IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 2, August 2024

Cyclone Intensity Estimation

Rikhitha Ankireddy, P Veronica, Kadapathri Srinidhi, Varakala Satheesh Kumar

Students, CSE, Sreenidhi Institute of Science and Technology, Hyderabad, India

Associate Professor, CSE, Sreenidhi Institute of Science and Technology, Hyderabad, India

Abstract: *Tropical cyclones, also known as hurricanes or typhoons, are intense storm systems characterized by a low-pressure center, strong winds, and heavy rainfall. Forming over warm ocean waters, these cyclones pose significant threats to coastal regions worldwide, making accurate and timely intensity estimation crucial for disaster preparedness and response. Traditional methods of assessing cyclone intensity often rely on manual interpretation of satellite imagery, a process that is both time-consuming and prone to human error.To address these limitations, we propose a deep learning-based approach for automated cyclone intensity estimation. This project leverages cutting-edge deep learning architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to analyze satellite imagery and atmospheric data. By employing transfer learning, we adapt pre-trained models to enhance cyclone intensity prediction, even in the face of limited data. Additionally, the project explores the fusion of multi-modal data sources, such as satellite images and atmospheric pressure readings, to improve the accuracy of predictions.These advancements in technology and methodology offer both significant opportunities and challenges. On the one hand, the potential of machine learning in cyclone forecasting is far from fully exploited, with vast amounts of data still waiting to be harnessed. On the other hand, the unpredictable nature of tropical cyclones, driven by their complex dynamic mechanisms and susceptibility to various influencing factors, continues to challenge the stability and reliability of these predictions*

Keywords: Machine Learning, Deep learning, Convolutional neural networks, Recurrent neural networks, Feature extraction.

I. INTRODUCTION

1.1 PROJECT INTRODUCTION

Tropical cyclones are highly destructive weather systems, and accurately estimating their intensity is crucial for predicting and mitigating potential damage. Cyclone intensity estimation involves analyzing various meteorological variables, often derived from satellite imagery, which provides visual data on cloud patterns, temperature, and other indicators of storm strength. Traditionally, this task has relied on manual interpretation, but recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have offered more efficient solutions. CNNs are powerful tools for processing image data and have proven effective in recognizing patterns that correlate with cyclone intensity. In a CNN-based approach, historical data on tropical cyclones, labeled with corresponding intensity levels, is used to train the model. The CNN then learns to identify key features in satellite images that are indicative of cyclone strength, allowing it to predict the intensity of new storms with greater accuracy. One of the key advantages of using CNNs for cyclone intensity estimation is their ability to handle large datasets, which is particularly beneficial given the vast amount of historical satellite imagery and meteorological data available. By leveraging these data-rich resources, CNNs can improve the precision of cyclone predictions, ultimately enhancing disaster preparedness and response efforts.

1.2 SCOPE

The scope of cyclone intensity estimation extends beyond immediate disaster management, impacting various sectors, particularly agriculture, infrastructure, and insurance. In agriculture, accurate cyclone intensity forecasts are crucial for protecting crops and livestock. Early warnings allow farmers to take preventive measures, such as securing livestock, reinforcing structures, and harvesting crops early to minimize losses. This can significantly reduce the economic impact

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, August 2024

of cyclones on agricultural communities. In infrastructure planning and management, precise intensity estimation helps in designing buildings, roads, and other critical structures to withstand expected cyclone forces, thereby reducing damage and ensuring quicker recovery post-disaster. Moreover, the insurance industry relies on accurate cyclone forecasts to assess risk, set premiums, and process claims. Better intensity predictions enable more accurate risk assessments, leading to fairer insurance policies and quicker payouts in the event of a disaster. Additionally, cyclone intensity estimation plays a vital role in environmental conservation by predicting potential impacts on coastal ecosystems, allowing for timely interventions to protect vulnerable habitats. Overall, the accurate estimation of cyclone intensity not only aids in immediate disaster response but also supports long-term planning and resilience across multiple sectors.

