Cyclone Forecasting System

Aditya Garudkar [1], Vaibhav Jadhao [2], Yash Dhekne [3], Prof. Neha Bhagwat [4]
Computer Engineering Department [1,2,3,4]
Nutan Maharashtra Institute of Engineering and Technology, Pune, Maharashtra [1,2,3,4]

Abstract - Tropical cyclones (TCs) stand as dynamic and complex atmosphere-sea interaction phenomena, their behavior contingent upon a delicate interplay of oceanic and atmospheric conditions. Their emergence, dissipation, or intensification presents a challenge for accurate prediction, and as such, the development of precise diagnostic models holds immense potential for saving lives and safeguarding property. Existing techniques for diagnosing tropical cyclone wind speeds have displayed varying degrees of success, often limited by their reliance on specific points in time and satellite data. This paper introduces a groundbreaking paradigm shift by presenting a deeplearning-based objective diagnostic estimation of tropical cyclone intensity. Leveraging the power of deep learning, the model promises to transcend the limitations of traditional methods, offering a more nuanced and accurate representation of cyclonic behavior. A key innovation lies in the integration of an infrared satellite imagery-based diagnostic system. This method represents a new visualization gateway in addition to improving intensity estimation accuracy. This portal is not merely a scientific tool; it stands as one of the first systems to seamlessly translate deep learning results into a user-friendly interface, presenting not only raw data but also contextual information to end users. This move towards user accessibility marks a significant stride in bridging the gap between advanced scientific methodologies and practical, realworld applications

Keywords: Deep learning, wind speed estimation, Convolutional neural network, Estimation, Cyclone, Disaster management

I. INTRODUCTION

Hurricanes can kill more than 1,000 people in a single event and cause more than 100,000 deaths worldwide. Many hurricanes in the past few years have caused economic losses estimated at over $50 billion, and some hurricanes in history have caused over $100 billion in damage, including inflation. Insurance agencies report that more than $10 trillion of coastal property is vulnerable to hurricane damage in the United States alone. [1] There are many dangers associated with hurricanes, many of which can lead to eventual death and destruction. Hurricane damage models use exponents or powers of wind speed to estimate risk. Therefore, being able to accurately predict the temperature and storm intensity (defined as the maximum surface wind speed) is important for disaster preparedness and response. [2] Direct measurements of wind in tropical cyclones are variable, especially offshore. For this reason, monitoring the intensity of storms began to be done using satellite measurements. An accurate assessment using satellite data is still difficult because the National Hurricane Centre (NHC) has a 10–20% uncertainty in its weighted assessment using only satellite observations. Similarly, the average 24-hour forecast for a hurricane has an error of about 10–20%, according to the NHC report. Therefore, improving the initial estimate from satellite images could mean a significant improvement in short-term forecasts, thus improving our country's disaster preparedness and response capabilities.

II. LITERATURE SURVEY

Convolutional Neural Networks for Tropical Cyclone Intensity Estimation: This paper by Pradhan et al. (2018) proposed a convolutional neural network (CNN) model for estimating tropical cyclone intensity from satellite imagery. The authors utilized infrared and water vapor channel images from geostationary satellites as input to the CNN model. Their approach achieved better performance than traditional methods based on feature engineering and machine learning algorithms. [3] Deep Learning for Tropical Cyclone Intensity Forecasting from Satellite Images: In this study, Alemany et al. (2019) developed a deep learning framework for forecasting tropical cyclone intensity using satellite imagery. They employed a combination of CNN and long short-term memory (LSTM) networks to capture spatial and temporal patterns in the data. Their model outperformed operational models used by meteorological agencies. [4] Tropical Cyclone Intensity Estimation from Satellite Data using Deep Learning: Chen et al. (2020) proposed a deep learning model that integrates CNN and recurrent neural networks (RNNs) to estimate tropical cyclone intensity from satellite data. Their approach leveraged both spatial and temporal information from various satellite channels, including infrared, water vapor, and visible channels.

