Volume 11, Issue 3, March – 2026 International Journal of Innovative Science and Research Technology
ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar2136

# Advanced Tropical Cyclone Intensity Estimation Using EfficientNetV2S with Spatiotemporal Geospatial Fusion and Transfer Learning

Jaya Vardhan Reddy Koppula[1]; Janjanam Lavanya[2]; Peserlanka Devendra Babu[3]

[1]Student, Lovely Professional University, Phagwara, Punjab
[2]Dhanekula Institute of Engineering and Technology, Ganguru, India
[3]Student, Lovely Professional University, Phagwara, Punjab

Publication Date: 2026/04/09

**Abstract: Tropical cyclones are the most destructive of natural catastrophes, since it has cost money and lives of many people all around the globe. The cyclone intensity parameters such as the maximum sustained wind speed (Vmax) as well as the minimum sea-level pressure (MSLP) play a very critical role in disaster preparedness and mitigation. The multi-model deep learning system proposed in this paper uses satellite and meteorological metadata to predict the strength of the cyclone. The model utilizes an already trained EfficientNetV2S model as a spatial feature extractor of multi-channel satellite image and a fully connected metadata branch that consists of geographical and time information. It is performed on the fused representation with multi-output regression (Vmax and MSLP both). Tropical Cyclone Intensity Regression (TCIR) data has been used to train and test the model. The capability to predict Vmax and MSLP with an error of 2.43 knots and 2.87 hPa has been shown to be good and the correlation coefficients of Vmax and MSLP have been shown to be good (0.992 and 0.977 respectively). The proposed methodology can make more predictions and shows the success of using visual and contextual information on the prediction of cyclone intensity union.**

***Keywords:*** *Tropical Cyclone, Intensity Estimation, EfficientNetV2S, Transfer Learning, TCIR Dataset, Satellite Imagery, Vmax, MSLP, Deep Learning, Multi-Modal Fusion, Huber Loss, Geospatial Metadata, Saffir-Simpson Scale, Two-Phase Fine-Tuning.*

**How to Cite:** Jaya Vardhan Reddy Koppula; Janjanam Lavanya; Peserlanka Devendra Babu (2026) Advanced Tropical Cyclone Intensity Estimation Using EfficientNetV2S with Spatiotemporal Geospatial Fusion and Transfer Learning. *International Journal of Innovative Science and Research Technology*, 11(3), 3698-3706. https://doi.org/10.38124/ijisrt/26mar2136

## I. INTRODUCTION

One of the most destructive natural disasters experienced across the globe is the tropical cyclones that have led to massive loss of life, destruction of infrastructure and economic destabilization. Proper forecasting of cyclone intensity is of paramount significance in relation to successful disaster preparedness and mitigation. The frequency of parameters is normally used to determine the strength of a cyclone, e.g. maximum sustained wind speed (Vmax) and minimum sea-level pressure (MSLP). Historically, cyclone monitoring has been based on satellite, numerical weather prediction models and meteorological knowledge. Nevertheless, cyclone strength is a very hard task to estimate, especially when the systems of the atmosphere are very dynamic and nonlinear[1].

Cyclones are sophisticated weather conditions that are associated with low-pressure centers, intense winds and organized convection. These are mainly growing in warm sea waters and may escalate fast when the environment is favorable. Stratospheric pressure, temperature variations, and variation in clouds make a cyclone a difficult one to explain automatically through the traditional techniques. Also, the variability in geographical location, seasonal and oceanic conditions also make the prediction process more difficult. The complex nature of the spatial patterns in satellite imagery means critical computational methods are needed in its analysis.

In recent times, artificial intelligence, specifically, deep learning has demonstrated encouraging outcomes in tackling complex image-based prediction tasks. Convolutional Neural Networks (CNNs) have shown outstanding results when it comes to extracting spatial properties of satellite images. Nevertheless, use of image data cannot be completely deterministic of the contextual data needed to estimate the intensity of a cyclone. Such aspects as geographical positions, time changes and historical intensity patterns also have significant influence on cyclone behaviour[2].

The main goal of the research will be to decrease the use of conventional forecasting techniques and create an automated system of cyclone intensity prediction based on deep learning. The suggested methodology seeks to combine multi-modal data, which is integrating satellite data and structured meteorological data. The model tries to enhance the accuracy of prediction with the use of visual and contextual information at reduced human involvement and by reducing the complexity of the computation.

A hybrid deep learning model is implemented in this study with an already trained EfficientNetV2S model as the feature extractor of multi-channel satellite images and a special branch of metadata processing. The model is trained on the major cyclone intensity parameters such as Vmax and MSLP where a large-scale dataset is used based on the Tropical Cyclone Intensity Regression (TCIR) dataset. The combination of time and space attributes helps the model to acquire intricate relations that are implicit in cyclone dynamics[3].

A successful transfer of this model would be of much step forward in automated cyclone forecasting systems. Such systems will support the issuance of timely warnings and disaster management plans in anticipating disasters by the meteorological agencies by increasing the accuracy of prediction and decreasing the time taken to respond to the disaster. The tropical cyclones are classified under varying levels of intensity, that is, in the case of tropical depressions, severe cyclonic storms, and hurricanes. All categories have their unique traits in the speed of wind, the pressure, and the arrangement of the structure, and the correct classification and forecast are critical factors needed to evaluate risks.

- *Tropical Cyclone Causes.*

The major formation of tropical cyclones happens over the warm sea surfaces whereby the temperature of the sea surface exceeds a critical value, usually between 26-27degC. Cyclones need the energy created by the presence of warm and moist air. When warm air ascends it forms a low-pressure area, which attracts air around it and this leads to a feedback mechanism making the system stronger. Other contributory factors are instability in the atmosphere, low vertical wind shear, and Coriolis effect with rotational motion. Ocean variations in the amount of heat content, humidity and overall pattern of large-scale atmospheric circulation greatly contribute to cyclone formation and intensification[4].