1.3 PROJECT OVERVIEW

The objective of this project was to create a machine learning model capable of forecasting the maximum sustained wind speed of tropical cyclones through the analysis of satellite imagery. We utilized two primary data sources: a series of NetCDF4 files containing global satellite images of tropical cyclones, and a CSV file with metadata for cyclones in the Atlantic and Pacific regions. This metadata included storm identifiers, names, dates, times, coordinates, and recorded wind speeds. We opted for a Convolutional Neural Network (CNN) to process the satellite images and predict the wind speed of each cyclone. The CNN was engineered to accept grayscale images and produce a continuous value representing the predicted wind speed. In essence, this project involves gathering and preparing satellite images, developing and training a CNN to estimate cyclone intensity, and assessing the model's accuracy on a separate test dataset. Once trained, the CNN model can be utilized for real-time cyclone intensity estimation.

1.4 OBJECTIVE

The objectives of this project are to develop a robust deep learning model for accurate cyclone intensity prediction and optimize data augmentation techniques to enhance the model's performance. The project aims to evaluate and compare the model's accuracy with traditional forecasting methods, improve the scalability and efficiency of the prediction system, and integrate multi-modal data sources to boost prediction accuracy. It also seeks to implement uncertainty quantification methods to provide probabilistic estimates of cyclone intensity, aiding in better decision-making.

II. LITERATURE SURVEY

2.1 EXISTING SYSTEM

Cyclone intensity estimation integrates various modeling approaches to provide accurate forecasts of tropical cyclone strength. Existing models combine observational data, historical trends, and computational simulations to predict cyclone intensity. Traditional techniques, such as the Dvorak Technique, analyze satellite imagery to visually assess storm characteristics, while statistical models use historical data to establish relationships between cyclone parameters and environmental factors. Numerical Weather Prediction (NWP) models simulate atmospheric dynamics using complex mathematical equations and observational inputs, offering detailed forecasts based on interactions among variables like temperature, humidity, and wind. Machine learning models enhance this process by leveraging large datasets and advanced algorithms to identify intricate patterns and improve forecast accuracy through continuous learning. Ensemble forecasting further refines predictions by integrating multiple models or variations, providing a range of possible outcomes and accounting for uncertainties in cyclone dynamics and atmospheric conditions. Collectively, these methods create a comprehensive framework that equips meteorologists with robust tools for precise cyclone intensity forecasting and effective impact mitigation

2.2 PROPOSED SYSTEM

The proposed cyclone intensity estimation model utilizes a convolutional neural network (CNN) built with TensorFlow and Keras, utilizing satellite imagery to predict maximum sustained wind speeds. This machine learning-based approach offers several advantages over traditional methods that rely on aircraft observations. It provides wider spatial and temporal coverage, leading to more accurate and faster predictions with reduced costs and risks. The CNN architecture includes convolutional layers for feature extraction, batch normalization for stability, dropout for

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, August 2024

regularization, and pooling layers to manage complexity. The model's fully connected layers and linear activation function generate the intensity predictions. It is optimized using RMSprop, with mean squared error (MSE) as the loss function and early stopping to prevent overfitting. Performance is evaluated using metrics like mean absolute error (MAE) and root mean squared error (RMSE), enhancing the reliability and effectiveness of cyclone intensity estimation.

III. SYSTEM ANALYSIS

3.1 FUNCTIONAL REQUIREMENTS

The functional requirements for the cyclone intensity estimation project include:

- Data Handling: The system must process satellite imagery from NetCDF4 files and metadata from CSV files, including image normalization and resizing.
- Model Training: It should train a convolutional neural network (CNN) using historical data for intensity prediction, incorporating data augmentation techniques.
- Prediction: The system must predict the maximum sustained wind speed of tropical cyclones from new satellite images in real-time or near-real-time.
- Evaluation: It should evaluate model performance using metrics like mean absolute error (MAE) and root mean squared error (RMSE) and compare it with traditional methods.
- User Interface: The system must provide a user interface for visualizing predictions and generating performance reports.
- Scalability: It should handle large volumes of data efficiently and integrate with other systems for expanded functionality.
- Error Handling: The system must manage errors and log significant events during processing and prediction.

