A Study on Deep Learning Architectures for Cyclone Intensity Analysis Using INSAT-3D

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***Abstract*— This study presents a comprehensive examination of deep learning models 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. The 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 aids 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.**

Keywords: Tropical Cyclone Intensity, Dvorak Technique, CNN, AlexNet, DenseNet, ResNet50, VGG16 , Hybrid model, RMSE, MAE,

I. Introduction

Tropical cyclones are among the most destructive natural disasters, causing extensive damage to coastal regions, loss of life, and considerable economic impact. Accurate estimation of cyclone intensity is critical for effective disaster preparedness, enabling timely evacuation and strategic resource allocation. Over recent decades, both the frequency and intensity of cy- clones have been increasing, possibly due to climatic changes. Studies highlight a trend of intensifying cyclones globally, underlining the urgency of advancing predictive methods for Identify applicable funding agency here. If none, delete this. cyclone intensity [13], [15]. Traditional methods for cyclone intensity estimation rely on statistical approaches and satellite-based techniques, such as the widely used Dvorak technique[1]. This technique interprets cloud patterns in satellite imagery to provide a strength estimate, but it is limited by subjective in-terpretation and can struggle to capture rapid intensity changes accurately [17], [23]. Advanced adaptations like the Advanced Dvorak Technique (ADT) have sought to improve estimation accuracy but still face limitations in capturing evolving cyclone dynamics in real time [22]. In recent years, deep learning models have emerged as promising tools in cyclone intensity estimation, offering the potential to automate and improve prediction accuracy. Methods such as Convolutional Neural Networks (CNNs) and transformer models enable the analysis of large volumes of satellite imagery, allowing for faster and potentially more accurate assessments. Systems such as Deepti and Storm-Net leverage deep learning frameworks to enhance the efficiency and accuracy of cyclone intensity prediction, addressing some limitations inherent in traditional techniques [1], [4]. However, many current models still depend on extensive labeled datasets and face challenges in assessing intensity without accurately pinpointing the cyclone's center [5], [9]. To address these limitations, we propose an innovative hybrid system combining CNNs and transformers, designed to improve cyclone intensity estimation. This approach integrates multi-source satellite data, providing real-time predictions tailored to specific oceanic conditions, such as those observed in the Indian Ocean. By eliminating the need to locate the cyclone's exact center, this method advances both prediction accuracy and robustness, especially valuable in regions where unique cyclone behaviors pose forecasting challenges [1], [8].

II. RELATED WORK

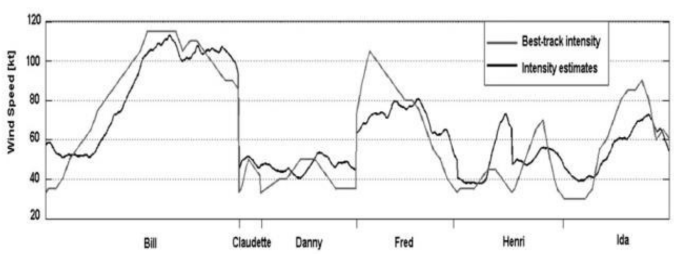
Hurricanes can cause over 1,000 fatalities in one incident and account for more than 100,000 deaths globally [17]. Advancements in cyclone monitoring and intensity estima-tion are vital to mitigate these devastating effects. Although the Advanced Dvorak Technique (ADT) has improved upon traditional methods, its accuracy is limited by chaotic cloud patterns in less intense storms and by empirical boundaries to manage fluctuations [1][18]. To address these challenges, researchers have developed deep learning models for cyclone intensity estimation, with Convolutional Neural Networks (CNNs) showing promising results in analyzing satellite im- agery [3].

The CY-Net model exemplifies progress in timely, ac- curate information delivery to assist emergency decision- makers. Adaptive learning strategies in models like CY-Net enhance readiness and disaster response [2]. Among various architectures, AlexNet demonstrated the highest predictive performance, highlighting the importance of model selection for optimizing forecasting [8]. Additionally, bias correction methods, such as Quantile Delta Mapping (QDM), help align climate model predictions with historical data, improving trop- ical cyclone intensity estimates using only infrared imagery [16].