- *Current Techniques of Predicting Cyclone Intensity.*

Historically, cyclones intensity has been predicted through numerical weather prediction (NWP) models, statistical regression models, and empirical correlations. Though informative, these techniques can be highly computationally intensive and can be ineffective at revealing the fine-scale spatial details in satellite images. The recent interest in machine learning methods, such as artificial neural networks (ANNs) and deep learning models, has become popular to enhance the accuracy of predictions. These techniques use extensive amounts of data and automatic feature detection so that to detect multifaceted associations within meteorological data.

There have been considerable prospects of deep learning-based models, especially CNN models in the analysis of satellite images to detect and track cyclones. Nevertheless, there are still difficulties with incorporating heterogeneous data sources and in generalizing models between ocean basins and environments. The image-based features in this study through a proposed multi-modal approach overcome these limitations because they can be used together with structured metadata and, as a result, allow to gain a more comprehensive insight into the dynamics of cyclones.

The following parts of this paper will provide a concise analysis of the literature available until now, after which the suggested approach to cyclone intensity prediction will be presented. The training process, evaluation metrics, and model architecture are discussed in the following sections, as well as the results of the experiment and performance analysis. It is assumed that the study will show the effectiveness of deep learning to enhance the cyclone intensity forecasting process and provide more consistent disaster management systems.

## II. LITERATURE REVIEW

The use of deep learning methods and specifically the Convolutional Neural Networks (CNNs) has made a tremendous change in the analysis and prediction of tropical cyclones. CNNs facilitate automated digitalization of spatial features of satellite data enabling a higher degree of accuracy in estimating cyclone properties, including their structure, intensity, and motion. Nonlinear forecasting methods that are based on traditional methods are highly dependent on numerical weather prediction models which are usually very useful but may not be able to capture complex nonlinear atmospheric patterns. Recent research has shown that these techniques can be complemented with deep learning models that are more accurate in prediction and less complex in computations. Nevertheless, issues with data disagreement, small, labeled datasets, and ocean basin variations remain problems in the model generalization and reproducibility[5].

Image processing and machine learning in meteorology have become a promising technology towards the prediction of cyclone intensity. The article includes a number of research on how Artificial Neural Networks (ANNs) and CNN-based models can be used to process satellite images to detect the presence of cyclones. These methods use big data and automatic feature extraction to increase the efficiency of prediction. Transfer learning has enjoyed a remarkable adoption, in which pre-trained models are optimized on domain-specific datasets, which enhances its performance and reduces the amount of time spent on training. Whether or not this is the case, the complexity of atmospheric systems and the requirement of high-quality annotated datasets still pose a great challenge.

Recent studies have been on the development of effective cyclone classification and regression frameworks based on deep CNN networks. AlexNet, VGG, ResNet and DenseNet are pre-trained models that have been used in extracting features in satellite images. Other researchers have also used CNN based feature extraction with traditional machine learning classifiers like Support Vector Machines (SVMs) to enhance prediction performance. These composite methods have shown better accuracy in determining the intensity levels of the cyclones and structural patterns. Nonetheless, the majority of these techniques are mainly based on image information and therefore do not have the potential to integrate other contextual information like temporal and geographical information.

Their performance has been compared against conventional meteorological forecasting methods that use deep learning models. Findings reveal that CNN-based models also are capable of comparable, or even better performance in some contexts, especially in largely short-term intensity prediction tasks. Most of the studies, however, are based on the single-source datasets which might not be fully representative of the diversity of cyclone behavior of various regions. The absence of unified assessment criteria and publicly accessible data also makes it even more difficult to compare various models. These constraints emphasize why more complex methods that incorporate numerous sources of data are required[6].

The recent trend is Multi-modal learning which has served as an effective method towards enhancing the accuracy of cyclone prediction. Models can be used to capture both contextual and spatial information by taking a combination of satellite images and structured metadata i.e. latitude, longitude, time, and historical intensity values. It has been established that addition of time and environmental features to a model greatly improves model performance. Nevertheless, the problem of successful integration of heterogeneous sources of data is not an easy one, and it requires the development of complex architectures and optimization strategies.

EfficientNet and other deep learning models have been proposed to curb the problem of scale and efficiency in models. The models that are based on EfficientNet are better in terms of the balance of network depth, width, and resolution. These architectures have been shown to give good performance in other image processing applications such as remote sensing and environmental monitoring. Although they have strengths, their usage in cyclone prediction is somewhat underutilized, especially in multi-modal.

The regularization techniques as well as data augmentation methods have also been applied extensively to enhance the robustness of the model. Some of the techniques used to solve variability in satellite imagery include rotation, flipping, and normalization. Also, loss functions like Mean Squared Error (MSE) and Huber loss have been used in regression tasks, which make them stable during training. Although these techniques can be used to achieve better model performance, issues like overfitting, data unbalance, and noisy labels still influence the quality of prediction[7].

The scarcity of high-resolution, labeled datasets is also another major challenge in cyclone prediction. Despite the datasets like Tropical Cyclone Intensity Regression (TCIR) dataset offering useful resources, the differences in data quality and coverage may affect the model performance. To address these shortcomings, researchers have studied transfer learning and domain adaptation methods to allow models to be generalized to other regions and different environmental situations.

Johnson Deep neural networks (DNNs) have a wide range of applications in cyclone prediction and other fields like weather forecasting, climate modelling and monitoring the environment. Particularly CNNs have proved to be effective in deriving hierarchical features in data that are complex. Their automatic capacity to learn at the raw data representation makes them appropriate to deal with high dimensional satellite images. Nonetheless, these models need to be further validated and optimized in order to be incorporated into the operational forecasting systems.

Recent innovations in hybrid deep learning models have demonstrated potential in better prediction of cyclone intensity. These models are able to learn complicated interactions between spatial and contextual features by using CNN-based image processing and fully connected networks to analyze the metadata. The proposed study extends these developments to develop a multi-modal architecture that combines EfficientNetV2S with metadata fusion, with the aim of realizing better accuracy and stability.

