Dr. Babasaheb Ambedkar Technological University, Lonere, Raigad

A PROJECT REPORT ON

"Hybrid Deep Learning for Cyclone Intensity Estimation using Multi-Source Satellite Data"

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For the Partial Fulfillment

Bachelor of Technology in Department of Computer Science Engineering – Artificial Intelligence

SUBMITTED BY:

Aman Maner	**(2164191913028)**
Pratik Gade	**(2164191913030)**
Arpita Phalke	**(2164191913047)**
Kirti Rachkar	**(2164191913051)**

UNDER THE GUIDANCE OF

Mrs. Priyanka Vyas

Department Of Computer Science Engineering – Artificial Intelligence

PCET- NMVPM's,

Nutan College of Engineering and Research, Talegaon, Pune

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CERTIFICATE

This is to certify that the project report entitled **"Hybrid Deep Learning for Cyclone Intensity Estimation using Multi-Source Satellite Data"**, which is being submitted by, **Aman Maner**, **Pratik Gade**, **Arpita Phalke** and **Kirti Rachkar** as partial fulfillment for the Degree of Bachelor of Technology (Computer Science Engineering –Artificial Intelligence) of **DBATU, Lonere**

This is bonafide work carried out under my supervision and guidance.

Place: Pune

Date:

Mrs. Priyanka Vyas
Guide Name

Mrs. Priyanka Vyas
Project Coordinator

Prof. (Dr.) Sagar Shinde
Head of Department

Prof. (Dr.) Aparna Pande
Principal

External Examiner

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Name and Signature of student:

Sr.no	Name	Sign
1	**Aman Maner**	
2	**Pratik Gade**	
3	**Arpita Phalke**	
4	**Kirti Rachkar**	

ABSTRACT

Cyclones are highly destructive natural disasters, especially in coastal areas, causing loss of life, displacement, and economic damage. Accurate cyclone intensity prediction is vital for disaster management. Traditional methods like the Dvorak Technique rely on manual analysis and lack real-time accuracy. Recently, deep learning models—especially CNNs—have improved predictions using satellite images, but they struggle with long-range and temporal patterns.

To address this, we propose a dual-branch architecture combining Vision Transformer (ViT) features with handcrafted cyclone-specific features. The ViT-base-patch16-224 model extracts 768-dimensional embeddings, which are reduced using PCA (retaining 95% variance). Simultaneously, seven handcrafted features—including Cloud Anisotropy Index (CAI), Cloud Top Temperature Variance (CCTV), Optical Flow Magnitude, and Symmetry Score—are computed from the images.

Both branches are processed through separate neural networks and then fused using a residual-enhanced fusion layer. The final output is generated by a regression neuron that predicts cyclone intensity. The model is trained using Huber loss and optimized with Adam, using callbacks like Early Stopping for better performance.

Our model improves upon previous baselines, showing enhanced accuracy in predicting cyclone intensity.

Keywords: Cyclone Intensity Estimation, Hybrid Deep Learning, Vision Transformer (ViT), Convolutional Neural Networks (CNNs), Early Stopping.

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1. INTRODUCTION

Cyclones are among the most devastating natural disasters, particularly affecting coastal regions with destructive winds, torrential rains, and storm surges. Their impact includes loss of human lives, large-scale displacement, infrastructure damage, and significant economic disruption. Accurate and timely estimation of cyclone intensity is crucial for effective disaster management and early warning systems. Traditional methods, such as the Dvorak Technique and its advanced variant (ADT), have long been used by meteorological agencies. However, these approaches rely heavily on manual interpretation and often struggle to provide real-time, accurate predictions.

In recent years, advancements in deep learning have offered transformative solutions for cyclone intensity prediction by learning complex patterns from satellite data. Convolutional Neural Networks (CNNs), including VGG16, ResNet50, DenseNet, and MobileNet, have demonstrated their potential in analyzing infrared imagery to extract storm-relevant spatial features. However, CNNs are limited in modeling long-range spatial dependencies and temporal dynamics, which are critical in capturing the evolving nature of cyclones. To address these gaps, newer models such as Vision Transformers (ViT) and hybrid architectures that integrate domain-specific handcrafted features have emerged.

This project proposes a hybrid deep learning framework that leverages the strengths of Vision Transformers for spatial analysis along with meteorological features such as Cloud Anisotropy Index (CAI), Cold Cloud Top Variation (CCTV), Optical Flow, and Sea Surface Temperature. The model is trained using a curated dataset of INSAT-3D infrared satellite images, which provides high-resolution spatial data specific to the Indian Ocean region. The hybrid architecture, with dual-branch fusion and regression output, enhances both accuracy and robustness, particularly in real-time cyclone monitoring scenarios.

To facilitate real-world application, the proposed model is integrated into a web-based interface using Fast API and React.js, allowing users to upload satellite images and receive instant cyclone intensity predictions. The interface is designed to be user-friendly, interpretable, and responsive, making it accessible for both experts and non-specialists involved in disaster management. Comparative experiments demonstrate that the hybrid ViT model significantly outperforms traditional CNNs like VGG16, particularly in terms of Mean Absolute Error (MAE), offering more consistent and reliable predictions.

Overall, this work underscores the growing importance of AI-driven approaches in meteorology. By combining deep learning with domain knowledge and real-time deployment tools, the project provides a scalable, localized, and highly effective solution for cyclone intensity estimation. This not only addresses the limitations of traditional techniques but also lays the groundwork for future developments in climate resilience, predictive analytics, and emergency preparedness.

Hybrid Deep Learning for Cyclone Intensity Estimation using Multi-Source Satellite Data

1.1 History

The estimation of tropical cyclone intensity has evolved significantly over the past several decades. In the 1970s, the Dvorak Technique was introduced as a manual method for assessing cyclone intensity using satellite imagery. This approach relied heavily on visual interpretation of cloud patterns and storm structures, making it subjective and dependent on the expertise of the meteorologist. Despite its widespread adoption, the technique had limitations in rapidly changing weather conditions and lacked the responsiveness required for real-time prediction.

To overcome these shortcomings, the Advanced Dvorak Technique (ADT) was later developed. It automated several aspects of the original method, improving consistency and reducing human error. However, ADT still struggled with accurately identifying cyclone centres and capturing the rapid intensification or weakening of storms, particularly in the early formation stages.

In the 1990s and early 2000s, statistical and dynamical models were introduced. Statistical models used historical cyclone data to make predictions, offering quick outputs but limited accuracy. In contrast, dynamical models such as the Global Forecast System (GFS) simulated atmospheric behavior using physical equations. While more accurate, these models required significant computational resources and were sensitive to input errors, which limited their use for real-time forecasting.

The emergence of deep learning in the mid-2010s marked a major shift in cyclone intensity estimation. Convolutional Neural Network (CNN)-based models like AlexNet, VGG16, and ResNet50 enabled automatic feature extraction from satellite imagery, reducing dependency on manual interpretation and improving prediction accuracy and scalability

1.2 Literature Review

Table 1: Literature Review of Deep Learning Approaches for Cyclone Intensity Estimation

SR. NO	TITLE	IMAGE PROCESSING	METHODOLOGY USED	RMSC	OUTCOME
1	Deepti: Deep Learning-based Tropical Cyclone Intensity Estimation System [1]	Infrared images with data augmentation	CNN-based regression model	13.62 knots	Achieved real-time cyclone intensity estimation; integrated into a visualization portal
2	A Deep Learning Model for Effective Cyclone Intensity Estimation [2]	INSAT 3D infrared images, resized and normalized	CY-Net CNN architecture	Not specified	Accurate prediction of cyclone intensity; includes real-time monitoring application
3	Cyclone Intensity Estimation Using Deep Learning [3]	Infrared images with preprocessing and augmentation	Convolutional Neural Networks (CNNs)	Not specified	Developed a DL-based solution for cyclone intensity estimation, improving prediction accuracy
4	Storm-Net: Advancing Cyclone Intensity Forecasting with Deep Learning on INSAT 3D IR Imagery [4]	INSAT-3D IR imagery for cloud segmentation	Tailored CNN with LSTM integration	Not specified	Automates intensity estimation, enhances early warning systems
5	Deep Learning-Based Cyclone Intensity Estimation Using INSAT-3D IR Imagery:A Comparative Study [5]	INSAT-3D IR images, resized and normalized	CNN, RNN, CNN-models	Not specified	CNN-RNN model shows high potential for cyclone intensity estimation
6	Cyclone Intensity Estimation Using INSAT-3D IR Imagery [6]	INSAT-3D preprocessing, resizing, segmentation	CNN, R-CNN, K-Means, Detectron2	Not specified	Model aids early detection and intensity prediction
7	Classification of tropical cyclone rain patterns using convolutional autoencoder [7]	IMERG data cropped to 96x96 pixels	Convolutional Autoencoder, k-means clustering	Not specified	Classified six rain pattern clusters for different TC stages

8	A Deep Learning Structure for Forecasting Cyclone Intensity [8]	Infrared satellite images	YOLO, CNN, Google Net, Alex Net	Not specified	Enhanced intensity prediction and insights into cyclone dynamics
9	Deep Learning Based Cyclone Intensity Estimation [9]	Infrared and raw imagery	Capsule CNN (Caps Net)	Not specified	Enhanced intensity prediction over traditional CNNs
10	Tropical Cyclone Intensity Estimation Using Himawari-8 Satellite Cloud Products and Deep Learning [10]	16 spectral bands from Himawari-8	CNN with attention and residual learning	3.43 m/s	Enhanced TC intensity estimation using Himawari-8 data
11	Physics-Augmented Deep Learning to Improve TC Intensity and Size Estimation from Satellite Imagery [11]	IR images processed with CNNs	CNN architecture (Deep TC Net)	Not specified	Enhanced estimation by integrating physical knowledge with DL
12	A Statistical Analysis of Tropical Cyclone Intensity [12]	None	Statistical analysis of intensity limits	Not specified	Identified environmental limits on storm intensity
13	The Increasing Intensity of the Strongest Tropical Cyclones [13]	Not specified	Analysis of satellite-derived wind speeds	Not specified	Found evidence of strongest cyclones intensifying with increasing SST
14	Improvement of Advanced Microwave Sounding Unit Tropical Cyclone Intensity and Size Estimation Algorithms [14]	Not specified	Enhanced microwave algorithms	Not specified	Improved accuracy in TC intensity and size estimation
15	Recent Increases in Tropical Cyclone Intensification Rates [15]	Processed images for intensity mapping	Analysis of TC intensification trends with climate models	Not specified	Identified recent intensification trends
16	Recent Progress in Tropical Cyclone Intensity Forecasting [16]	N/A	Statistical & dynamical models	Not specified	Enhanced TC intensity forecast accuracy
17	The Advanced Dvorak Technique: Continued Development of an Objective Schema to Estimate Tropical Cyclone [17]	N/A	Transition to Objective and Advanced Objective Dvorak Technique (ODT, AODT)	Not specified	Reliable operational intensity estimation, enhanced objectivity