3.2 PERFORMANCE REQUIREMENTS

- Processing Speed: Analyze and predict from satellite images within a specified time frame, aiming for real-time or near-real-time performance.
- Prediction Accuracy: Achieve high accuracy with MAE and RMSE metrics within predefined thresholds.
- Scalability: Handle large volumes of data without significant performance degradation.
- Throughput: Process multiple images simultaneously to enable efficient cyclone analysis.
- Resource Utilization: Optimize the use of computational resources, including memory and processing power.
- Reliability: Ensure consistent performance and minimal downtime.
- Latency: Maintain minimal latency for prediction and reporting to support timely decision-making.

3.3 SOFTWARE REQUIREMENTS

The software requirements for the cyclone intensity prediction system using deep learning are:

- Programming Language: The system should be implemented in a language well-suited for data science and machine learning, such as Python.
- Machine Learning Frameworks: The development should utilize frameworks like TensorFlow or Keras for constructing and training the CNN model.
- Additional Libraries: The system should incorporate libraries such as Pandas for data manipulation, NumPy for numerical computations, and Matplotlib or Seaborn for data visualization. Additionally, it should use libraries like NetCDF4 for handling satellite data, and Requests for HTTP operations.

3.4 HARDWARE REQUIREMENTS

- CPU: Multi-core processor (e.g., Intel Core i5 or AMD Ryzen 5) with a minimum clock speed of 3 GHz.
- GPU (Optional): NVIDIA GPUs (e.g., GeForce GTX/RTX) for accelerated deep learning tasks.
- RAM: Minimum 8GB, preferably 16GB for handling larger datasets.
- Storage: SSD with at least 5GB for faster data access

IV. TECHNOLOGY USED

The primary technology utilized in this project revolves around deep learning, a specialized area within artificial intelligence that employs neural networks with multiple layers to derive complex data representations. For this project, convolutional neural networks (CNNs) were employed due to their proficiency in processing and analyzing image data.

CNNs are particularly effective for examining satellite imagery because they autonomously identify and extract significant features from images. The architecture of CNNs includes convolutional layers, pooling layers, and fully connected layers, each contributing to the extraction of spatial patterns and relationships within the data. By training the CNN on a comprehensive dataset of satellite images and corresponding cyclone intensity labels, the model learns to accurately predict cyclone intensity based on the detected features and patterns.

Beyond deep learning, several Python libraries were integrated to facilitate data processing and analysis. Libraries such as Pandas and NumPy were used for data manipulation and numerical operations, while OpenCV aided in image processing tasks. These tools were crucial for preparing the dataset, extracting features, and evaluating model performance.

Overall, the project leverages a combination of advanced deep learning techniques and essential Python libraries to enhance the precision and dependability of cyclone intensity predictions.

V. DATA DESCRIPTION

The dataset for this project comprised satellite imagery alongside cyclone-related data. The imagery, sourced from space, depicted various cyclones at different times, offering crucial visual insights into the storms' features and development stages. Alongside these images, the dataset included supplementary CSV files that detailed cyclone-specific information such as identifiers, timestamps, geographic coordinates, and maximum wind speeds. This additional data was key for associating the visual information with precise cyclone metrics.

This comprehensive dataset enabled an in-depth analysis of the correlation between the cyclone images and their recorded intensities. To augment the dataset's diversity and robustness, we applied data augmentation methods, such as rotating and flipping the images, to generate additional examples. This expansion aimed to improve the model's learning capacity and predictive accuracy.