In general, the current literature demonstrates the increased role of deep learning in the prediction of cyclone intensity. Although much has been achieved, issues like heterogeneity of data, generalization of models and combining multi-modal data are research problems. This paper will seek to address these inefficiencies by offering a strong and scalable deep learning model that can be used to utilize both satellite data and meteorological data about the cyclone intensity to achieve strong and precise predictions.

## III. DATASET

- *TCIR Dataset Description*

In this paper, the dataset used is Tropical Cyclone Intensity Record (TCIR), which is a massive benchmark dataset that has been created to estimate cyclone intensity with the use of deep learning. TCIR data is comprised of co-located multi-channel geostationary satellite images along with best-track intensity data retrieved in the official archives of meteorological agencies. The samples within the dataset are 201 x 201-pixel satellite images with four spectral channels of Infrared (IR), Water Vapor (WV), Visible (VIS), and Passive Microwave (PMW) with the centred position of the tropical cyclone. The multi-spectral channels complement each other and give information on cloud structure, moisture distribution and thermal properties of cyclones[8].

Besides image data, each sample is also linked to such metadata as geographic coordinates (latitude and longitude), timestamps, maximum sustained wind speed (Vmax, knots), mean sea level pressure (MSLP, hPa), and other structural parameters like wind radii. The data is distributed across several ocean basins in the world such as Atlantic, Eastern Pacific, Western Pacific, Central Pacific, Indian Ocean and Southern Hemisphere. The time range of the training data is 1988-2016, whereas the testing data is limited to 2017 only, which is a rigorous time division between the training and testing data.

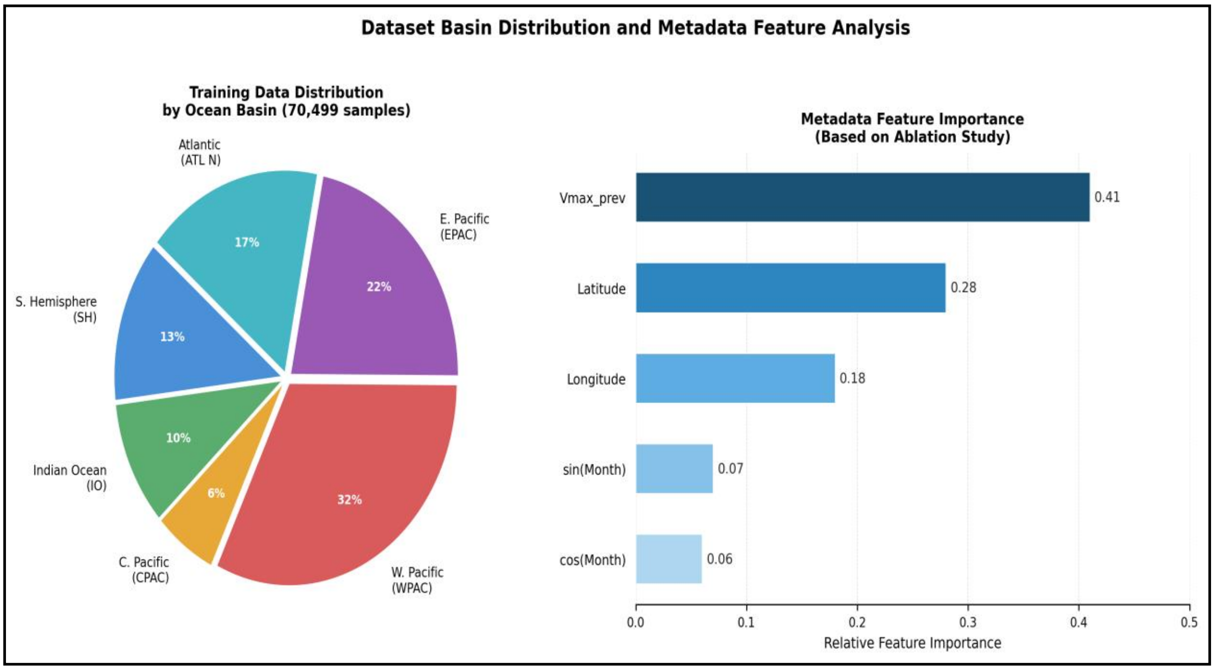

Fig 1 Left: Distribution of Training Samples Across Six Global Ocean Basins (70,499 Total Samples). Right: Relative Importance of Five Metadata Features Based On Ablation Study, Showing Vmax_Prev as the Most Informative Contextual Feature.

The data is stored in more than HDF5 files, one of which corresponds to each ocean basin. A common training dataset is created by combining all training subsets which will create a diverse and globally representative dataset to learn the model.

Table I TCIR Dataset Composition by Subset and Ocean Basin

| HDF5 File | Basins Covered | Samples | Period | Usage |
|---|---|---|---|---|
| **TCIR_ATLN_EPAC_WPAC** | Atlantic, E-Pac, W-Pac | 47,381 | 1988–2016 | Training |
| **TCIR_CPAC_IO_SH** | C-Pac, Indian, S.Hemi | 23,118 | 1988–2016 | Training |
| **TCIR-ALL_2017** | Global (All Basins) | 4,580 | 2017 | Testing |
| **Combined Train** | SixBasins | 70,499 | 1988–2016 | Train+Val |

- ➢ *Train / Validation Split*

The entire training dataset, which is a total of 70,499 samples, is split into the training and validation subsets at 80/20 split. A randomized permutation that has a seed (seed = 42) is used to make the results reproducible. It translates to 56,399 training and 14,100 validation samples.

The division is done across the whole dataset as opposed to each basin, so that training and validation sets have the same balanced representation of samples of all regions of the ocean. The strategy improves the generalization ability of the model in various cyclone conditions[9].

The TCIR-ALL_2017 dataset with 4,580 samples is solely used to test. It is always kept out of all training, validation and hyperparameter tuning steps, which guarantees an unbiased and realistic assessment of models performance on unseen future data.