18	Estimating Tropical Cyclone Intensity from Infrared Image Data [18]	Longwave IR satellite imagery	Deviation Angle Variance (DAV) calculation	14.7 knots	Provides intensity estimation method, with occasional overestimations noted
19	Objective Estimation of TC Wind Structure from Infrared Satellite Data [19]	Geostationary IR data	Regression with Rankine model	14.3 knots	Improves TC wind structure estimates
20	Multiple Linear Regression Model for TC Intensity Estimation from Satellite IR Images [20]	Geostationary IR satellite data	Multiple linear regression on 16,126 images	12.69 knots	Reference model for real- time TC intensity estimation, suited for intense typhoons

Table 1 provides a comprehensive overview of various studies dedicated to cyclone intensity estimation, detailing key aspects such as methodologies, image processing techniques, accuracy metrics, and overall outcomes. The image processing column outlines the types of satellite images used, particularly infrared (IR) images, along with the preprocessing methods applied, such as data augmentation and normalization. The methodology section focuses on features deep learning architectures, especially Convolutional Neural Networks (CNNs), alongside hybrid models that incorporate diverse techniques. Accuracy metrics, including Root Mean Square Error (RMSE) and classification accuracy, are included to quantitatively assess model performance. The outcomes highlighted in these studies demonstrate significant advancements in cyclone intensity estimation, emphasizing their importance for effective disaster management. This review underscores the vital role of advanced deep learning method ologies in improving cyclone intensity predictions, marking a transition from traditional forecasting methods to more innovative strategies. By implementing hybrid models that fuse multiple deep learning techniques, researchers can achieve notable improvements in prediction accuracy. This integration of various approaches enhances the reliability of models, aiding timely disaster response and preparedness. Accuracy can be improved when hybrid models are used, allowing for better utilization of diverse data sources and providing real time insights for effective disaster management. Ultimately, these advancements will enhance the effectiveness of early warning systems, offering better protection for communities vulnerable to cyclone threats.

Table 2: Recent Research on Cyclone Intensity Estimation Using INSAT-3D and Advanced Deep Learning Models

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	LSTM optimized by Cat Swarm Optimization.	IBTrACS (2003–2019) with TC	Limited region and high computation	Boosts speed and accuracy over

	Track Prediction in the Bay of Bengal Using LSTM-CSO Method		parameters.	cost.	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 2 presents a focused survey of recent advancements of year 2022–2024 in tropical cyclone intensity estimation using deep learning methodologies, with special emphasis on models utilizing INSAT-3D infrared satellite imagery. The reviewed works explore diverse architectures, including CNNs, LSTMs, ConvLSTMs, and Transformer-based models, aimed at capturing both spatial and temporal features of cyclones for improved prediction accuracy. Several studies propose hybrid and optimized models, such as LSTM with Cat Swarm Optimization and Temporal Attention Mechanism ConvLSTM, which significantly enhance the precision and granularity of cyclone track and intensity forecasts. Notably, multiple papers leverage INSAT-3D data due to its high-resolution IR imaging capabilities, enabling reliable and automated intensity assessments that surpass traditional manual techniques. These contributions collectively highlight the trend towards more explainable, scalable, and real-time deep learning solutions for cyclone intensity prediction — a direction that aligns closely with our project's goals of leveraging hybrid deep learning on INSAT-3D imagery for early warning and disaster preparedness.

The literature review from the previous semester (Table 1) provided a broad foundation by surveying research papers, emphasizing deep learning methods such as CNNs and hybrid models for cyclone intensity estimation across diverse datasets, image modalities, and evaluation metrics. In contrast, this semester's review (Table 2) offers a more focused and in-depth exploration of recent innovations, particularly involving INSAT-3D IR imagery and temporal sequence modeling using architectures like LSTM, ConvLSTM, and Transformers. While the earlier studies highlighted the potential of deep learning for cyclone analysis, the more recent works reveal a maturity in methodology, showcasing fine-tuned models, hybrid optimizations, and improved spatio-temporal accuracy. This progression reflects a clear evolution in the research landscape from experimental model development to application-specific, real-world implementations perfectly aligning with our project’s transition from theoretical groundwork to a functional hybrid deep learning system for cyclone intensity estimation.

1.3 Gap Finding

Early Detection Challenges: Current methods struggle to provide accurate cyclone intensity estimates early in the cyclone's development, highlighting the need for improved prediction techniques.

Subjectivity in Existing Techniques: Traditional intensity estimation methods require manual analysis, leading to inconsistencies and subjective interpretations, which can affect reliability.

Real-Time Monitoring Needs: While satellite imagery is utilized, the integration of real-time data visualization and monitoring tools is lacking in existing systems, which hampers timely decision- making for disaster management.

Automation of Intensity Estimation: There is a gap in leveraging advanced deep learning methods to automate cyclone intensity estimation without needing to identify the storm's center, which can enhance speed and accuracy.

Training Data Limitations: Existing models may not utilize a comprehensive dataset from the Indian Ocean for training, indicating a need for more extensive historical data to improve predictive capabilities.

1.4 Problem Formulation

Cyclones in the Indian Ocean pose severe threats to coastal communities, yet accurately predicting their intensity remains a significant challenge. Existing forecasting systems often struggle to provide timely real-time updates and effectively process the vast amounts of multi-source satellite data. Furthermore, many models trained on global cyclone data are not fully optimized for the unique meteorological and oceanographic conditions of the Indian Ocean region. This gap leads to suboptimal intensity predictions, limiting the effectiveness of disaster preparedness and early warning systems. Additionally, the complexity of current models often results in outputs that are difficult for meteorologists to interpret and trust. The lack of robust real-time data pipelines and interpretable prediction systems restricts their practical utility, risking lives and property in vulnerable coastal areas.

1.5 Problem Solution

To overcome the limitations of traditional and standalone deep learning methods for cyclone intensity estimation, this project introduces a hybrid deep learning architecture that integrates both deep and handcrafted features. By employing a Vision Transformer (ViT)—specifically the ViT-base-patch16-224 model—the framework captures complex global spatial relationships across satellite imagery, something that convolutional architectures struggle with due to their limited receptive fields. The ViT extracts a 768-dimensional feature vector from each infrared satellite image, which is then reduced using Principal Component Analysis (PCA) to remove redundancy and retain only the most informative features. This deep feature representation ensures the model is capable of capturing subtle variations in cloud structure and evolution, even during the early stages of cyclone formation.

In parallel, the model incorporates handcrafted features, including:

- Cloud Anisotropy Index (CAI)
- Cloud Top Temperature Variance (CCTV)
- Optical Flow Magnitude
- Symmetry Score

These domain-informed features are designed to address the interpretability gap by providing intuitive metrics that meteorologists can relate to, such as motion intensity, texture variability, and brightness symmetry. The handcrafted features allow the model to leverage expert meteorological knowledge that purely data-driven approaches might miss, especially when trained on limited regional datasets.

One of the primary challenges in cyclone analysis is the reliance on manually identifying the cyclone centre. This framework circumvents that need by designing the entire pipeline to operate on the full image, learning both spatial context and feature interactions without requiring explicit centre localization. This reduces processing complexity and makes the system more suitable for real-time deployment. Moreover, by training the model on INSAT-3D satellite data specifically over the Indian Ocean region, the model is better tuned to the local atmospheric and oceanographic patterns, significantly improving generalizability and predictive accuracy for this area.

Finally, to ensure robustness and reduce overfitting, the architecture includes regularization techniques such as dropout layers and batch normalization, as well as optimization strategies like the Adam optimizer with early stopping and learning rate scheduling. This end-to-end hybrid framework not only automates the intensity estimation process but also offers improved accuracy, reliability, and explainability—directly addressing the core gaps identified in current operational cyclone forecasting systems.

1.6 Objectives

- To collect and preprocess multi-source satellite imagery and atmospheric data for cyclones across the Indian Ocean.

- To implement hybrid deep learning architectures combining Convolutional Neural Networks (CNNs) with transformer-based models for cyclone intensity estimation.

- To evaluate and validate the performance of the developed deep learning model for cyclone intensity prediction using metrics such as root mean squared error (RMSE)

- To explore transfer learning techniques by fine-tuning pre-trained global cyclone models for Indian Ocean-specific cyclone intensity estimation.

- To develop a dynamic real-time deep learning model that updates cyclone intensity estimates using real-time satellite imagery.

- To develop a web interface and interpretable AI models that provide result for their predictions of cyclone intensity, enhancing trust and usability for meteorologists.