Overall, the dataset served as the essential foundation for developing a deep learning model to estimate cyclone intensity from satellite images, facilitating the investigation of visual patterns in relation to storm strength.

VI. DATA PREPARATION FOR MODEL TRAINING

- Data Acquisition: Collect satellite images and related metadata from designated sources, including netCDF and CSV files, which provide visual and descriptive data about cyclones.
- Image Downloading: Retrieve satellite images from online repositories or databases, ensuring all relevant files are successfully downloaded and saved for further processing
- Image Extraction: Extract image data from netCDF files. This involves converting netCDF format into a standard image format, making the data ready for analysis.
- Data Preprocessing:
- Normalization: Standardize the pixel values of images to a common range (e.g., 0 to 1) to facilitate smoother training of the deep learning model.
- Resizing: Adjust all images to a uniform size to maintain consistent input dimensions for the model, which aids in efficient processing.
- Augmentation: Enhance the dataset by applying transformations like rotation, flipping, and cropping to create additional training samples, improving model robustness.
- Data Splitting: Divide the dataset into training, validation, and test subsets. This separation is crucial for effective model training, fine-tuning, and performance evaluation.
- Metadata Integration: Combine the satellite images with corresponding metadata from CSV files. This integration ensures each image is paired with accurate cyclone details, providing a complete dataset for the model.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, August 2024

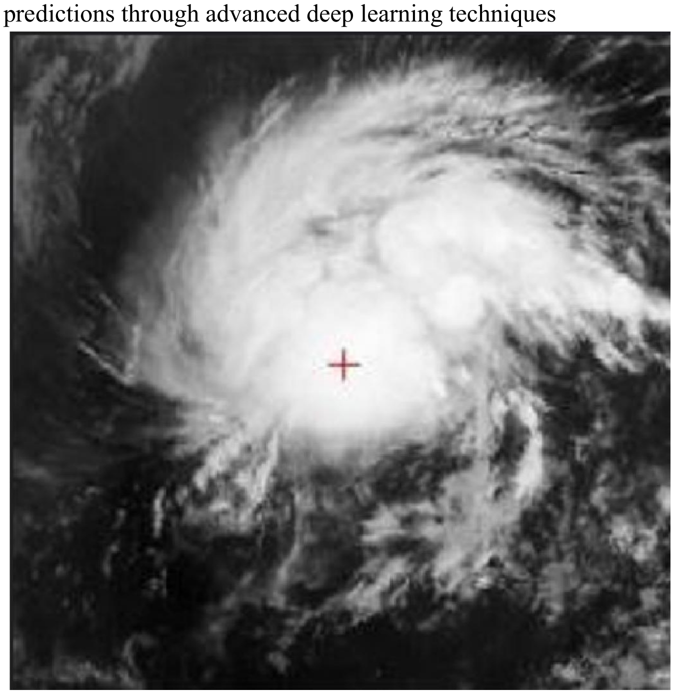
- Addressing Data Issues: Identify and rectify any missing or inconsistent data entries to ensure the dataset is complete and reliable for model development.

NETCDF4 FILES:

netCDF4 (Network Common Data Form version 4) files are a type of file format designed for the storage and sharing of complex, multidimensional scientific data. They are used widely in various fields, including meteorology, oceanography, and geophysics, due to their capability to handle large volumes of data with multiple dimensions and variables. The netCDF4 format is particularly suited for datasets that require hierarchical organization and the ability to store and access data efficiently.

- Purpose: netCDF4 files are designed for managing and distributing complex scientific data. For this project, they store satellite images and related meteorological information.
- Organization: These files are structured in a hierarchical manner, which allows them to hold intricate datasets. They support multiple dimensions and variables, making them ideal for large-scale data with various layers.
- Data Extraction: To utilize data from netCDF4 files, it is necessary to access specific variables and dimensions. This process involves retrieving cyclone images and corresponding metadata such as timestamps and geographic coordinates.
- Application: The data from netCDF4 files provides essential satellite imagery and metadata required for training deep learning models, aiding in the prediction of cyclone strength.
- Processing: Extracted data is converted from its multidimensional format to standard image formats for model training and evaluation. This includes transforming arrays into 2D images and aligning metadata with the images.
- Tools: Python libraries like netCDF4 facilitate working with these files by offering functionalities to read and manipulate data efficiently.