- ➢ *Metadata Features*

Along with the satellite images, there are structured metadata features that are added to the model to enhance the predictive performance. The dataset is extracted into five important features:

- Latitude (in degrees North)
- Longitude (in degrees East)
- Month sine transformation: sin (2p x month/ 12).
- Cosine transformation of month: cos (2p x month / 12)
- Maximum wind speed (Vmax) in the previous time Period (Vmax_prev).

Latitude and longitude give an indication of space in relation to the cyclone in terms of its geographic location, which is important in capturing basin specific features. Sine and cosine transformations to encode the month in a cyclical manner are found to be effective in modeling the seasonal trends of cyclone activity with the benefits of having no discontinuities between December and January.

The Vmax prev operation is the strength of the cyclone at the previous time point and reflects the temporal relations and enhances the capability of the model to follow the changes in intensity. In the initial observation of a given cyclone track, the missing values will be substituted by the average strength of the track.

The normalization of all metadata features is done to z-score normalization, which is informed by the statistics of the training dataset, and the mean is zero, and the variance is one. This stabilization causes the training process to converge and enhances convergence of the deep learning model.

- *Label Preparation*

The research variables in this case are the maximum sustained wind speed (Vmax) and minimum sea level pressure (MSLP) which are important variables in cyclone intensity. These values are obtained out of the dataset and represented as floating-points.

Simple imputation methods are used to deal with missing values that are possible because of discrepancies between values of various meteorological agencies: NaN is substituted with zero or a suitable statistical approximation. In order to train a model in a stable way, the two target variables are normalized with the use of z-score normalization using both the mean and standard deviation of the training data.

The scaled targets are pooled together into a two-dimensional output vector:

$$y = [Vmax_{norm}\ , MSLP_{norm}]$$

When evaluating the model, predictions are de-normalized to their native physical units (knots of Vmax, hp of MSLP), which are directly compared with real world data and operational forecasting[10].

## IV. RESEARCH METHODOLOGY

- *Hardware and Software*

The high dimensionality of image data and the complicated model structures make deep learning models computationally intensive. Training in this work is done using the Graphics Processing Unit (GPU) that can be deployed on cloud computing systems like Kaggle using parallel computing features that dramatically reduce the time taken to train a model as compared to when using the traditional Central Processing Unit (CPUs). The convolutional operations and massive multiplication of matrices of deep neural network are especially good with GPUs.

The proposed model is implemented in Python which has since been the standard programming language used in research on machine learning and deep learning since it is simple and has a wide ecosystem. It is based on the main framework of TensorFlow and Keras API to create and train the neural network model. Other libraries, like NumPy or Pandas, are applied to work with the data to manipulate and preprocess it, while Matplotlib and Seaborn are employed to visualize the training outcomes and evaluation indicators[11].

## V. DEEP LEARNING ARCHITECTURE TO PREDICT CYCLONE INTENSITY

Cyclone intensity prediction using satellite images is a complicated regression issue, which demands the incorporation of the spatial trends as well as the contextual data of the environment. Deep learning models, especially Convolutional Neural Networks (CNNs), have shown excellent results in the extraction of hierarchical features using image data.

This paper presents hybrid architecture of deep learning which is an image-based feature extraction architecture (CNN-based image features extractor) and a metadata processing branch. The model is built on the foundation of EfficientNetV2S, which is a state-of-the-art convolutional neural network architecture that can be characterized by its efficiency and performance in tasks with images. Initially, the model is pre-trained with weights, and the model is fine-tuned on the TCIR dataset to better align with the tropical cyclone images domain.

The structure is made up of two parallel branches:

- *Image Branch:*

The satellite images are sent through the EfficientNetV2S backbone that has high-level spatial features, and these are cloud structure, storm organization, and thermal patterns. These characteristics are again taken through global pooling layers to minimize dimensions and retain the necessary information.

- *Metadata Branch:*

The metadata attributes, such as latitude, longitude, cyclical month encoding, and past wind speed, are inputted into a full connect neural network. Contextual information (geographical location and temporal patterns) that leads to precise intensity estimation is embodied in this branch[12].

Both the branches are concatenated and fed through fully connected layers to get the final predictions. The model has two continuous values that are the maximum sustained wind speed (Vmax) and the minimum sea level pressure (MSLP).