2. SYSTEM ARCHITECTURE AND METHODOLOGY

2.1 Block Diagram of Proposed Work

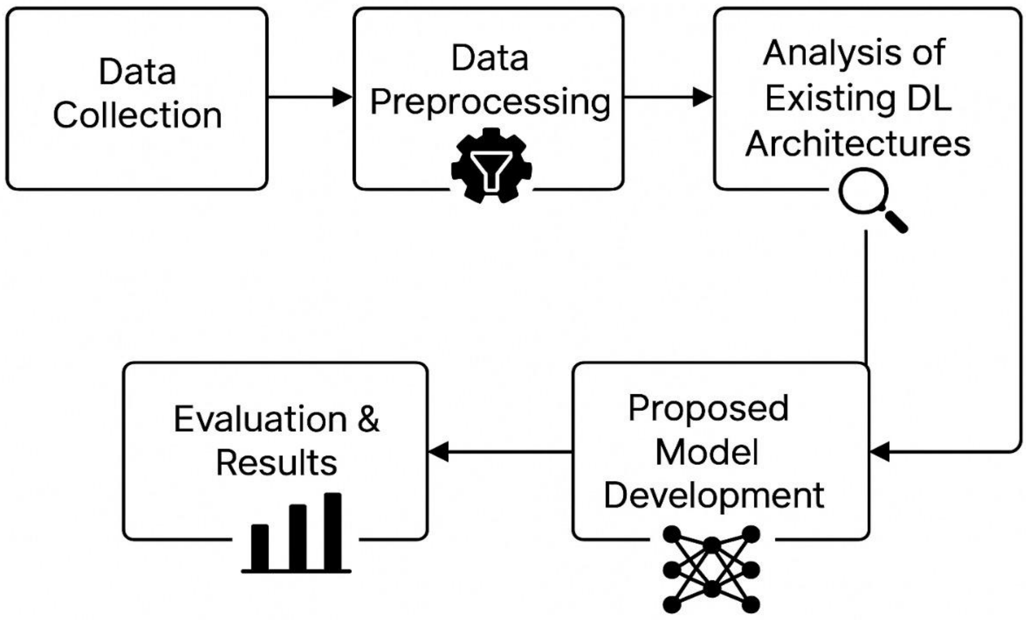

Fig 1: Proposed Methodology for Cyclone Intensity Prediction

The block diagram shown in Figure 1 illustrates the overall workflow of our proposed cyclone intensity estimation system.

Data Collection:

The first step involves collecting multi-source satellite imagery, primarily from INSAT-3D IR channels. These images provide critical temporal and spatial data required for cyclone analysis over the Indian Ocean region.

Data Preprocessing:

The raw satellite data undergoes preprocessing steps including resizing, normalization, enhancement, and noise reduction to ensure the data is in a suitable format for training deep learning models.

Analysis of Existing DL Architectures:

In this stage, a thorough literature review and empirical analysis of existing deep learning models including CNNs, LSTMs, ConvLSTM, and Transformers is conducted. This analysis helps identify the strengths and limitations of current approaches.

Proposed Model Development:

Based on insights from the previous step, a hybrid CNN-ViT (Vision Transformer) architecture is proposed and implemented. This model leverages both convolutional feature extraction and global attention mechanisms to better capture cyclone structures in satellite imagery.

Results:

The performance of the proposed model is rigorously evaluated using metrics such as accuracy, precision, recall, and RMSE. The results are compared with existing baselines to validate the model's effectiveness in predicting cyclone intensity.

This iterative process ensures a data-driven, research-informed, and performance-optimized solution to cyclone intensity estimation, with potential real-world applications in disaster preparedness and early warning systems.

2.2 Methodology

2.2.1 Collection and Preprocessing of Datasets:

For training the model, we used the INSAT 3D Infrared & Raw Cyclone Imagery (2012-2021) dataset. This dataset consists of high-resolution infrared imagery of the Indian Ocean captured by the INSAT 3D meteorological satellite, developed by ISRO. The imagery spans the years 2012-2021, providing valuable data on temperature distribution and cloud cover, which are critical for weather forecasting and cyclone prediction.

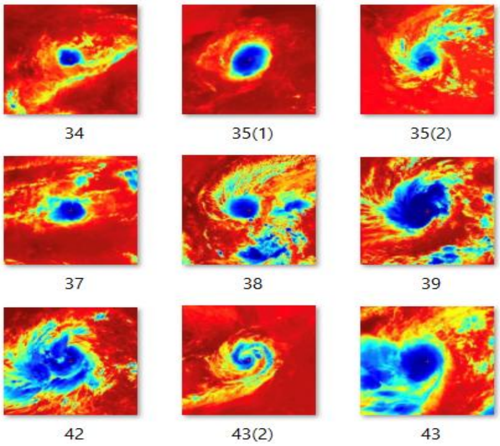

Fig 2: Insat3d IR Cyclone Images

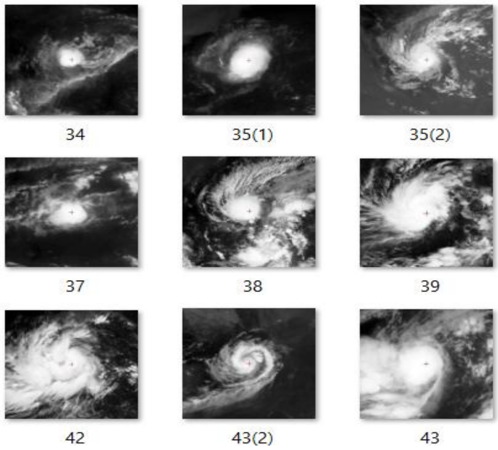

Fig 3: Insat3d Raw Cyclone Images

The dataset contains timestamped coordinates, allowing for the tracking of temporal and spatial changes in weather patterns. In the preprocessing stage, all images were resized to ensure uniform input size before being fed into the Convolutional Neural Network (CNN). The dataset was then divided into training and validation sets to optimize model performance and prevent overfitting.

The INSAT 3D satellite is equipped with an infrared imager that provides detailed imagery of Earth's surface and atmosphere, offering critical insights into temperature variations and cloud formations. These infrared images play a crucial role in monitoring weather patterns, detecting severe weather events, and improving predictions of natural disasters, especially cyclones in the Indian subcontinent and surrounding regions. The dataset is regularly updated and freely available ISRO Meteorological Data Archive, making it an essential resource for meteorologists, researchers, and policymakers.

Table 3 : Comprehensive Overview of Multisource Datasets for Cyclone and Weather Monitoring

Sr. No.	Name	Interval	Description	Region	Source
1	INSAT3D Infrared & Raw Cyclone Imagery	2012-2021	Infrared and raw cyclone imagery labeled with intensity in knots, sourced from MOSDAC, timestamped to intensity-time graphs.	Indian Ocean	Kaggle
2	INSAT3D Infrared & Raw Cyclone Imagery	2012-2022	Infrared and raw imagery dataset for cyclone tracking and intensity analysis.	Indian Ocean	MOSDAC server
3	The Imperial College Storm Model (IRIS) Dataset	1980-2021	Synthetic dataset with modeled 10,000-year outputs, reflecting 42 years of observed tropical cyclone climate patterns.	U.S.	IBTrACS, WMO data
4	NOAA-Himawari-Dataset	2014-2021	Himawari-8/9 satellite data for constant weather system and typhoon observation over East Asia and the Pacific regions.	East Asia, West & Central Pacific Region	Japan Meteorological Agency (JMA)

5	Geo-KOMPSAT-2A (GK2A) Satellite Data	2019-2023	High-resolution real-time weather monitoring and disaster data from the GK2A geostationary satellite.	Western North Pacific	Korea Meteorological Administration (KMA)
6	Communication, Ocean, and Meteorological Satellite (COMS) Data	2011–2019	Multi-purpose geostationary satellite data for meteorology, oceanography, and communication.	Asia-Pacific, Korean Peninsula, Indian Ocean	Korea Meteorological Administration (KMA)

2.2.2 Proposed Methodology

2.2.2.1 Analysis of Existing Deep Learning Architectures

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 feature use. 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.

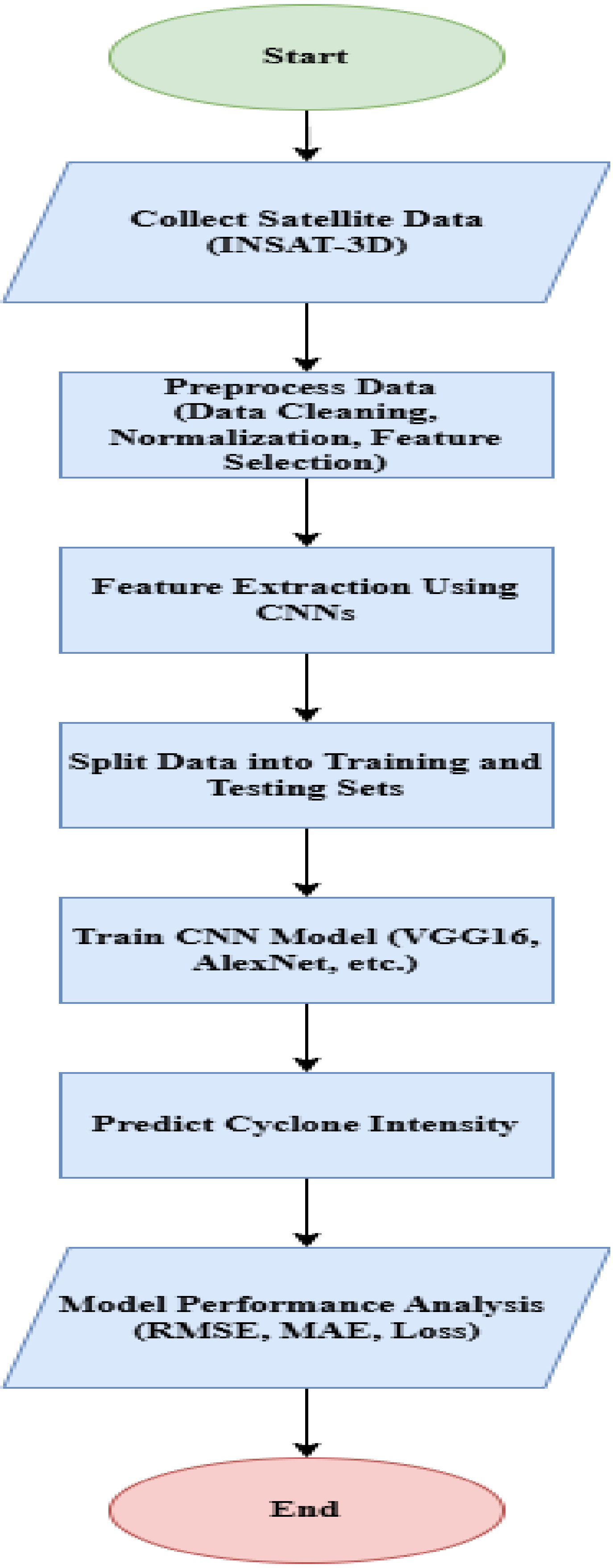

Fig 4: Existing Models Testing Process.

