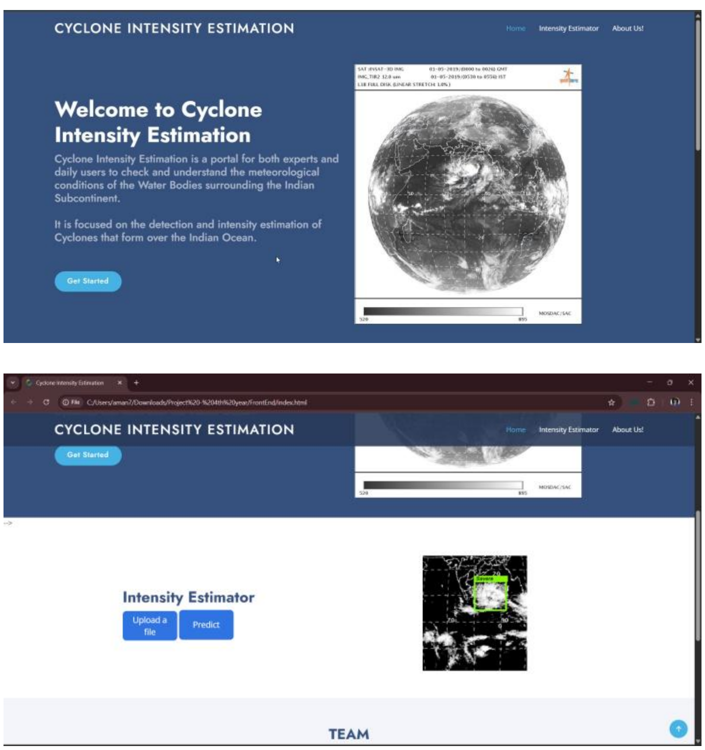



Fig 8 : Front Page of web interface

*D. Evaluation Metrics*

1.Mean Absolute Error:

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

Where,

MAE = mean absolute error

$y_i$ = prediction

$x_i$ = true value

n = total number of data points

2.Mean Squared Error:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \quad (2)$$

Where,

MSE = Mean Squared Error

n = number of observations in the dataset

$y_i$ = observed values

$y_i$ = predicted values

3.Root Mean Squared Error :

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \quad (3)$$

RMSE = Root Mean Squared Error

n = number of observations in the dataset

$yi$ = observed values

$\hat{yi}$ = predicted values

## E. *Performance Comparison*

To rigorously assess the efficacy of the proposed Vision Transformer (ViT)-based hybrid architecture for cyclone intensity estimation, we conducted a comparative analysis against a traditional convolutional neural network (CNN), specifically the VGG16 model, which had previously exhibited robust performance in our prior investigations. Both models were subjected to identical experimental conditions, utilizing the same dataset and evaluation metrics, thereby ensuring a fair and unbiased comparison. The evaluation focused on two primary regression metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

| **Model** | **RMSE** | **MAE** |
|---|---|---|
| VGG | 19.37 | 22.5037 |
| ViT | 19.67 | 17.8716 |

To thoroughly evaluate the effectiveness of our proposed Vision Transformer (ViT)-based hybrid architecture for estimating cyclone intensity, we compared it with a traditional convolutional neural network (CNN), specifically the VGG16 model, which has shown strong performance in our previous studies. We ensured a fair comparison by subjecting both models to the same experimental conditions, using the same dataset and evaluation metrics. Our evaluation focused on two key regression metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The MAE measures the average size of prediction errors, while the RMSE highlights larger errors due to its squared error component. The results, detailed in the table below, show that while the VGG16 model achieved a slightly lower RMSE, indicating better performance in handling extreme outliers, the ViT-based hybrid model had a significantly lower MAE, with a 27.7% reduction. This indicates that the ViT model provides more consistent and reliable predictions across the dataset, making it more effective for practical cyclone intensity forecasting. The improved MAE of the ViT model can be attributed to its ability to capture global contextual information through self-attention mechanisms, which are particularly effective at understanding the spatial complexities found in satellite imagery. Furthermore, the model benefits from the integration of handcrafted meteorological features—such as the Cloud Anisotropy Index (CAI), Cloud Top Temperature Variance (CCTV), optical flow, and symmetry metrics—which enhance its interpretive capabilities by incorporating domain-specific insights. Overall, these findings highlight the benefits of using a hybrid modeling approach that combines deep learning with expert-informed features. The ViT-based architecture not only surpasses traditional CNN models in prediction reliability but also sets a strong foundation for future advancements in estimating cyclone intensity from satellite imagery