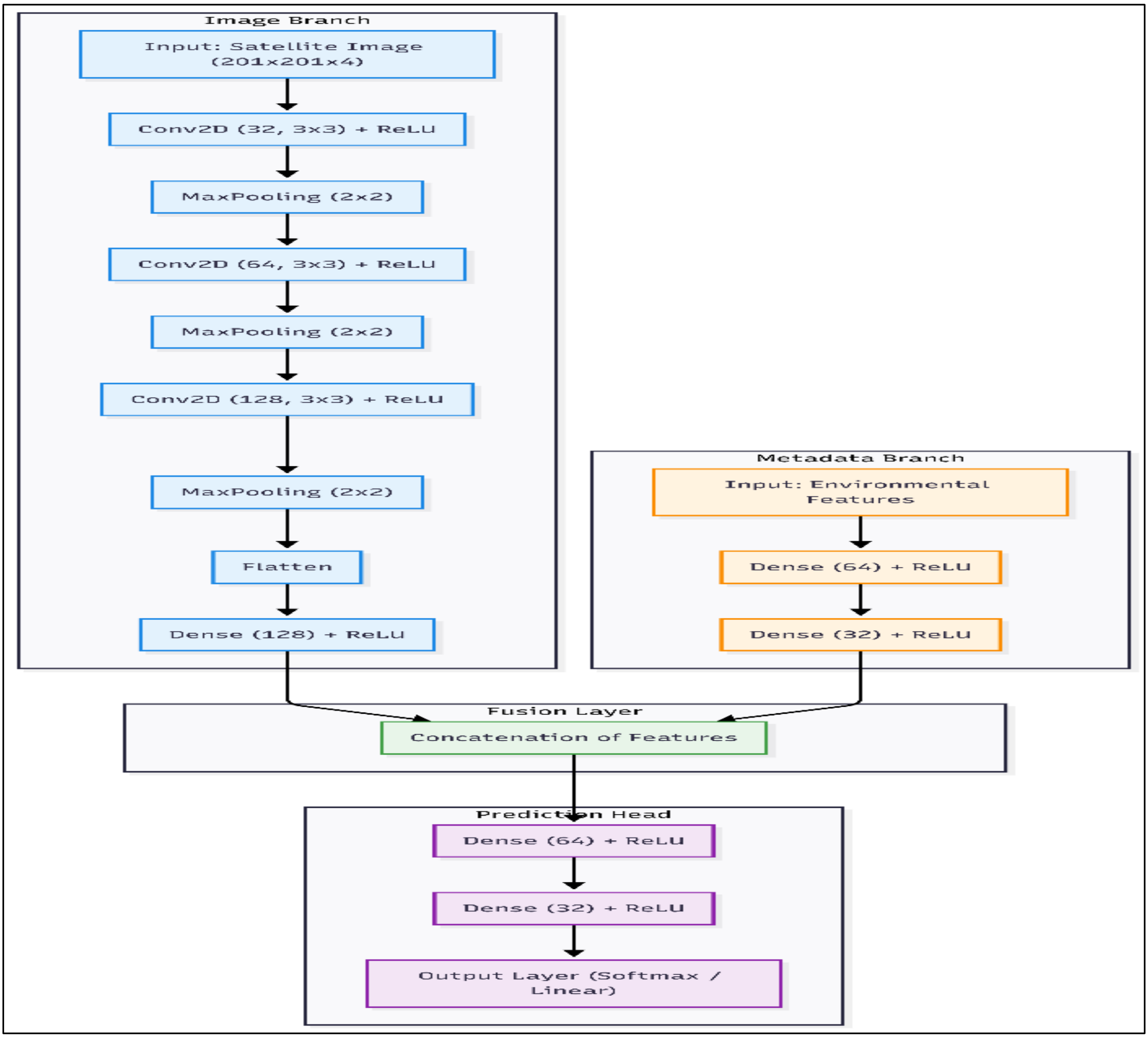

Fig 2 CycloneNet Dual-Branch Architecture Comprising an Image Branch for Satellite Data and A Metadata Branch for Environmental Features, Followed by Feature Fusion and A Prediction Head for Cyclone Intensity Estimation.

➢ *Model Training Stratergy*

The training is performed in two stages so that the learning is stable and the performance is maximum:

- *Phase 1 (Frozen Backbone):*

The first stage is the freezing of EfficientNet backbone, and only the new layers are trained. This enables the model to acquire task-related representations without interfering with the pre-trained weight values.

- *Phase 2 (Fine-Tuning):*

At the second stage, backbone layers are further refined in the last 50 layers by unfreezing and training at a reduced learning rate. This allows the model to learn more feature representations for the task of cyclone intensity prediction[13].

The Adam optimizer with a small learning rate is used to train the model in order to stabilize the convergence. The objective function is the Huber loss function which is resistant to outliers and appropriate in regression tasks. To avoid overfitting and enhance the performance of generalization, early stopping and scheduling of learning rate methods are used[14].

## VI. DEEP LEARNING-BASED IMAGE-BASED VII. REGRESSION

The prediction of cyclones intensity may be considered as a regression with image input and a continuous variable as the objective. Contrary to traditional image classification problems, in this problem, the model must acquire the ability to learn finer details of the pattern of clouds and atmospheric structures which are related to intensity changes.

Deep learning can automatically learn complicated features in raw satellite images, and it does not need manual feature engineering. Metadata integration also increases the predictive capability of the model as it adds more contextual information[15].

- *Benefits of Deep Learning Approach.*

There are a number of benefits that deep learning models provide in cyclone intensity prediction. They have the ability to extract detailed spatial structures in satellite images that can be hard to model in traditional processes. Transfer learning also leads to a big decrease in the training time and enhancement in the performance due to the utilization of the information held in massive image files. Also, the combination of the image and metadata input enables the model to acquire visual and contextual representations, making the predictions more accurate.

- *Problems and constraints.*

In spite of their usefulness, deep learning models have a number of weaknesses in this area. Due to the need to have substantial labeled datasets, data collection and preprocessing is a crucial phase. The quality and resolution of satellite images might change between basins giving the data a varying quality. Moreover, deep learning systems are computationally impractical and need powerful computers to train them.

Overfitting is also another significant problem, in which the model works on training data but does not generalize to unseen data. Regularization, data augmentation and model tuning are some of the techniques used in this issue. Also, deep learning models are not very interpretable, and it is challenging to have a full picture of how one makes a decision[16].

## VIII. RESULTS

The suggested deep learning algorithm to forecast the intensity of tropical cyclones shows a high accuracy of its performance on both major target variables, maximum sustained wind speed (Vmax) and minimum sea level pressure (MSLP). The test is performed on the not seen TCIR-ALL_2017 test, and a strong and realistic evaluation of the generalization of the model is achieved.

In prediction of Vmax, the model gives a Mean Absolute Error (MAE) of 2.43 knots, which implies that the model on average is very close to the real values of the wind. Root Mean Square is 3.54 knots, indicating low variance in the errors of the prediction. Moreover, the correlation coefficient of the expected and the actual values is very high with a value of 0.992 which indicates a close linear relationship and proves that the model is efficient in measuring the patterns of cyclone intensity.