2.2.2.2 ViT Model Architecture

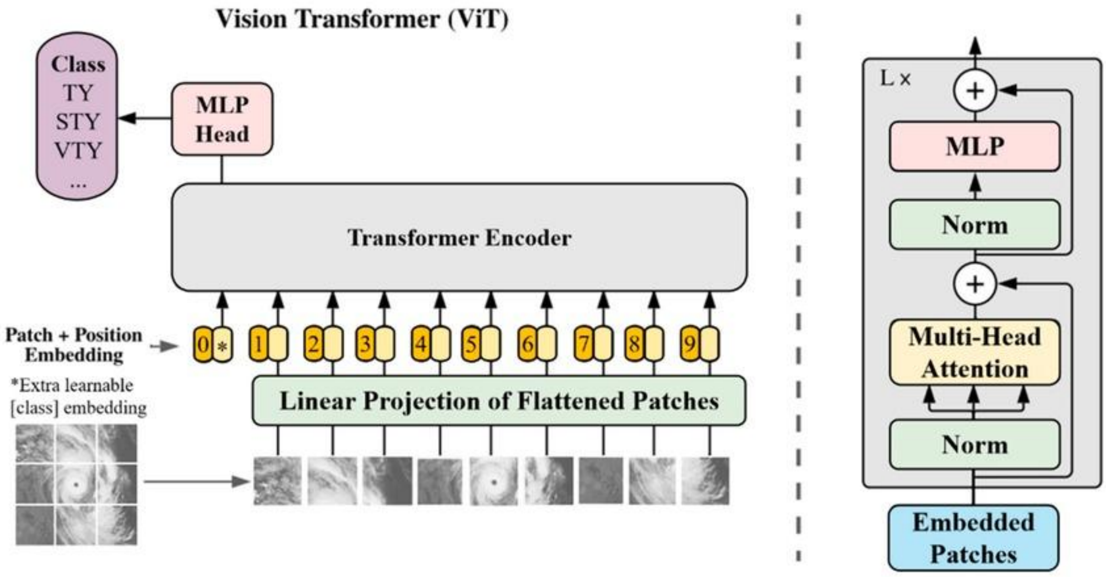

Fig 5: ViT Model Architecture

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 like shown in fig 5. 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 Hugging Face 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,

σ = Standard deviation of grayscale pixel intensities

μ = 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 Flareback 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.

The MAE quantifies the average magnitude of prediction errors, while the RMSE accentuates larger discrepancies due to its inherent squared error component. The subsequent table delineates the quantitative results for both models. Although the VGG16 model attained a marginally lower RMSE, indicating superior performance in the context of extreme outliers, the ViT-based hybrid model demonstrated a significantly reduced MAE—reflecting a 27.7% decrease. This outcome suggests that the ViT model provides more consistent and reliable predictions across the dataset, thereby enhancing its efficacy for practical cyclone intensity forecasting. The enhanced MAE of the ViT model is attributable to its capacity to capture global contextual information via self-attention mechanisms, which are particularly adept at deciphering the spatial complexities inherent in satellite imagery. Additionally, the incorporation of handcrafted meteorological features—such as Cloud Anisotropy Index (CAI), Cloud Top Temperature Variance (CCTV), optical flow, and symmetry metrics—augments the model's interpretive capability by embedding domain-specific insights. Collectively, these findings underscore the advantages of employing a hybrid modeling strategy that integrates deep learning with expert-informed features. The ViT-based architecture not only outperforms conventional CNN-based models in terms of prediction reliability but also lays a robust foundation for future advancements in cyclone intensity estimation derived from satellite imagery.

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.

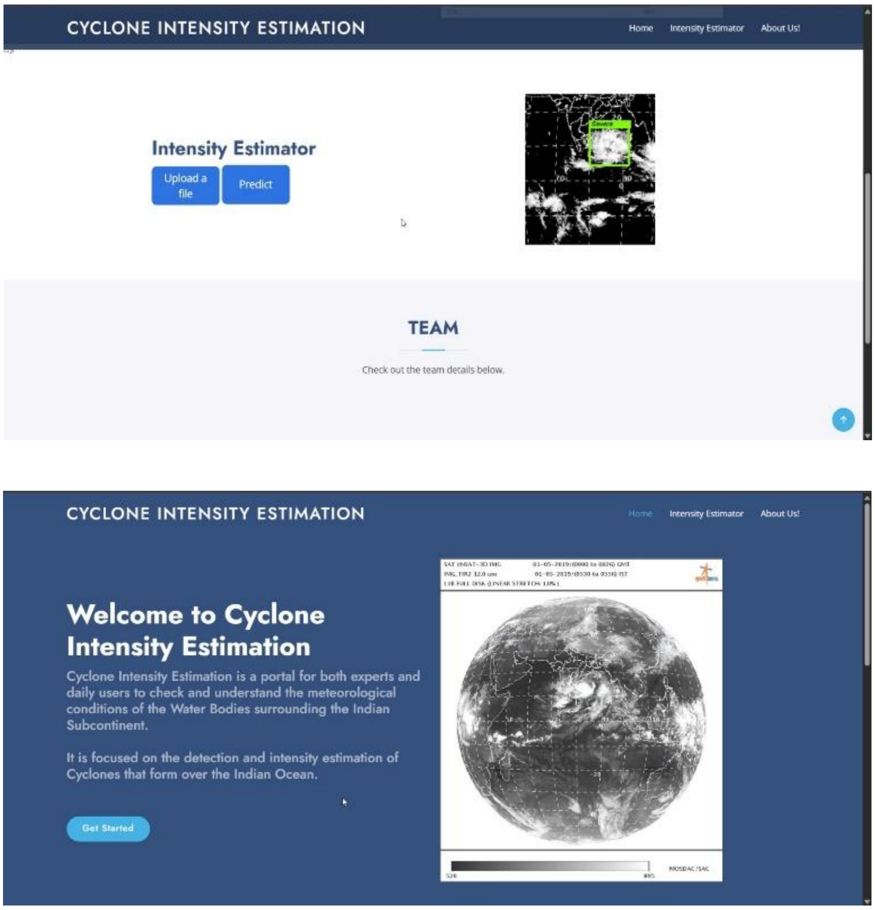

Fig 6: Front Page of web interface

2.3 Algorithm

i. Data collection

Collect satellite images of cyclones from sources like INSAT-3D.

ii. Data preprocessing

Resize, normalize, and augment the images. Then split the data into training, validation, and testing sets.

iii. Study of existing deep learning models

Analyse different DL models like CNN and ViT to understand their strengths.

iv. Proposed model development

- Use CNN to extract local image features (like cloud shape and texture).
- Use Vision Transformer (ViT) to learn global patterns and relationships.
- Combine CNN and ViT features and pass them through fully connected layers to predict intensity.

v. Model training

Train the model using suitable loss functions and optimizers until good accuracy is achieved.

vi. Evaluation

Test the model on unseen data and evaluate its performance using MAE, MSE, and RMSE.

2.4 Flowchart

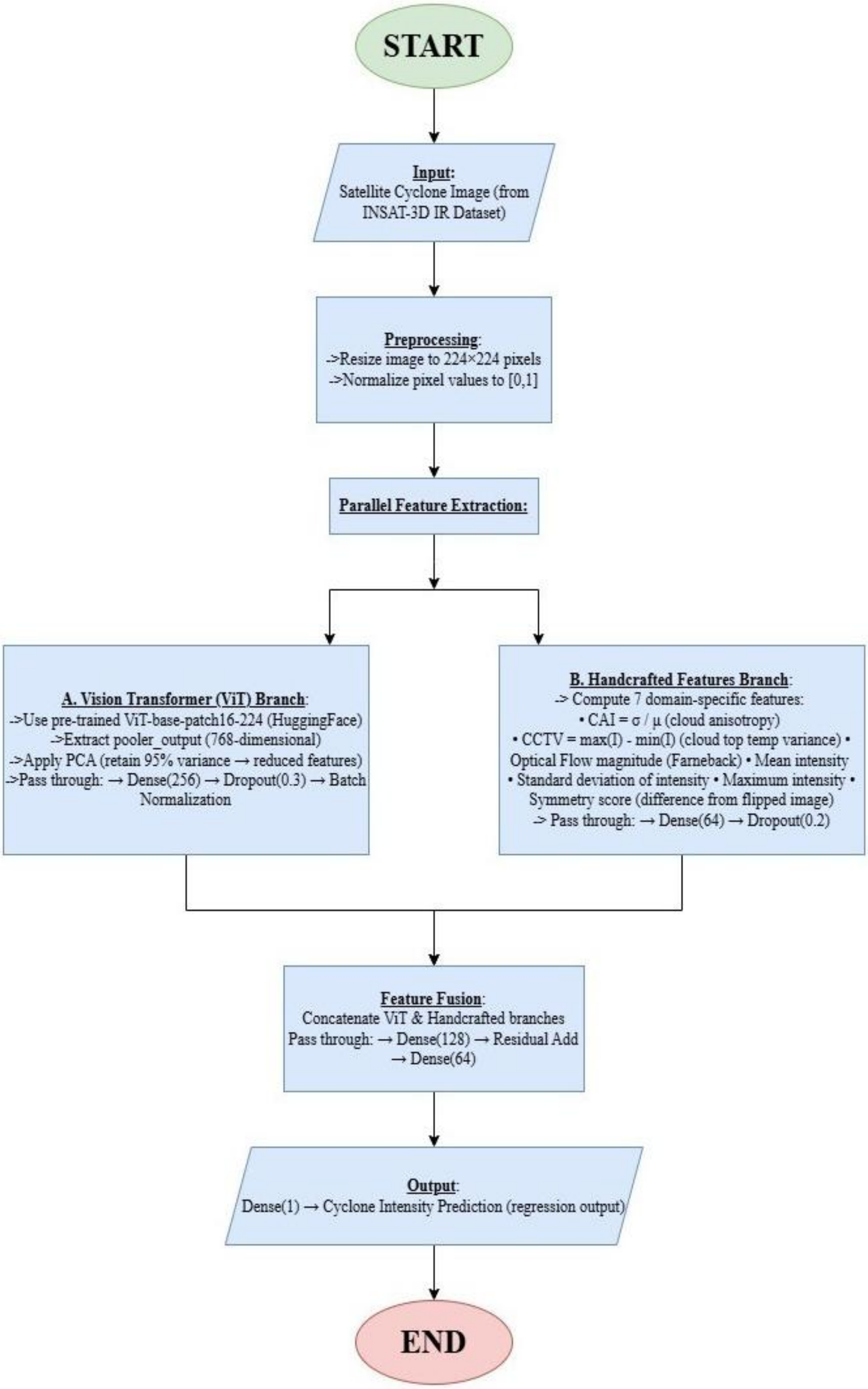

Fig 7: Proposed Methodology for Cyclone Intensity Prediction

The flowchart in fig 7 represents the complete pipeline of our proposed cyclone intensity estimation system using a hybrid deep learning architecture.