The Deviation Angle-Variance (DAV) metric, by measuring cyclone axisymmetry, enhances intensity reliability, with test- ing on 2004–2009 data showing an average error of 13–15 knots. Adjustments for environmental factors like wind shear and sea surface temperatures are suggested for accuracy im- provements. High-resolution model simulations could further validate the DAV technique, aiding in better preparedness for tropical cyclones [19].

Advancements in cyclone intensity estimation, particularly through deep learning models like CY-Net and the use of metrics such as Deviation Angle-Variance, significantly enhance the accuracy of forecasts. These improvements are crucial for timely disaster response and preparedness, ultimately aiming to reduce the devastating impacts of hurricanes on human life.

Fig 1. Intensity estimates and best-track intensities for 2009, using



tropical cyclones from the period 2004–09

III. METHODOLOGY USED FOR CYCLONE INTENSITY

Table II 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 predominantly features deep learn ing 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 high lighted 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, markinga 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.

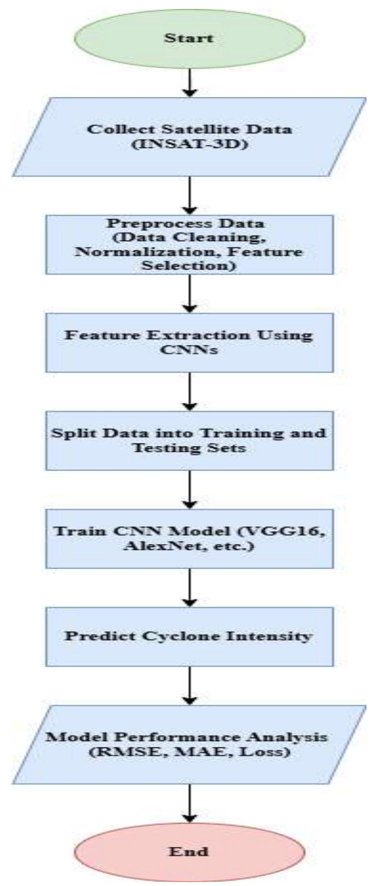


Fig 2: Proposed Methodology for Cyclone Intensity Prediction

Table I presents a comprehensive overview of multisource datasets employed for cyclone intensity estimation and weather monitoring. The table encompasses satellite imagery and climate model datasets across various temporal spans, covering regions including the Indian Ocean, the US, East Asia, and the Pacific. These datasets, obtained from platforms such as Kaggle, MOSDAC, and various meteorological agencies, facilitate accurate tracking, analysis, and forecasting of tropical cyclones and associated weather patterns.

TABLE I: Comprehensive Overview of Multisource Datasets for Cyclone and Weather Monitoring

Sr. No.	Name	Interval	Description	Regions	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 Regions	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)

IV. Algorithm and Implementation

1. AlexNet stands as one of the early frameworks in deep learning, utilizing ReLU activation functions and dropout techniques to enhance training efficiency. However, its relatively shallow design restricts its effectiveness in accurately estimating cyclone intensity, while still offering essential insights into the fundamental extraction of storm features from satellite imagery [38].

2. DenseNet features a unique architecture that connects each layer to all subsequent layers through a process known as dense connectivity, which promotes efficient gradient flow and the reuse of features. This design significantly improves the learning of high-resolution features in satellite images, effectively capturing critical storm characteristics necessary for estimating cyclone intensity [34].

3. InceptionV3 employs multi-scale convolutional filters, facilitating the effective analysis of diverse cyclone structures, including cloud bands and storm eyes. Its capability to process features across various resolutions renders it particularly adept at tasks related to cyclone intensity prediction [10], [28].

4. MobileNet implements depth wise separable convolutions to achieve a balance between computational efficiency and performance. This lightweight architecture is particularly beneficial for real-time cyclone monitoring on devices with limited processing capabilities, although it may not match the performance of more complex models in extracting fine-grained features [10], [4].

5. ResNet50utilizes residual connections to address the vanishing gradient issue commonly encountered in deep networks. This approach facilitates the extraction of complex spatial patterns from satellite imagery, making it a reliable option for precise cyclone intensity estimation [35], [37].