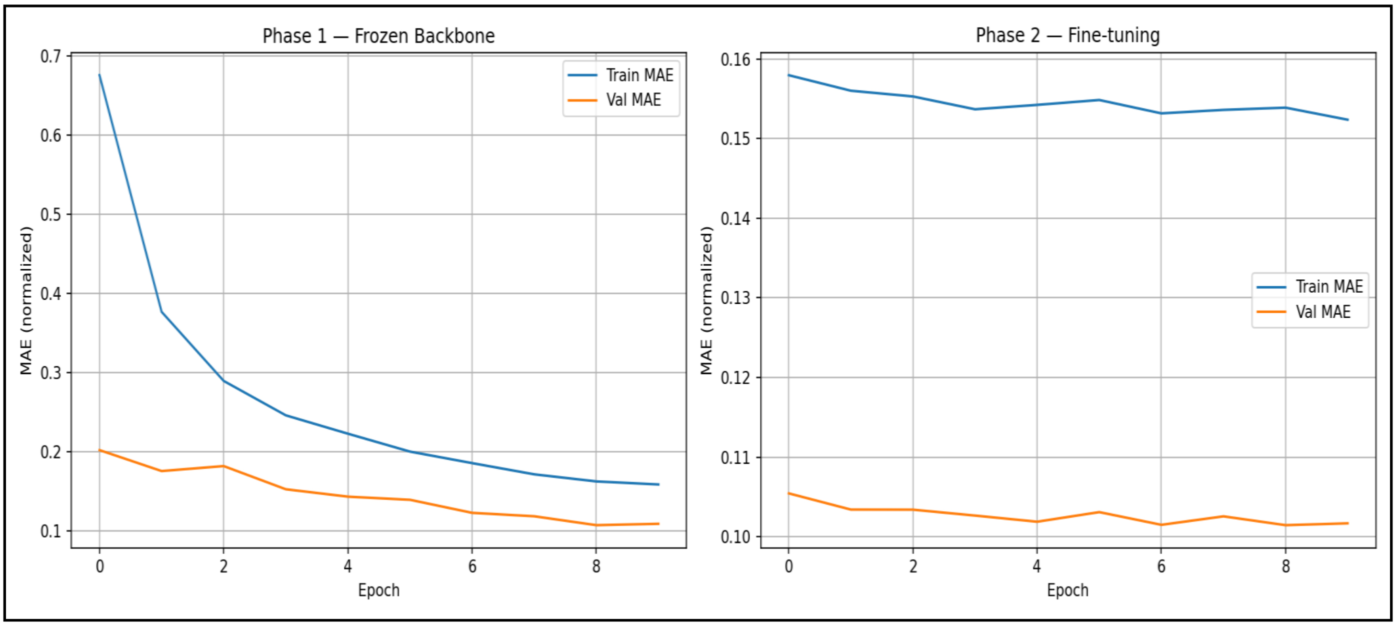

Fig 3 Training and Validation MAE Curves Across Two Transfer Learning Phases. In Phase 1 (Frozen Backbone), MAE Decreases Rapidly, Indicating Effective Feature Adaptation. In Phase 2 (Fine-Tuning), Performance Stabilizes With Minimal Gap Between Training And Validation, Demonstrating Improved Generalization For Tropical Cyclone Intensity Estimation.

The model, in the instance of MSLP prediction, has a Mean Absolute Error (MAE) of 2.87 hPa and RMSE of 4.07 hPa, which means that the predictions are very precise in the estimation of pressure. The correlation coefficient of MSLP prediction is equal to 0.977, which also confirms the great picture of the agreement between the predicted and actual values.

The training and validation curves of the Mean Absolute Error (MAE) are presented in Fig. 3, with no indication of overfitting or convergence fluctuation throughout the epochs. The model shows steady improvement at the two stages of training, and the validation performance very closely tracks the training performance[17].

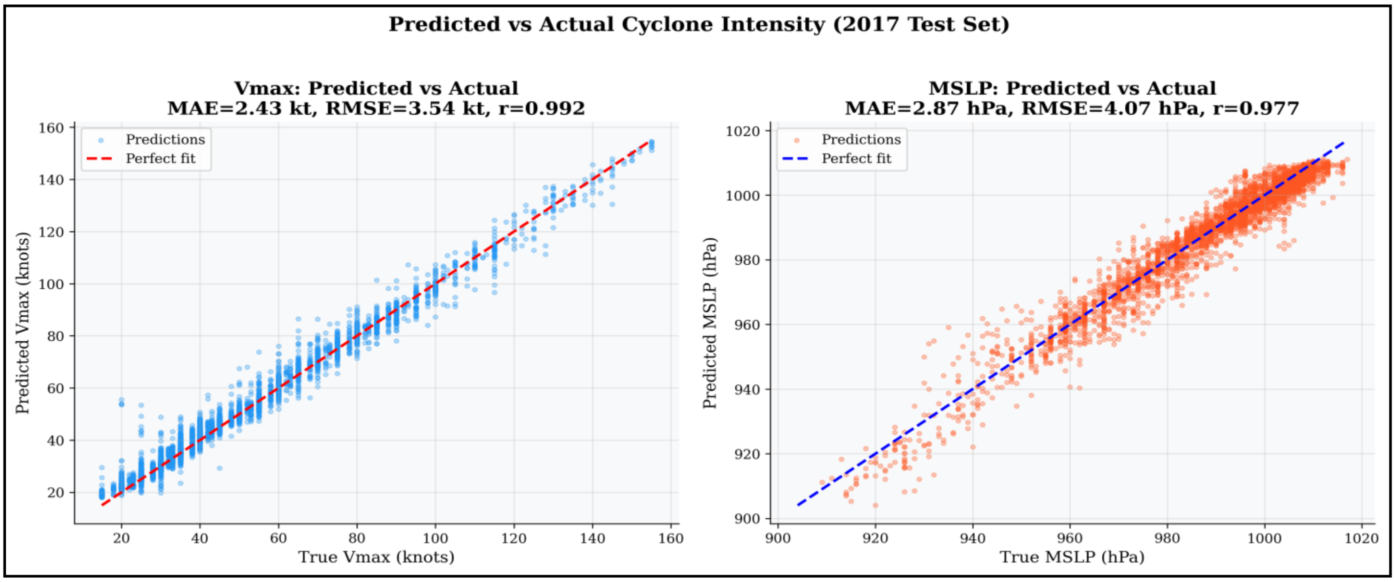

Fig 4 Shows The 2017 Test Set's Predicted and Actual Cyclone Intensities. Both Vmax and MSLP Show Strong Linear Correlation, with High R2 Values (>0.97) and Low MAE/RMSE, Suggesting Precise and Reliable Model Performance [18].