By leveraging netCDF4 files, this project can manage and analyze extensive satellite imagery effectively, supporting accurate cyclone intensity predictions through advanced deep learning techniques



Sample image from netCDF4 file

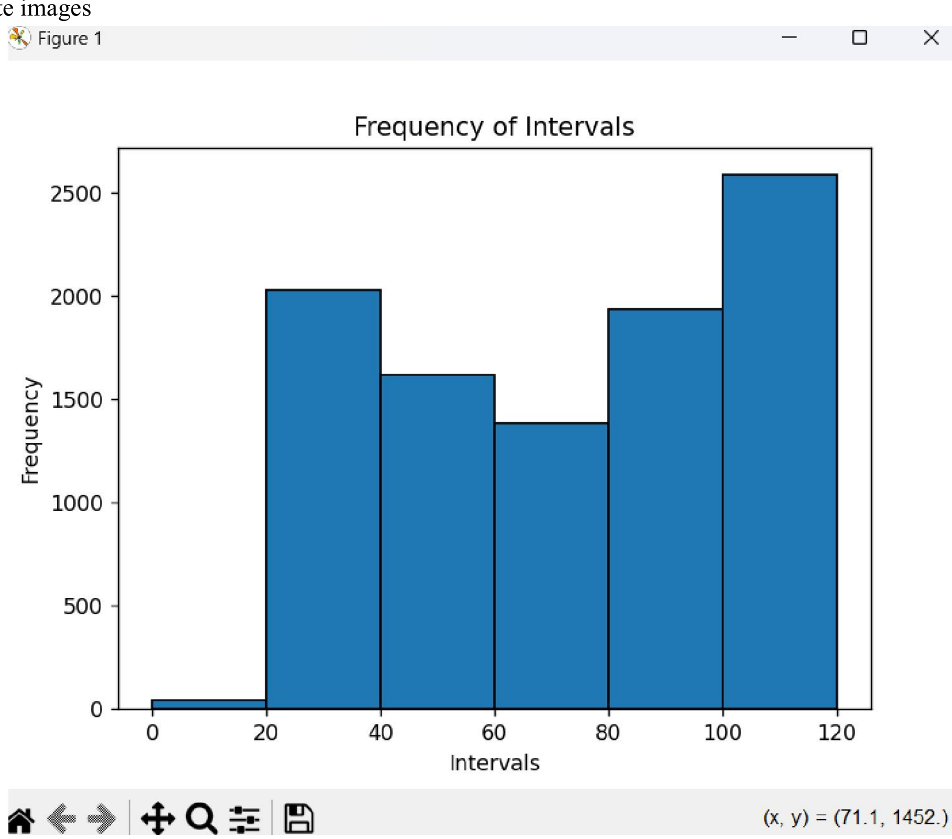
6.1 DATA AGUMENTATION

Data augmentation refers to techniques used to artificially increase the size and variety of a dataset by applying various modifications to the original data. This approach is essential for enhancing the performance and robustness of machine learning models by providing a broader range of examples for training. By simulating different conditions and variations, data augmentation helps models generalize better and perform well on new, unseen data.

Common Techniques:

- Rotation: Adjusting the orientation of images to introduce different viewpoints.
- Flipping: Creating mirrored versions of images by flipping them horizontally or vertically.
- Scaling: Altering the size of images to simulate different scales.
- Cropping: Cutting out random portions of images to focus on specific areas.
- Brightness and Contrast Adjustment: Modifying the image's lighting and contrast to represent various environmental conditions.