Deep Learning for Hurricane Intensity Forecasting from Satellite Imagery: Kimberly et al. (2021) developed a deep learning model based on U-Net architecture for hurricane intensity forecasting using satellite imagery. Their model showed improved performance compared to traditional methods, particularly in predicting rapid intensification events. [5] A Multimodal Deep Learning Approach for Tropical Cyclone Intensity Estimation: Liu et al. (2022) proposed a multimodal deep learning framework that combines satellite imagery, reanalysis data, and cyclone track information for tropical cyclone intensity estimation. Their approach demonstrated the potential of integrating multiple data sources for improved intensity estimation.

III. PROPOSED WORK

The proposed system automates the process of cyclone intensity estimation using INSAT-3D IR satellite imagery. It begins by retrieving satellite images through web scraping and automation techniques implemented in Python. [6] These images undergo preprocessing, including noise reduction and normalization, to prepare them for input into a convolutional neural network (CNN) model. The CNN model, developed using TensorFlow or PyTorch, evaluates the cyclone intensity level depicted in the images based on learned patterns and features. [7] The system generates output indicating the predicted intensity levels, which can be integrated into existing forecasting systems or decision support tools used by meteorological agencies and disaster management authorities. Overall, the system streamlines the intensity estimation process, enabling timely and accurate assessment of cyclone severity for improved disaster preparedness and response.

Methodology: Definition:

The objective is to develop an automated system for objectively estimating tropical cyclone wind speed using satellite imagery. Accurate estimation of tropical cyclone intensity (wind speed) is crucial for disaster preparedness and response, as it directly impacts the potential damage and risk assessment.

Current techniques, such as the Dvorak technique, suffer from subjectivity and reliance on empirical thresholds, highlighting the need for an objective and automated approach.

B. Data Collection and Analysis:

Initial training data is obtained from the tropical cyclone repository of the Marine Meteorology Division of U.S. Naval Research Laboratory (NRL) and NOAA's Comprehensive Large Array-data Stewardship System (CLASS). [7] Tropical cyclone satellite infrared (IR) images captured every 15 minutes are collected, along with wind speed information from HURDAT2 storm database. Additional data analysis reveals the need for higher temporal frequency and more samples, leading to the transition to raw GOES data for enhanced dataset creation. [8] Web scraping and automation techniques are employed using Python to automate the retrieval of satellite imagery and associated data from NRL and CLASS repositories.

C. Model Development and Evaluation:

Design a deep learning model for tropical cyclone intensity estimation using a convolutional neural network (CNN) architecture. [9] Iteratively develop and refine the CNN model through multiple phases of training, testing, and evaluation to optimize performance. Utilize a linear output approach for wind speed estimation at 1 kt resolution, leveraging insights from previous model iterations and evaluation results.

D. Performance Metrics:

Evaluate model performance using standard metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Bias, and Relative Root Mean Squared Error (RRMSE).

Continuously monitor and assess model performance across different datasets and scenarios to ensure reliability and accuracy.