## IV. RESULT

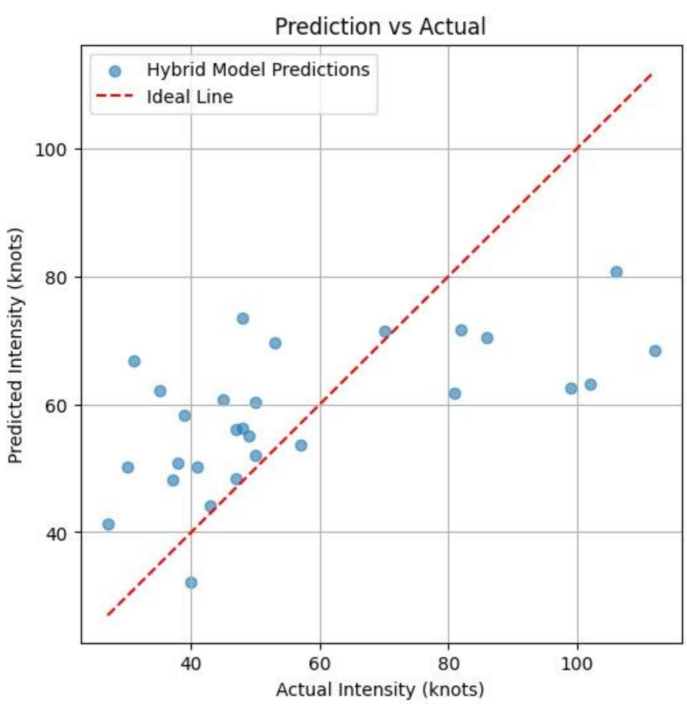
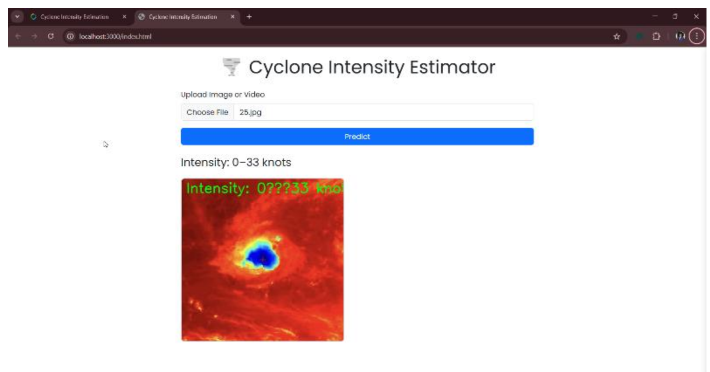
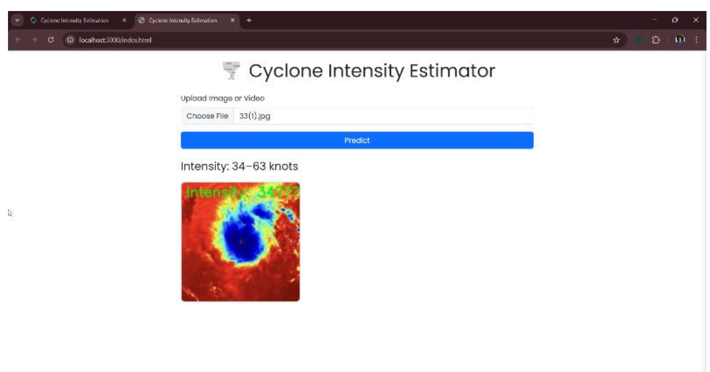



Fig 8: Scatter Plot of Predicted vs. Actual Cyclone Intensities

The presented graph delineates the relationship between the predicted cyclone intensities, represented on the y-axis, and the corresponding actual (true) intensities, depicted on the x-axis. In an ideal predictive model, one would anticipate the emergence of a perfect diagonal line characterized by the equation. This line signifies that the predicted values align precisely with the true intensity measurements, thereby indicating a model with optimal accuracy and reliability. Furthermore, the graph serves to elucidate the presence of outliers, which are data points that deviate significantly from the expected trend, potentially indicating anomalies in the prediction process or inherent variability in cyclone behavior. Additionally, the graphical representation provides insights into the distribution of errors across varying intensity levels, allowing for a comprehensive assessment of the model's performance across the spectrum of cyclone intensities. This analysis is crucial for understanding the limitations of the predictive model and for guiding future improvements in forecasting methodologies.




## V. CONCLUSION

To thoroughly assess how effective our new Vision Transformer (ViT)-based hybrid model is for estimating cyclone intensity, we compared it with a traditional convolutional neural network (CNN), specifically the VGG16 model, which has performed well in our previous research. We conducted the comparison under identical experimental conditions, using the same dataset and evaluation metrics to ensure fairness. Our evaluation centered on two important regression metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The MAE measures the average size of the prediction errors, while the RMSE emphasizes larger errors due to its squared nature. The results, summarized in the table below, indicate that while the VGG16 model achieved a slightly lower RMSE, suggesting it handles extreme outliers better, the ViT-based hybrid model demonstrated a much lower MAE, with a 27.7% reduction. This implies that the ViT model offers more consistent and reliable predictions across the dataset, making it more effective for practical cyclone intensity forecasting. The improved MAE of the ViT model can be attributed to its ability to capture global contextual information through self-attention mechanisms, which excel at understanding the spatial complexities in satellite images. Additionally, the model incorporates handcrafted meteorological features—like the Cloud Anisotropy Index (CAI), Cloud Top Temperature Variance (CCTV), optical flow, and symmetry metrics—which enhance its interpretative capabilities by integrating domain-specific insights. Overall, these findings underscore the advantages of using a hybrid modeling approach that combines deep learning with expert-informed features. The ViT-based architecture not only outperforms traditional CNN models in terms of prediction reliability but also lays a solid groundwork for future advancements in estimating cyclone intensity from satellite imagery.

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