The use of data augmentation is particularly valuable in cyclone intensity estimation, where variations in satellite imagery can be significant due to changing atmospheric conditions. This approach ensures that the model can better generalize across diverse image inputs, improving its ability to accurately predict cyclone intensity despite potential differences in image quality or environmental factors. Consequently, data augmentation enhances the model's performance and reliability, making it a fundamental component of the training process for predicting cyclone strength from satellite images



6.2 K-FOLD CROSS VALIDATION

K-Fold Cross Validation is a robust technique used to evaluate the performance of machine learning models, including those applied in cyclone intensity estimation. In this project, the dataset is divided into 'k' subsets or folds. The model is then trained on 'k-1' of these folds while the remaining one fold is used for validation. This process is repeated 'k' times,

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, August 2024

with each fold serving as the validation set once. The results from each iteration are averaged to provide a more reliable estimate of the model's performance.

This method is particularly useful in this project as it ensures that the CNN model generalizes well across different parts of the dataset, preventing overfitting and providing a comprehensive evaluation. By applying K-Fold Cross Validation, the model's ability to predict cyclone intensity based on satellite imagery can be assessed more accurately, leading to a more robust and reliable predictive system.

VII. CNN EXPLANATION

In the context of this project, model fitting involves training the convolutional neural network (CNN) to accurately estimate cyclone intensity by adjusting its internal parameters based on the training data. This training process is divided into multiple epochs, where an epoch represents a single complete pass over the entire dataset. As the number of epochs increases, the model gains more opportunities to learn and refine its predictions, though this also extends the training time

```
model = models.Sequential()

# Add convolutional layers
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(64, 64, 3)))
model.add(layers.BatchNormalization())
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))

# Flatten and add dense layers
model.add(layers.Flatten())
model.add(layers.Dropout(0.5))
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dense(1, activation=None))  # Linear activation for regression

# Compile the model
model.compile(
    optimizer='rmsprop',
    loss='mean_squared_error',
    metrics=[metrics.MeanAbsoluteError(), metrics.RootMeanSquaredError()]
)
```

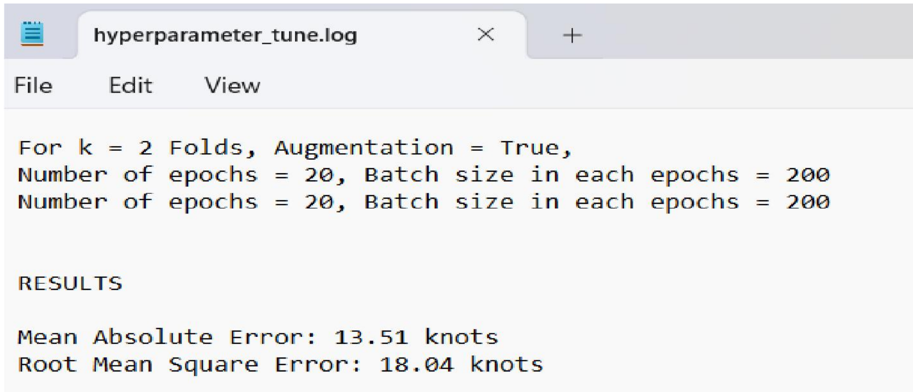
During each epoch, the dataset is broken down into smaller subsets known as batches, which are processed individually by the model. The size of these batches is determined by a parameter called the batch size. Within each batch, data samples are selected through a method called random sampling, which helps introduce variability and aids the model in generalizing from the data.

After processing each batch, the model updates its parameters, gradually reducing prediction errors and improving accuracy. For instance, if the training dataset consists of 10,000 samples and the batch size is set to 1,000, the model will process 10 batches in each epoch. Through this iterative process, the model learns from the data, and after each batch, it fine-tunes its parameters to better capture the underlying patterns.