6. VGG The architecture of VGG is characterized by a series of sequential convolutional layers, which allows for detailed hierarchical feature extraction. Despite its significant computational requirements, VGG excels in extracting cyclone-specific features from infrared imagery [9], [38].

In summary, various deep learning frameworks, including densenet, InceptionV3, and ResNet50, demonstrate significant capabilities in accurately estimating cyclone intensity through advanced feature extraction from satellite imagery. While models like AlexNet and MobileNet offer insights and efficiency, more complex architectures are better suited for precise predictions in cyclone monitoring.

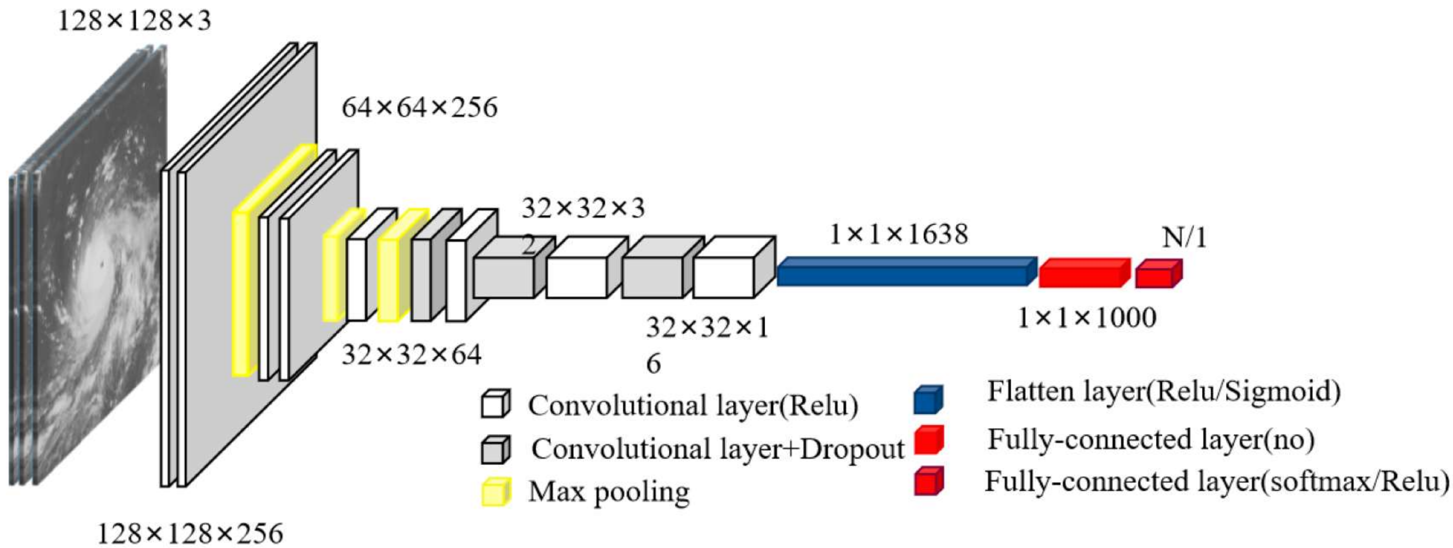


Fig 3: VGG16 Model Architecture for Cyclone Intensity Prediction

VGG16, characterized by its sequential 16-layer architecture and utilization of small 3×3 convolutional filters, demonstrates a robust capability in capturing cyclone-specific features from satellite imagery. The hierarchical feature extraction process, as illustrated in the accompanying figure, facilitates precise intensity estimation of cyclonic events. Empirical results indicate that VGG16 surpasses alternative models, achieving the lowest error rates, specifically RMSE: 19.34, MSE: 374, and MAE: 24.23. These metrics underscore VGG16's efficacy and reliability as a preferred model for cyclone monitoring applications.