1. Input:

   The system begins by taking a satellite infrared image of a tropical cyclone from the INSAT-3D dataset as input. These images capture the structure and intensity of cyclones in the Indian Ocean region.

2. Preprocessing:

   The input image is resized to a standard dimension of 224×224 pixels and normalized to a [0, 1] scale. This step ensures consistency and prepares the image for feature extraction.

3. Parallel Feature Extraction:

   The core strength of the system lies in parallel feature extraction using two complementary branches:

   A. Vision Transformer (ViT) Branch:

   This branch utilizes a pre-trained ViT-base model (from HuggingFace). It extracts deep, high-dimensional visual features (768-d) from the image. Principal Component Analysis (PCA) is then applied to reduce dimensionality while retaining important variance. The reduced features are passed through dense layers, dropout, and batch normalization for regularization and improved learning.

   B. Handcrafted Features Branch:

   In this branch, seven domain-specific features are computed from the image. These include:

   - Cloud Anisotropy Index (CAI)
   - Cloud Top Temperature Variance (CCTV)
   - Optical flow magnitude
   - Mean intensity, standard deviation, maximum intensity
   - Symmetry score (based on flipped image)

     These features are passed through a smaller dense network to enhance their representation.

4. Feature Fusion:

   The outputs from both branches are concatenated and passed through dense layers with residual connections to fuse the spatial and domain-specific information. This fusion helps the model capture both visual and physical cyclone characteristics effectively.

5. Output:

   Finally, the fused features are passed through a dense layer with one neuron to predict the cyclone intensity.

This hybrid framework enhances prediction performance by combining the power of deep visual features and expert-driven handcrafted features

3. EXPERIMENTAL RESULTS

3.1 Result of Analyzed Existing Deep Learning Architectures

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

Table 4: Evaluation matrix values of existing deep learning architectures

Table 4 shows Evaluation Metrics :

1. Mean Absolute Error (MAE):

   MAE measures the average absolute difference between the predicted and actual cyclone intensity values, indicating the overall prediction accuracy without emphasizing large errors.

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

Where,

MAE = mean absolute error

y_i = prediction

x_i = true value

n = total number of data points

2. Mean Squared Error (MSE):

   MSE calculates the average of the squared differences between predicted and actual values, giving more weight to larger errors in cyclone intensity predictions.

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

Where,

MSE = Mean Squared Error

n = number of observations in the dataset

Y_i = observed values

$\hat{Y}_i$ = predicted values

3. Root Mean Squared Error (RMSE) :

   RMSE is the square root of MSE and provides a measure of prediction error in the same units as the actual cyclone intensity, making it easier to interpret the model's performance.

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

Where,

RMSE = Root Mean Squared Error

n = number of observations in the dataset

yi = observed values

$\hat{y}i$ = predicted values

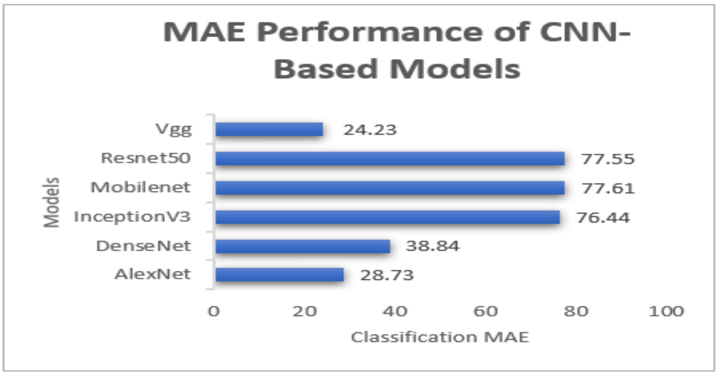

Fig 8: Mean Absolute Error (MAE) Comparison Of Deep Learning Models

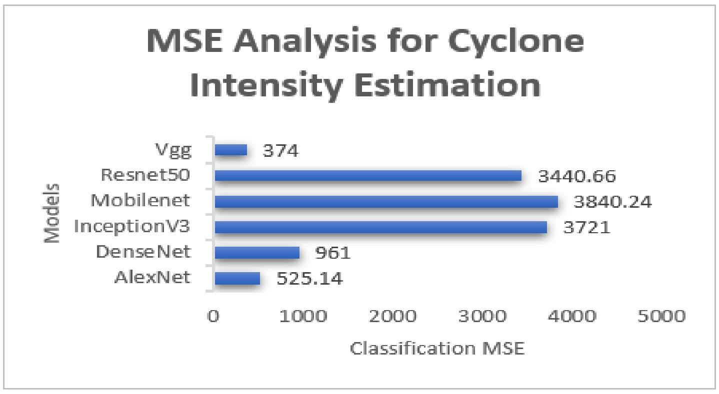

Fig 9: Mean Squared Error (MSE) Analysis for Cyclone Intensity Estimation

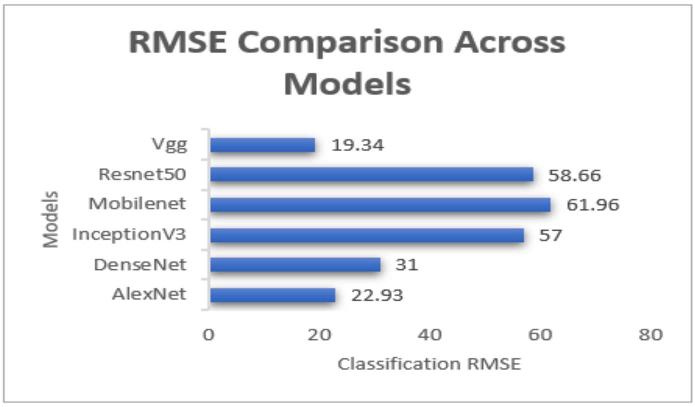

Fig 10: Root Mean Squared Error (RMSE) Performance of Various CNN Mode

This results in fig 8,9,10 shows 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 counter parts 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 above,VGG16 consistently exhibited the lowest error rates across these metrics, underscoring its effectiveness

3.2 Result of ViT Model Architecture

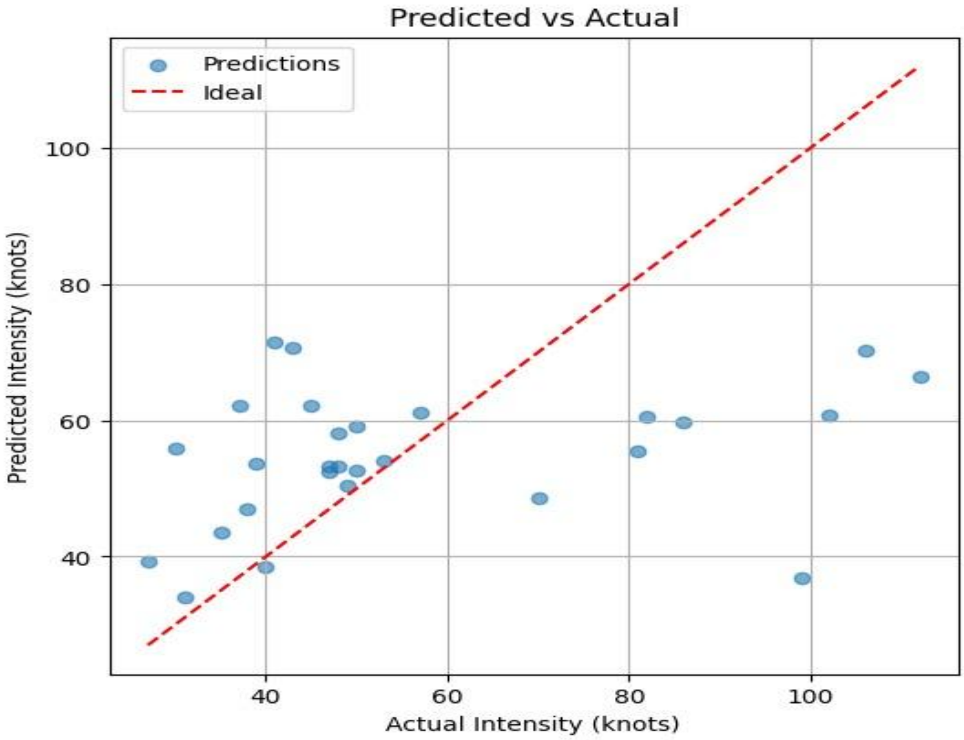

Fig 11: Scatter Plot of Predicted vs. Actual Cyclone Intensities

The presented graph in Fig 11 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.