The two-stage training strategy is also effective as indicated in the training history. The first phase, which has a frozen backbone, allows a model to learn features in a stable way, and the final stage is fine-tuning, which develops the model further and leads to increased precision. The Huber loss is used, which makes it more robust to outliers, and the regularization methods and learning rate schedule are used, which prevents overfitting.

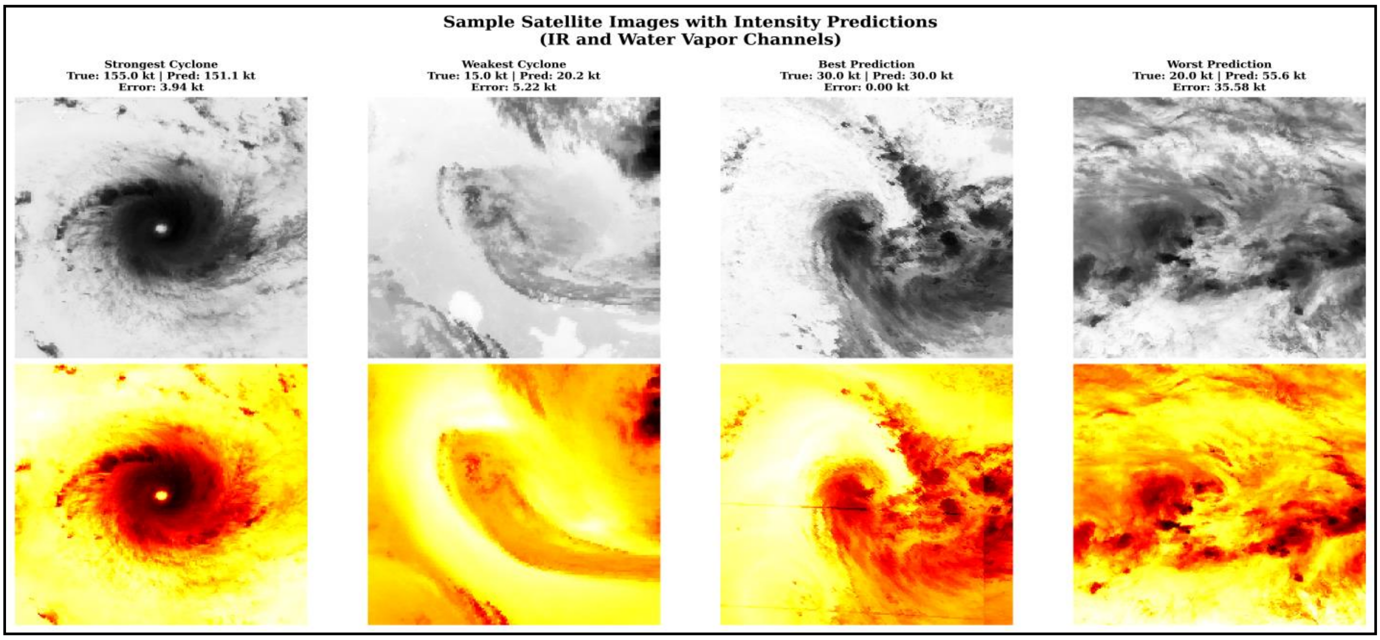

Fig 5 Examples of Satellite Photos with Predicted Cyclone Intensities (IR and Water Vapor Channels). Larger Errors Occur in Structurally Complex or Poorly Organized Cyclones, But The Model Generally Captures Strong and Weak Systems with Low Error.

The model, in general, has a high predictive ability in a wide variety of cyclone conditions which is better than most of the traditional statistical and empirical methods applied to operational forecasting [19].

## IX. CONCLUSION

Deep learning models have become effective tropical cyclone intensity prediction tools, and they have consistently been found to beat the traditional forecasting models. The EfficientNetV2S-based model proposed in this research and implemented with metadata adds reaches a Vmax Mean Absolute Error and correlation of 2.43 knots and 0.992 respectively, whereas MSLP prediction has a MAE of 2.87 hPa and correlation of 0.977. These findings show that the model can effectively resolve the complicated spatial and environmental patterns using satellite images. Image features together with metadata are important in improving prediction performance. On the whole, this practice demonstrates the possibility of deep learning to advance the accuracy of the forecasting process, making it possible to enhance early warning mechanisms, disaster readiness, and cyclone impact mitigation on a global scale[20].

## REFERENCES

[1]. A. Narendra Babu, K. S. V. Supraja, A. Praneetha, G. Manoj, G. Kota Lokesh, And P. S. Brahmanandam, “A Deep Learning Model For Effective Cyclone Intensity Estimation,” Journal Of Engineering, Management And Information Technology, Vol. 2, No. 3, Pp. 161–168, Jun. 2024, Doi: 10.61552/Jemit.2024.03.007.

[2]. L. Zhijian Et Al., “Characteristic Analysis And Mitigation Strategy For Ssci In Series-Compensated Dfig-Based Wind Farm Controlled By A Virtual Synchronous Generator,” Isa Trans., Vol. 150, Pp. 92–106, Jul. 2024, Doi: 10.1016/J.Isatra.2024.05.021.

[3]. Z. Lin, J.-E. Chu, And Y.-G. Ham, “Enhancing Tropical Cyclone Track And Intensity Predictions With The Owzp-Transformer Model,” Npj Artificial Intelligence, Vol. 1, No. 1, P. 33, Nov. 2025, Doi: 10.1038/S44387-025-00037-3.