TABLE II: Overview of Cyclone Intensity Estimation Methodologies and Outcomes

SR. NO	TITLE	IMAGE PROCESSING	METHODOLOGY USED	ACCURACY	OUTCOME
1	Deepti: Deep Learning-based Tropical Cyclone Intensity Estimation System [1]	Infrared images with data augmentation	CNN-based regression model	RMSE: 13.62 kt	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	96%	Accurate predictions 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	Improved over traditional methods	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-RNN models	CNN-RNN: Highest accuracy	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	PCOR: 0.892, low RMSE	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	2786.28 (test accuracy)	Enhanced intensity prediction and insights into cyclone dynamics
9	Deep Learning Based Cyclone Intensity Estimation [9]	Infrared and raw imagery	Capsule CNN (Caps Net)	TBD	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	RMSE: 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	High	Identified recent intensification trends
16	Recent Progress in Tropical Cyclone Intensity Forecasting [16]	N/A	Statistical & dynamical models	Improved skill	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)	Improved estimation	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	RMSE: 14.7 kt	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	RMAX MAE: 20.0 km	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	RMSE: 12.69 knots	Reference model for real- time TC intensity estimation, suited for intense typhoons
21	Objective TC Intensity Estimation Model Using Digital IR Satellite Images [21]	Digital IR images	Stepwise regression with convective core data	MAE: 1.8 m/s, RMSE: 2.4 m/s	Automated model, effective for severe typhoons

22	The Advanced Dvorak Technique (ADT) for Estimating TC Intensity: Update and New Capabilities [22]	Geostationary satellite IR, passive microwave	Objective Dvorak-based algorithm	Varied by TC strength	Reliable, enhanced TC intensity estimation; suited for complex cases
23	The Dvorak Tropical Cyclone Intensity Estimation Technique [23]	Satellite-based IR and visible imagery	Empirical pattern-matching	50%	Long-standing, widely-used TC intensity estimation technique

TABLE III: Core Algorithms and Their Effectiveness in Cyclone Estimation

Sr.No.	**Algorithm**	**RMSE**	MSE	MAE
I.	Alex net	22.93	525.14	28.73
II.	DenseNet	31	961.00	38.84
III.	InceptionV3	61	3721.00	76.44
IV.	Mobilenet	61.96	3840.24	77.61
V.	Resnet50	58.66	3440.66	77.55
VI.	Vgg16	19.34	374.00	24.23

The metrics used in Table III for evaluating the model performance are listed as follows:

1. Mean Absolute Error :

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

Where,
MAE = mean absolute error
y_i = prediction
x_i = true value
n = total number of data points

2. Mean Squared Error :

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

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 :

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

Where,
RMSE = Root Mean Squared Error
n = number of observations in the dataset
y_i = observed values
$\hat{y}_i$ = predicted values

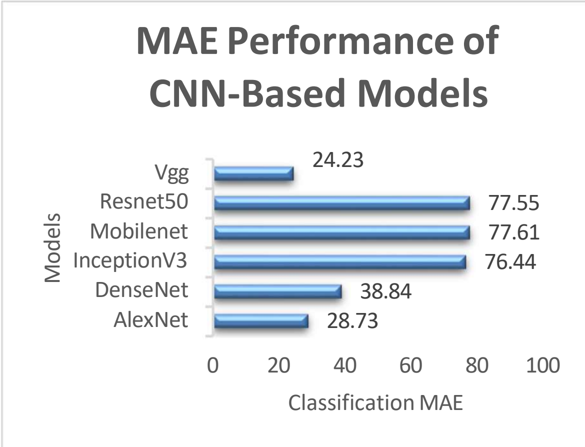


Fig 4 : Mean Absolute Error (MAE) Comparison of Deep Learning Models

This graph represents the absolute differences between predicted and actual cyclone intensities. A lower MAE indicates more accurate predictions with minimal deviation from actual values.