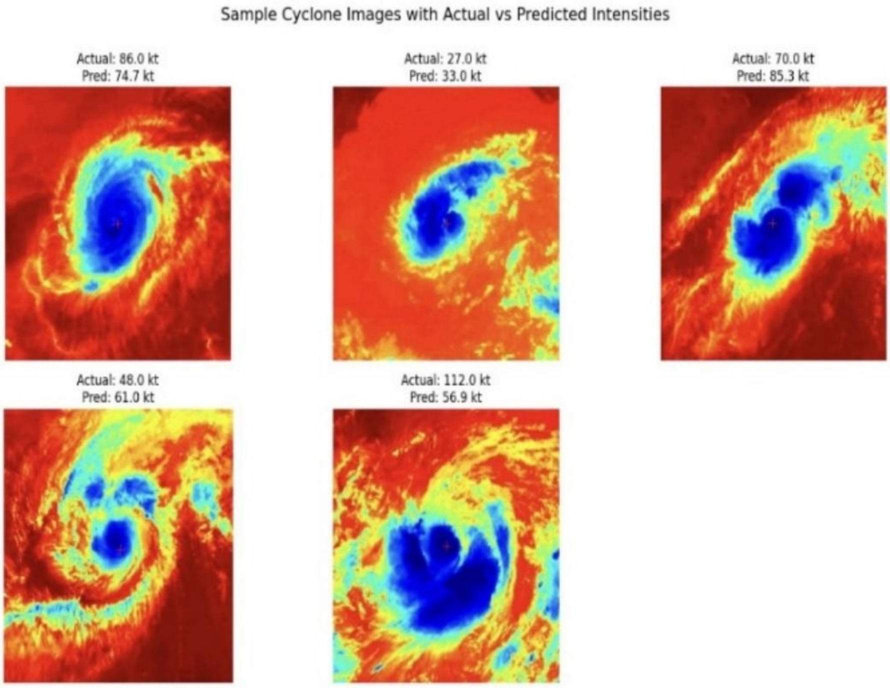

Fig 12: Sample Predictions of Cyclone Intensity from Satellite Imagery

Fig 12 displays five sample satellite images of cyclones along with their actual and predicted wind intensities (in knots). Each image is annotated with the ground truth (Actual) and the model's output (Predicted). The color variations in the images likely represent temperature or infrared intensity, where the cyclone eye appears in darker blue shades. The predictions show both underestimation (e.g., 112.0 kt predicted as 56.9 kt) and overestimation (e.g., 70.0 kt predicted as 85.3 kt), highlighting the challenges in accurately estimating cyclone intensity. Overall, the figure illustrates the visual complexity of cyclone structures and the performance of the prediction model.

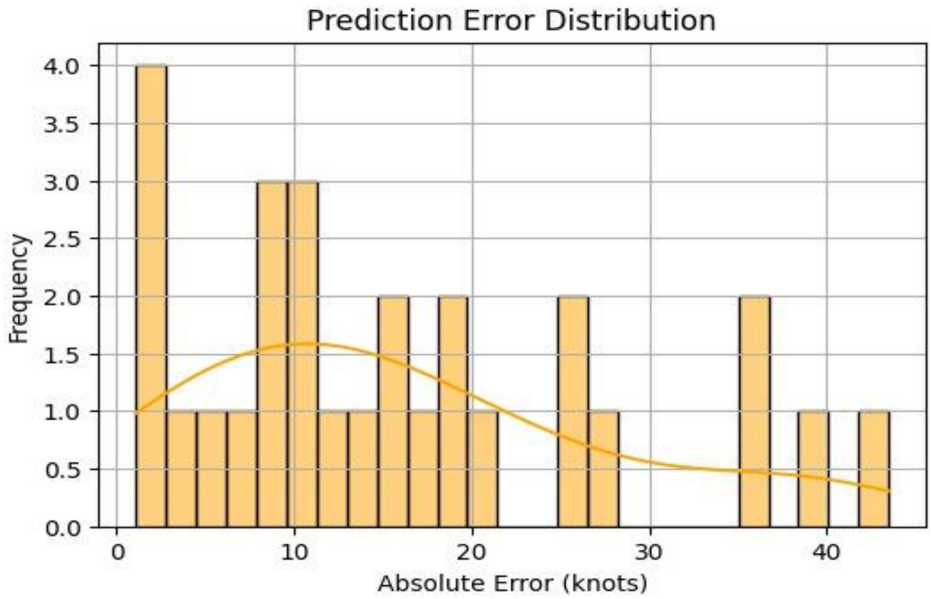

Fig 13: Histogram of Cyclone Intensity Prediction Errors

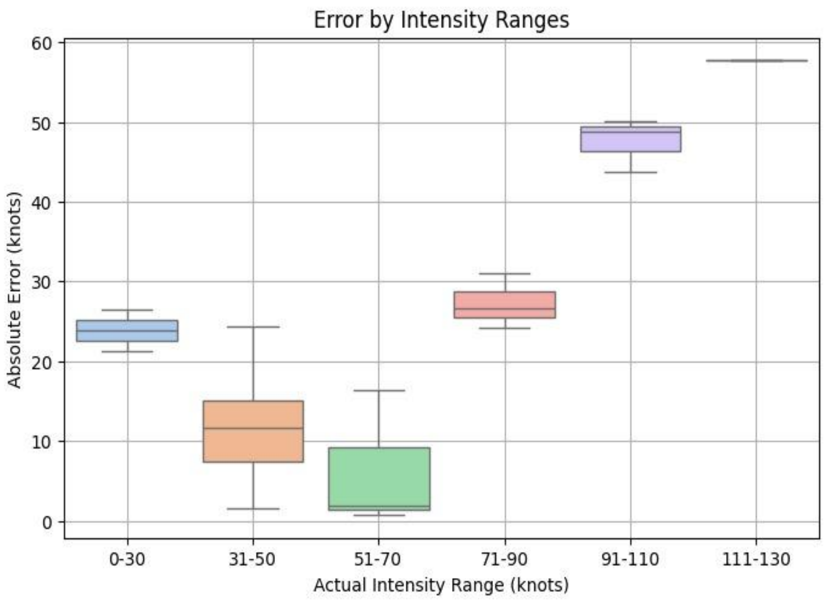

Fig 14: Box Plot of Absolute Prediction Error Across Cyclone Intensity Range

The histogram in fig 13 displays the distribution of absolute prediction errors (in knots) made by the cyclone intensity model. The x-axis represents the absolute error, while the y-axis indicates the frequency of predictions falling within each error range. Most errors lie below 15 knots, with a peak around the 5–10 knot range, suggesting that the model generally performs well for a majority of cases. However, the presence of a long tail extending beyond 30 knots indicates a few instances with large prediction errors. The overall distribution is right-skewed, highlighting occasional underperformance on certain samples.

The box plot shown in fig 14 shows the distribution of absolute prediction errors (in knots) for different actual cyclone intensity ranges. The x-axis represents binned intensity ranges (e.g., 0–30 kt, 31–50 kt), while the y-axis shows the absolute error between predicted and actual values. The model exhibits the lowest median error for the 51–70 kt range, suggesting better performance in mid-range intensities. However, higher intensity ranges (91–130 kt) show significantly larger errors, indicating the model struggles with accurately predicting very intense cyclones. The increasing trend in error for extreme intensities highlights a limitation in the model's generalization ability for severe storms.

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	17.8716

The ViT model outperforms the VGG model with lower RMSE and significantly lower MAE, indicating that ViT makes more accurate and consistent predictions of cyclone intensity. This suggests that the Vision Transformer is more effective than VGG in capturing the relevant features from satellite cyclone images for regression-based intensity estimation.