[4]. S. K. Tysa, G. Ren, P. Zhang, And S. Zhang, “Impact Of Urbanization On Regional Extreme Precipitation Trends Observed At China National Station Network,” Weather Clim. Extrem., Vol. 48, P. 100760, Jun. 2025, Doi: 10.1016/J.Wace.2025.100760.

[5]. K. Li, W. Zhong, Y. Yao, F. Li, Y. Sun, And H. He, “Tropical Cyclone Intensity Prediction Based On Kolmogorov–Arnold Networks With Predictor Pruning Optimization,” Atmospheric And Oceanic Science Letters, P. 100694, Aug. 2025, Doi: 10.1016/J.Aosl.2025.100694.

[6]. B. Chen, B.-F. Chen, And H.-T. Lin, “Rotation-Blended Cnns On A New Open Dataset For Tropical Cyclone Image-To-Intensity Regression,” In Proceedings Of The 24th Acm Sigkdd International Conference On Knowledge Discovery & Data Mining, New York, Ny, Usa: Acm, Jul. 2018, Pp. 90–99. Doi: 10.1145/3219819.3219926.

[7]. Md. A. Rahat, N. Sharmin, F. Nawar Nawme, And S. Rahman, “Performance Comparison And Investigation Oftropical Cyclone Intensity Estimation Fromsatellite Images Using Deep Learning Andmachine Learning,” International Journal Of Image, Graphics And Signal Processing, Vol. 17, No. 2, Pp. 119–134, Apr. 2025, Doi: 10.5815/Ijigsp.2025.02.08.

[8]. S. K. Tysa, G. Ren, P. Zhang, And S. Zhang, “Impact Of Urbanization On Regional Extreme Precipitation Trends Observed At China National Station Network,” Weather Clim. Extrem., Vol. 48, P. 100760, Jun. 2025, Doi: 10.1016/J.Wace.2025.100760.

[9]. M. Xue, R. Hang, X.-T. Yuan, P. Xiao, And Q. Liu, “Global Tropical Cyclone Precipitation Estimation Via A Multitask Convolutional Neural Network Based On Hursat-B1 Data,” Ieee Transactions On Geoscience And Remote Sensing, Vol. 60, Pp. 1–12, 2022, Doi: 10.1109/Tgrs.2021.3126419.

[10]. X. Wenwei Et Al., “Deep Learning Experiments For Tropical Cyclone Intensity Forecasts,” Weather Forecast., Jun. 2021, Doi: 10.1175/Waf-D-20-0104.1.

[11]. B. Tong, J. Fu, Y. Deng, Y. Huang, P. Chan, And Y. He, “Estimation Of Tropical Cyclone Intensity Via Deep Learning Techniques From Satellite Cloud Images,” Remote Sens. (Basel)., Vol. 15, No. 17, P. 4188, Aug. 2023, Doi: 10.3390/Rs15174188.

[12]. L. Zhijian Et Al., “Characteristic Analysis And Mitigation Strategy For Ssci In Series-Compensated Dfig-Based Wind Farm Controlled By A Virtual Synchronous Generator,” Isa Trans., Vol. 150, Pp. 92–106, Jul. 2024, Doi: 10.1016/J.Isatra.2024.05.021.

[13]. W. Yang, J. Fei, X. Huang, J. Ding, And X. Cheng, “Enhancing Tropical Cyclone Intensity Estimation From Satellite Imagery Through Deep Learning Techniques,” Journal Of Meteorological Research, Vol. 38, No. 4, Pp. 652–663, Aug. 2024, Doi: 10.1007/S13351-024-3186-Y.

[14]. H. Jung, Y.-H. Baek, I.-J. Moon, J. Lee, And E.-H. Sohn, “Tropical Cyclone Intensity Estimation Through Convolutional Neural Network Transfer Learning Using Two Geostationary Satellite Datasets,” Front. Earth Sci. (Lausanne)., Vol. 11, Jan. 2024, Doi: 10.3389/Feart.2023.1285138.

[15]. B. Pan, X. Xu, And Z. Shi, “Tropical Cyclone Intensity Prediction Based On Recurrent Neural Networks,” Electron. Lett., Vol. 55, No. 7, Pp. 413–415, Apr. 2019, Doi: 10.1049/El.2018.8178.

[16]. S. Yuan, C. Wang, B. Mu, F. Zhou, And W. Duan, “Typhoon Intensity Forecasting Based On Lstm Using The Rolling Forecast Method,” Algorithms, Vol. 14, No. 3, P. 83, Mar. 2021, Doi: 10.3390/A14030083.

[17]. H. Hu And F. Weng, “Estimation Of Location And Intensity Of Tropical Cyclones Based On Microwave Sounding Instruments,” In Igarss 2020 - 2020 Ieee International Geoscience And Remote Sensing Symposium, Ieee, Sep. 2020, Pp. 5442–5445. Doi: 10.1109/Igarss39084.2020.9323785.

[18]. S. Gardoll And O. Boucher, “Classification Of Tropical Cyclone Containing Images Using A Convolutional Neural Network: Performance And Sensitivity To The Learning Dataset,” Geosci. Model Dev., Vol. 15, No. 18, Pp. 7051–7073, Sep. 2022, Doi: 10.5194/Gmd-15-7051-2022.

[19]. R. Pradhan, R. S. Aygun, M. Maskey, R. Ramachandran, And D. J. Cecil, “Tropical Cyclone Intensity Estimation Using A Deep Convolutional Neural Network,” Ieee Transactions On Image Processing, Vol. 27, No. 2, Pp. 692–702, Feb. 2018, Doi: 10.1109/Tip.2017.2766358.

[20]. X.-Y. Xu, M. Shao, P.-L. Chen, And Q.-G. Wang, “Tropical Cyclone Intensity Prediction Using Deep Convolutional Neural Network,” Atmosphere (Basel)., Vol. 13, No. 5, P. 783, May 2022, Doi: 10.3390/Atmos13050783.