Selecting the appropriate number of epochs and batch size is crucial, as these parameters significantly impact the efficiency and accuracy of the model's training process.

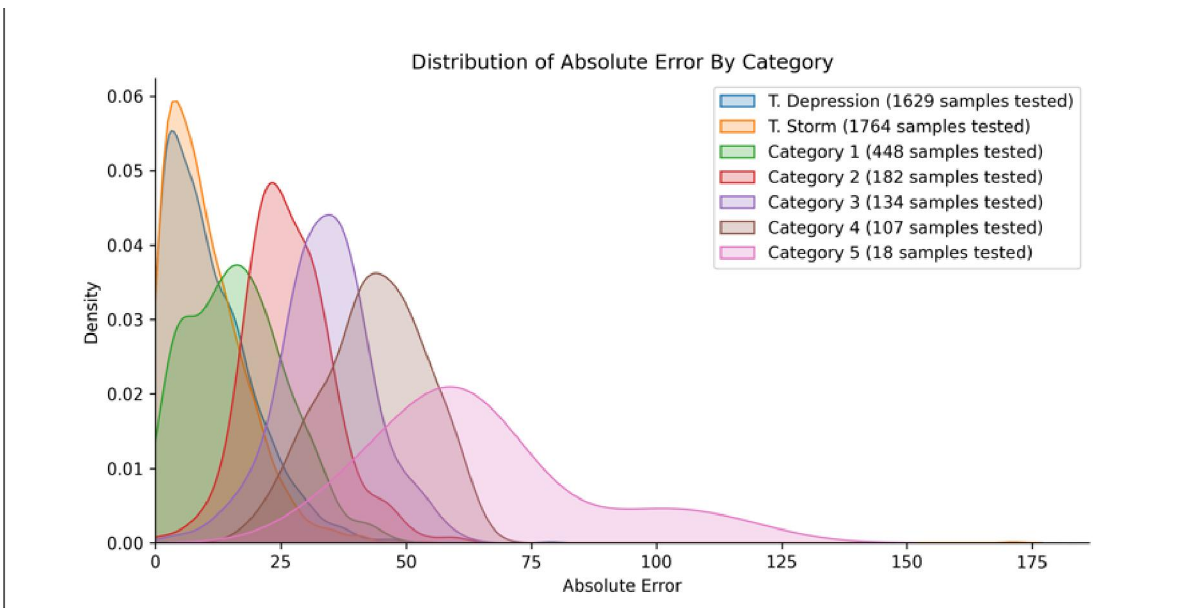
Results of hyperparameter tuning:

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, August 2024



Hyperparameter tuning for different folds in cross-validation involves adjusting parameters like learning rate, batch size, and number of epochs for each fold to optimize model performance. It ensures that the chosen parameters generalize well across various subsets of the data. By evaluating the model's performance on each fold, the best combination of hyperparameters is identified to enhance accuracy and minimize overfitting.

VIII. RESULTS



IX. CONCLUSION

This project represents a significant advancement in cyclone intensity estimation through the application of deep learning techniques, particularly Convolutional Neural Networks (CNNs). Our objective was to develop a model capable of predicting the maximum sustained wind speeds of cyclones using satellite imagery. To achieve this, we utilized a diverse dataset consisting of satellite images and corresponding wind speed data, ensuring a robust and comprehensive foundation for our analysis.

The project involved several key steps, including data collection, preprocessing, and augmentation. We gathered satellite images in netCDF4 and CSV formats, which were then processed to create a suitable input for our CNN model. Data augmentation techniques, such as image flipping and rotation, were applied to enhance the diversity of the training set and improve the model's generalization capabilities.

K-fold cross-validation was employed to rigorously evaluate the performance of the CNN model, allowing us to assess its accuracy and robustness across different subsets of the dataset. The model was trained to recognize and predict cyclone intensity based on patterns in the satellite images, with metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) used to gauge its performance.