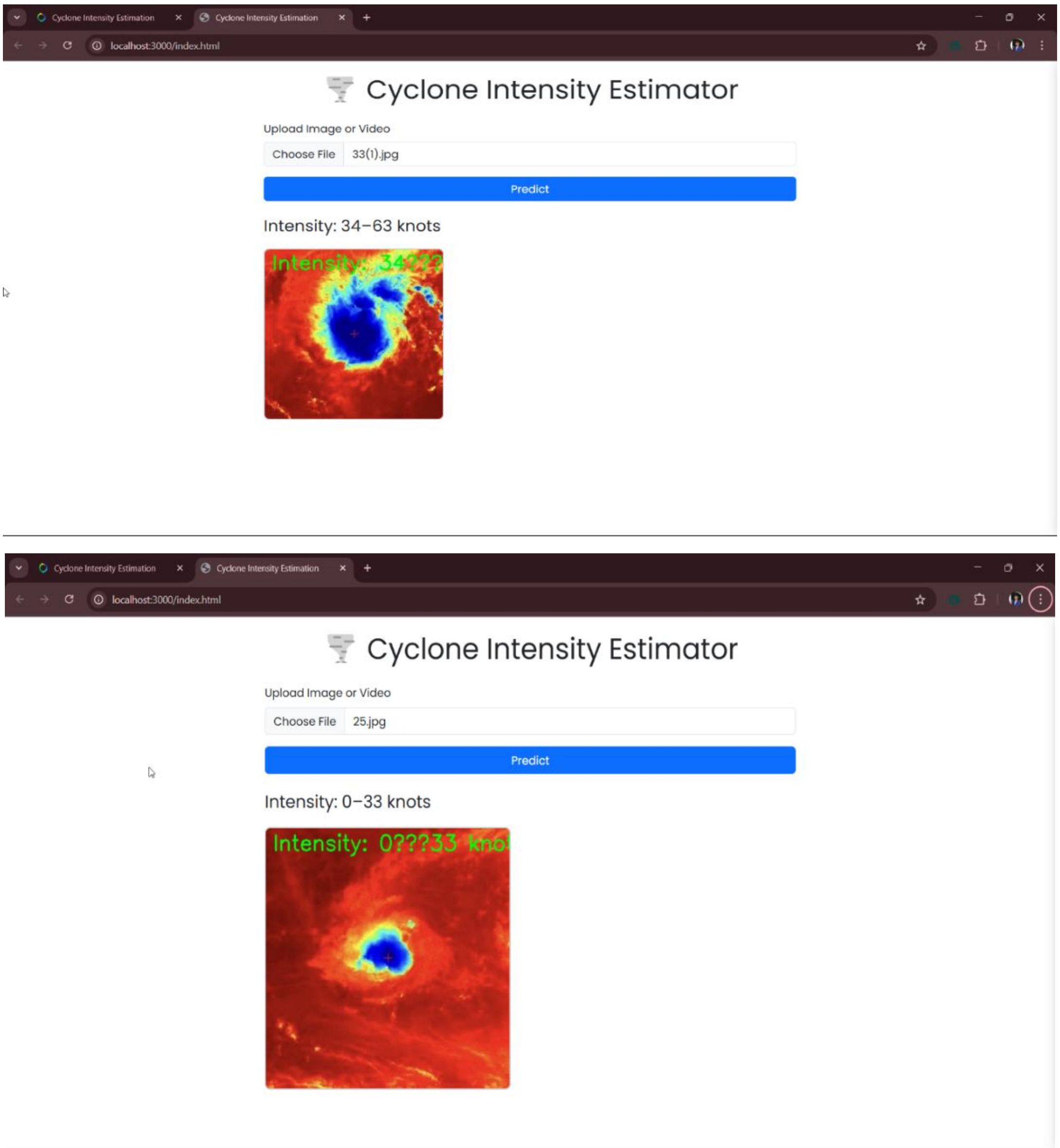

Fig 15: Web Interface Cyclone Intensity Prediction

This is a screenshot of the web application interface for the Cyclone Intensity Estimator. The user uploads an image (e.g., satellite image of a cyclone), and upon clicking the "Predict" button, the system displays the estimated intensity range—in this case, 0–33 knots. This interface provides a user-friendly way to estimate cyclone intensity using machine learning.

4. CONCLUSIONS

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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9th International Conference on Control Communication, Computing and Automation : Submission (211) has been created.

1 message

Microsoft CMT <email@msr-cmt.org> Sat, 29 Mar, 2025 at 10:15 pm
Reply to: Microsoft CMT - Do Not Reply <noreply@msr-cmt.org>
To: kirtirachkar@gmail.com

Hello,

The following submission has been created.

Track Name: Signal and Image Processing

Paper ID: 211

Paper Title: Cyclone Intensity Analysis Using State-of-Art Deep Learning Architectures For INSAT-3D

Abstract:
This study presents a comprehensive analysis of state-of-art deep learning architectures aimed at estimating tropical cyclone intensity utilizing INSAT-3D satellite information. Conventional methods, like the Dvorak Technique, depend on heuristic strategies, which frequently result in subjective and variable forecasts. Current techniques depend on heavy datasets and facing challenges in assessing intensity targeting cyclone's center. This investigation assesses the efficacy of convolutional neural networks (CNNs), such as AlexNet, DenseNet, ResNet50, and VGG16, by analyzing critical metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and loss functions. Comparative findings indicate that VGG16 achieves the highest accuracy, outperforming other models with an RMSE 19.34, MSE of 374 and MAE of 24.23, ensuring reduced error margins and enhanced reliability in cyclone estimation. Furthermore, hybrid CNN models that incorporate sophisticated optimization methods are investigated to improve predictive precision. This study fosters in the progression of more dependable, data-driven early warning systems, assisting meteorological organizations in making educated choices in the face of escalating climatic variability.

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Authors:
- kirtirachkar@gmail.com (Primary)
- priyanka06vyas@gmail.com
- gadepratik040@gmail.com
- amanmaner011@gmail.com
- phalkearpita7@gmail.com

Secondary Subject Areas: Not Entered

Submission Files:
Cyclone Intensity Analysis Using State-of-Art Deep Learning Architectures For INSAT-3D.pdf (440 Kb, Sat, 29 Mar 2025 16:44:37 GMT)

Submission Questions Response: Not Entered

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1 message

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To: kirtirachkar@gmail.com

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The following submission has been created.

Track Name: EITES2025

Paper ID: 167

Paper Title: Cyclone Intensity Analysis Using State-of-Art Deep Learning Architectures For INSAT-3D

Abstract:
This study presents a comprehensive analysis of state-of-art deep learning architectures aimed at estimating tropical cyclone intensity utilizing INSAT-3D satellite information. Conventional methods, like the Dvorak Technique, depend on heuristic strategies, which frequently result in subjective and variable forecasts. Current techniques depend on heavy datasets and facing challenges in assessing intensity targeting cyclone's center. This investigation assesses the efficacy of convolutional neural networks (CNNs), such as AlexNet, DenseNet, ResNet50, and VGG16, by analyzing critical metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and loss functions. Comparative findings indicate that VGG16 achieves the highest accuracy, outperforming other models with an RMSE 19.34, MSE of 374 and MAE of 24.23, ensuring reduced error margins and enhanced reliability in cyclone estimation. Furthermore, hybrid CNN models that incorporate sophisticated optimization methods are investigated to improve predictive precision. This study fosters in the progression of more dependable, data-driven early warning systems, assisting meteorological organizations in making educated choices in the face of escalating climatic variability.

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Authors:
- kirtirachkar@gmail.com (Primary)
- priyanka06vyas@gmail.com
- gadepratik040@gmail.com
- amanmaner011@gmail.com
- phalkearpita@gmail.com

Secondary Subject Areas: Not Entered

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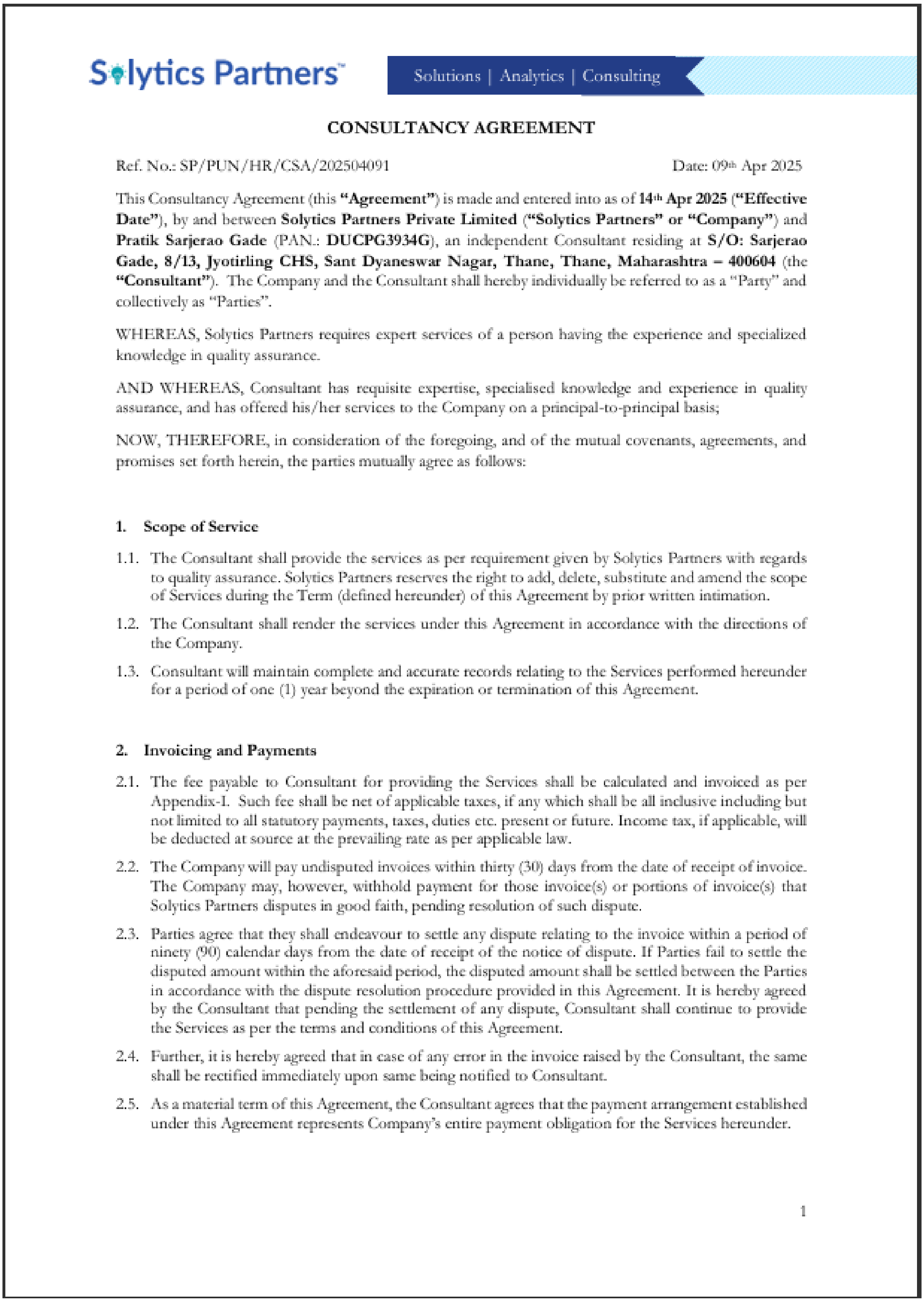
Thanks,
CMT team.



Solytics Partners™ Solutions | Analytics | Consulting

CONSULTANCY AGREEMENT

Ref. No.: SP/PUN/HR/CSA/202504091 Date: 09th Apr 2025

This Consultancy Agreement (this **"Agreement"**) is made and entered into as of **14th Apr 2025** (**"Effective Date"**), by and between **Solytics Partners Private Limited** (**"Solytics Partners" or "Company"**) and **Pratik Sarjerao Gade** (PAN.: **DUCPG3934G**), an independent Consultant residing at **S/O: Sarjerao Gade, 8/13, Jyotirling CHS, Sant Dyaneswar Nagar, Thane, Thane, Maharashtra – 400604** (the **"Consultant"**). The Company and the Consultant shall hereby individually be referred to as a "Party" and collectively as "Parties".

WHEREAS, Solytics Partners requires expert services of a person having the experience and specialized knowledge in quality assurance.