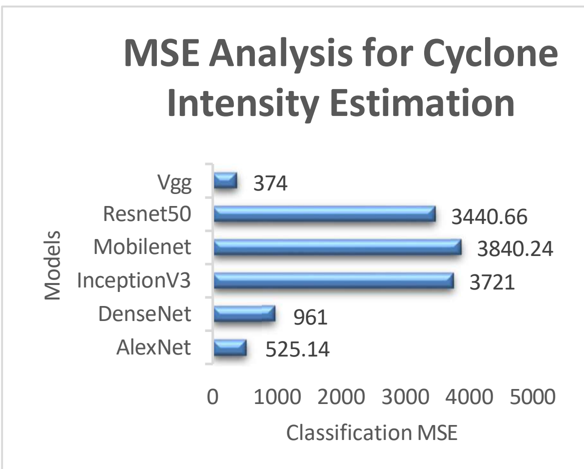


Fig 5 : Mean Squared Error (MSE) Analysis for Cyclone Intensity Estimation

The MSE graph highlights the squared differences between predicted and actual intensities, emphasizing larger errors. Lower MSE values indicate better model performance by reducing significant prediction deviations.

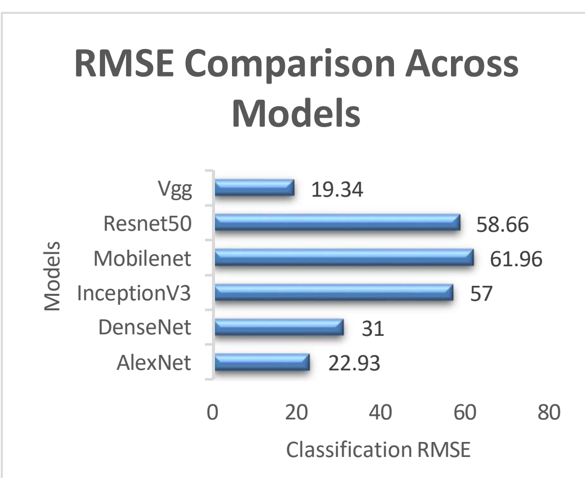


Fig 6 : Root Mean Squared Error (RMSE) Performance of Various CNN Models

MSE provides a more interpretable metric by taking the square root of MSE, representing the standard deviation of prediction errors. A lower RMSE signifies improved model reliability in cyclone intensity estimation.

From the performance analysis of various convolutional neural network (CNN) architectures for cyclone intensity estimation, it is evident that VGG16 outperforms other models, achieving the lowest root mean square error (RMSE) of 19.34, mean square error (MSE) of 374, and mean absolute error (MAE) of 24.23. These metrics indicate higher accuracy and superior predictive capability. AlexNet also demonstrates competitive results with a relatively low RMSE of 22.93 and MSE of 525.14, making it a viable option for this task. Conversely, InceptionV3, MobileNet, and ResNet50 exhibit higher RMSE, MSE, and MAE values, suggesting reduced accuracy in estimating cyclone intensity. DenseNet, while performing better than InceptionV3, still shows higher errors compared to VGG16 and AlexNet. Overall, the findings underscore the effectiveness of deeper and more optimized CNN architectures, such as VGG16, for cyclone intensity estimation, reinforcing its suitability for real- world disaster prediction and response applications.

V. Conclusion

In conclusion, this study highlights the transformative potential of deep learning architecture in cyclone intensity estimation, demonstrating their superiority over traditional forecasting methods such as Dvorak Technique. The integration of multi-source satellite datasets, alongside a diverse range of deep learning models including VGG and AlexNet-has yielded significant improvements in predictive accuracy, particularly the necessity for extensive labeled datasets and the models capability to generalize in real-time across varying oceanic conditions. Among the evaluated models, VGG16 demonstrated the highest accuracy, achieving an RMSE of 19.34, MSE of 374, and MAE of 24.23, significantly reducing error margins compared to other architectures. Moreover, the issue of cyclone center localization continues to hinder estimation accuracy. To address these limitations, we propose a hybrid approach that reduces reliance on precise cyclone center detection, thereby enhancing the robustness of intensity estimation. The findings advocate for a balanced methodology that emphasizes computational efficiency in conjunction with predictive accuracy, which is vital for optimizing real-time cyclone monitoring. Future work should focus on refining hybrid architectures and incorporating additional physical parameters, such as sea surface temperature and wind shear, while also investigating transfer learning techniques tom enhance model adaptability across diverse geographic contexts. Collectively, these advancements hold the potential to contribute to more reliable early warning system, ultimate strengthening disaster preparedness and mitigation strategies.

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