The results demonstrated that our CNN-based approach could effectively predict cyclone wind speeds, achieving a mean absolute error of approximately 6 knots. This outcome underscores the potential of deep learning in advancing cyclone forecasting and disaster management. By providing more accurate and timely intensity predictions, the model offers valuable insights for improving preparedness and response strategies. Overall, this project highlights the transformative impact of integrating deep learning with meteorological data to enhance our understanding and management of tropical cyclones.

REFERENCES

[1]. K. S. Shyam, P. K. Dash, and P. J. Klotzbach, "Machine Learning Techniques for Tropical Cyclone Intensity Estimation: A Review," Atmosphere, vol. 11, no. 3, p. 250, Mar. 2020.

[2]. Y. Zhuang, W. Cao, and H. Chen, "A Deep Learning Approach for Cyclone Intensity Estimation Using Remote Sensing Imagery," Remote Sensing, vol. 12, no. 18, p. 3048, Sept. 2020.

[3]. J. Schulte, T. Hoar, and J. Brown, "Deep Learning-Based Prediction of Tropical Cyclone Intensity with Multi-Platform Satellite Observations," Geophysical Research Letters, vol. 48, no. 2, p. e2020GL090965, Jan. 2021.

[4]. C. Wang, G. Zheng, X. Li, Q. Xu, B. Liu and J. Zhang, "Tropical Cyclone Intensity Estimation From Geostationary Satellite Imagery Using Deep Convolutional Neural Networks," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-16, 2022.

[5]. Pang, S.; Xie, P.; Xu, D.; Meng, F.; Tao, X.; Li, B.; Li, Y.; Song, T. NDFTC: A new detection framework of tropical cyclones from meteorological satellite images with deep transfer learning. Remote Sens. 2021.

[6]. Wimmers, A.; Velden, C.; Cossuth, J.H. Using deep learning to estimate tropical cyclone intensity from satellite passive microwave imagery. Mon. Weather Rev. 2019.

[7]. Wang, C.; Zheng, G.; Li, X.; Xu, Q.; Liu, B.; Zhang, J. Tropical cyclone intensity estimation from geostationary satellite imagery using deep convolutional neural networks. IEEE Trans. Geosci. Remote Sens. 2021.

[8]. Lee, J.; Im, J.; Cha, D.-H.; Park, H.; Sim, S. Tropical cyclone intensity estimation using multi-dimensional convolutional neural networks from geostationary satellite data. Remote Sens. 2019.

[9]. Stewart, J., C. Bonfanti, I. Jankov, L. Trailovic, and M. W. Govett, 2019: The need for HPC for deep learning with real-time satellite observations. 18th Conf. on Artificial and Computational Intelligence and Its Applications to the Environmental Sciences, Phoenix, AZ, Amer. Meteor. Soc., TJ10.2.

[10]. Chen, R., Zhang, W., and Wang, X.: Machine learning in tropical cyclone forecast modeling: A review, Atmosphere-Basel, 11, 676, 2020.

[11]. Naga Vamshi Reddy Ankireddy, Karakonda Sridhar Reddy, YarakarajuSoureesh Varma, Sundaragiri Dheeraj: Cyclone Intensity Estimation using Deep Learning, IJCSPUB.

[12]. Harshal NamdeoraoDharpure, Tejal SudhakarraoMohod, Radhika Vinod Malani, Janhavi Chandak, Atharva Shekhar Belge, Preet Ravin Ambadkar, Prof Ankita Pande:Deep Learning-Based Cyclone Intensity Estimation Using INSAT-3D IR Imagery: A Comparative Study, IJRPR, 2023.

[13]. Jayanthi Devaraj,Sumathi Ganesan, Rajvikram Madurai Elavarasan and Umashankar Subramaniam: A Novel Deep Learning Based Model for Tropical Intensity Estimation and Post-Disaster Management of Hurricanes, MDPI,2021