AND WHEREAS, Consultant has requisite expertise, specialised knowledge and experience in quality assurance, and has offered his/her services to the Company on a principal-to-principal basis;

NOW, THEREFORE, in consideration of the foregoing, and of the mutual covenants, agreements, and promises set forth herein, the parties mutually agree as follows:

1. Scope of Service

1.1. The Consultant shall provide the services as per requirement given by Solytics Partners with regards to quality assurance. Solytics Partners reserves the right to add, delete, substitute and amend the scope of Services during the Term (defined hereunder) of this Agreement by prior written intimation.

1.2. The Consultant shall render the services under this Agreement in accordance with the directions of the Company.

1.3. Consultant will maintain complete and accurate records relating to the Services performed hereunder for a period of one (1) year beyond the expiration or termination of this Agreement.

2. Invoicing and Payments

2.1. The fee payable to Consultant for providing the Services shall be calculated and invoiced as per Appendix-I. Such fee shall be net of applicable taxes, if any which shall be all inclusive including but not limited to all statutory payments, taxes, duties etc. present or future. Income tax, if applicable, will be deducted at source at the prevailing rate as per applicable law.

2.2. The Company will pay undisputed invoices within thirty (30) days from the date of receipt of invoice. The Company may, however, withhold payment for those invoice(s) or portions of invoice(s) that Solytics Partners disputes in good faith, pending resolution of such dispute.

2.3. Parties agree that they shall endeavour to settle any dispute relating to the invoice within a period of ninety (90) calendar days from the date of receipt of the notice of dispute. If Parties fail to settle the disputed amount within the aforesaid period, the disputed amount shall be settled between the Parties in accordance with the dispute resolution procedure provided in this Agreement. It is hereby agreed by the Consultant that pending the settlement of any dispute, Consultant shall continue to provide the Services as per the terms and conditions of this Agreement.

2.4. Further, it is hereby agreed that in case of any error in the invoice raised by the Consultant, the same shall be rectified immediately upon same being notified to Consultant.

2.5. As a material term of this Agreement, the Consultant agrees that the payment arrangement established under this Agreement represents Company's entire payment obligation for the Services hereunder.

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PRISMIRE SOFTWARE SOLUTIONS PVT LTD

PRISMIRE

1004,10th floor, Jain Sadguru Capital Park, Madhapur, Hyderabad-500081, Email id- info@prismire.com.

Date: 21st May, 2025

TO WHOM SO EVER IT MAY CONCERN

This is to certify that **Mr. Aman Maner** successfully completed as a **Jr. Accessibility Tester** with **Prismire Software Solutions Pvt. Ltd.** from **November 2024 to May 2025**.

During the internship period, he was actively involved in accessibility testing tasks, including:

- Conducting accessibility audits using tools such as WAVE, Axe, and NVDA.
- Evaluating websites and applications against WCAG (Web Content Accessibility Guidelines) standards.
- Reporting accessibility issues and contributing to remediation strategies.
- Participating in team reviews and improving accessibility compliance across digital platforms.

Aman Maner demonstrated a keen understanding of digital accessibility principles, attention to detail, and a proactive approach to learning and problem-solving.

We appreciate his contributions and wish him success in all future endeavors.

Yours truly,

For Prismire Software Solutions PVT LTD.,

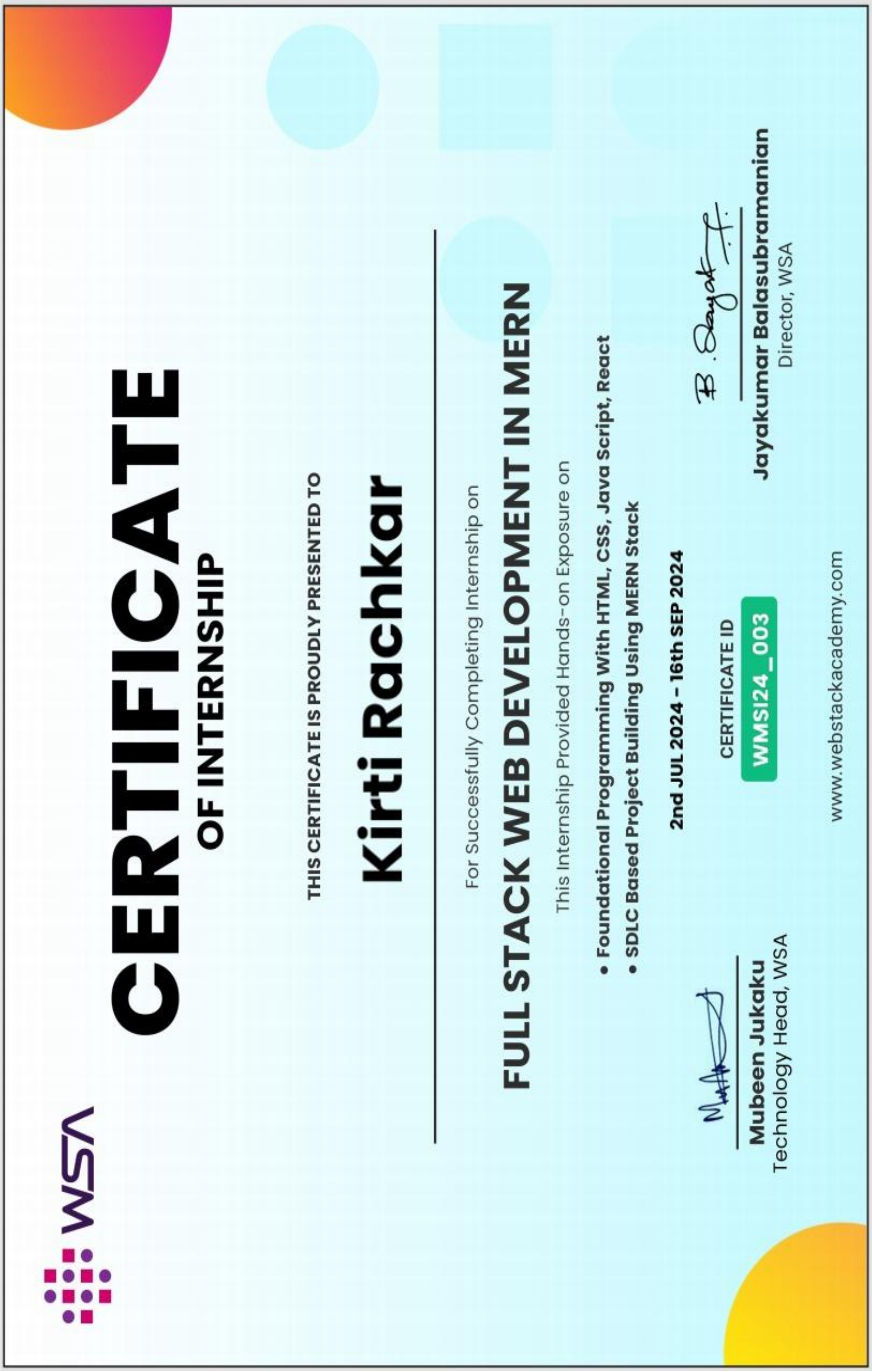
P. Prapul

PRISMIRE SOFTWARE SOLUTION PVT. LTD. HYDERABAD

HR Operations

1004,10th floor, Jain Sadguru Capital Park, Madhapur, Hyderabad-500081

+91 7601077112 www.prismire.com info@prismire.com



WSA

CERTIFICATE
OF INTERNSHIP

THIS CERTIFICATE IS PROUDLY PRESENTED TO

Kirti Rachkar

For Successfully Completing Internship on

FULL STACK WEB DEVELOPMENT IN MERN

This Internship Provided Hands-on Exposure on

- Foundational Programming With HTML, CSS, Java Script, React
- SDLC Based Project Building Using MERN Stack

2nd JUL 2024 – 16th SEP 2024

CERTIFICATE ID
WMSI24_003

Mubeen Jukaku
Technology Head, WSA

Jayakumar Balasubramanian
Director, WSA

www.webstackacademy.com

edunet foundation

Internship Offer Letter

Dear Mr./Ms. **ARPITA SUNIL PHALKE** **Date:** 2025-05-16

AICTE Student ID: STU6719ca7d4619d1729743485

Internship ID: INTERNSHIP_174365314467ee0918e7994

We would like to congratulate you on being selected for 4 - week Internship Program brought to you by Edunet Foundation, on the **AI Azure,** helping you build a strong base for advanced professional learning and industry-relevant applications. The internship will commence on **13th May 2025.**

During this internship, you will work individually and be assigned a mentor who will guide you to identify a solution to the problem and develop it into a project. The internship will be providing the following benefits:

- Learn and demonstrate AI and Cloud skills to enhance your employability and boost your confidence in emerging technologies
- Gain access to curated learning content through Microsoft Learn and the LMS Portal
- Participate in interactive masterclasses led by industry experts
- Work on real-world problem statements with hands-on practice and mentorship
- Earn a Co-branded certificate with the AICTE logo, enhancing your career credentials.

The structure of the internship is as follows:

Week	Topic
Week-1	Introduction to the program, Registration in Microsoft Learn & LMS Portal, what is AI, Machine Learning (ML), and Deep Learning (DL), Real-world applications of AI, Basic concepts: data, features, labels, models, training
Week-2	Supervised Vs Unsupervised, Supervised learning- Classification Hands-On, Different types of Regressions, Supervised learning- Regression Hands-On, what is Un-Labeled Data, UnSupervised Learning- Hands-ON
Week-3	What is Gen -AI, Gen AI- Azure Pratical Demo, Image Classification- Computer Vision, Azure Custom Visions Pratical Demo
Week-4	Introduction to Neural Networks and Deep Learning, Deep Learning - Pratical HandsOn, Students Hands-On, Project Demo

Criteria for certification:

- Participation in weekly sessions with mentors is mandatory
- Registration on MS Learn and Edunet LMS
- Completion of Courses on LMS
- Submission of a project presentation required

Stipend:

There will be NO stipend for this internship. If you agree to the above terms of the offer, please indicate acceptance of the offer letter and below undertaking to the undersigned.

Sincerely,
Nagesh Singh
Chairman – Edunet Foundation