1. Mean absolute error (MAE)

$1n_{*}\sum|Xp-Xt|$

2. RMSE

$1n_{*}\sum(Xp-Xt)$

3. Bias

$1n_{*}\sum(Xp-Xt)$

4. Relative RMSE

$\sum(Xp-Xt)2n-1$ ——————— $\sqrt{}Xp$

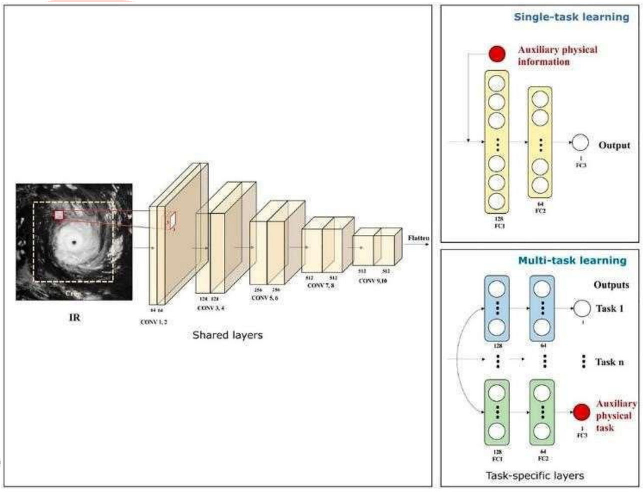


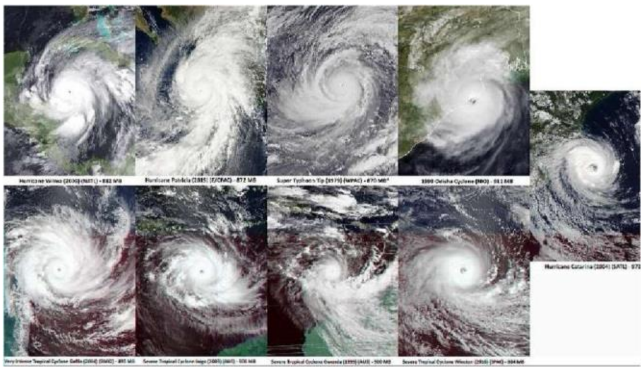
Figure 1 : Cyclone Estimation working Using CNN

E. Model Interpretability:

Employ techniques such as class activation maps (CAMs) to understand how the CNN model determines cyclone intensities from satellite imagery. Validate the model's decision-making process by analyzing the contribution of specific image features to intensity predictions, aligning with physical science knowledge and existing techniques.

F. Deployment to Production System:

Integrate the trained CNN model into the production system for automated cyclone intensity estimation. Develop interfaces for seamless data input and output integration with existing forecasting systems or decision support tools used by meteorological agencies and disaster management authorities. [10] Ensure scalability, reliability, and real-time performance of the deployed system for operational use.



IV. ADVANTAGES

1) Advantages:

   1) Early Warning: Cyclone estimation systems provide early warnings about the formation, movement, and intensity of cyclones, allowing authorities to take timely preventive measures and minimize the impact on human life and property.

   2) Improved Accuracy: Advances in technology and data assimilation techniques have improved the accuracy of cyclone forecasts. High-resolution satellite imagery, Doppler radar, and sophisticated computer models enable meteorologists to better track and predict the behaviour of cyclones.

   3) Better Preparedness: Accurate cyclone forecasts enable governments, disaster management agencies, and communities to better prepare for impending storms. This includes pre-positioning emergency supplies, evacuating vulnerable areas, and mobilizing response teams ahead of time.

   4) Impact Assessment: Cyclone estimation systems help assess the potential impacts of a cyclone, such as storm surges, heavy rainfall, and strong winds. This information is vital for decision-makers to prioritize resources and plan response and recovery efforts effectively.

   5) Research and Development: Continuous improvements in cyclone estimation systems contribute to advancing our understanding of tropical cyclones and their behavior. This knowledge helps researchers develop better forecasting models and improve preparedness strategies.

V. APPLICATIONS

Cyclone forecasting systems play a crucial role in mitigating the impacts of cyclones, which are powerful and potentially destructive weather events. Here are some applications of cyclone forecasting systems:

1) Early Warning Systems: Cyclone forecasting systems provide early warnings about the formation, movement, and intensity of cyclones. [11] This allows authorities to issue timely alerts to residents in the affected areas, giving them sufficient time to evacuate or take necessary precautions to protect life and property.

2) Disaster Preparedness and Response: Governments and disaster management agencies use cyclone forecasts to prepare for potential impacts. [12] This includes prepositioning emergency supplies, mobilizing rescue teams, and establishing evacuation plans to minimize casualties and damage.

3) Impact Assessment: Cyclone forecasting systems help in assessing the potential impacts of a cyclone, such as storm surges, heavy rainfall, and strong winds.[13] This information is vital for decision-makers to prioritize resources and allocate them effectively for response and recovery efforts.

4) Infrastructure Planning and Design: Engineers and urban planners use cyclone forecasts to design infrastructure that can withstand cyclonic conditions. [14] This includes constructing buildings to withstand high winds, designing drainage systems to manage heavy rainfall, and reinforcing coastal structures to resist storm surges.

5) Agricultural Planning: Farmers and agricultural authorities rely on cyclone forecasts to prepare for potential crop damage caused by heavy rainfall, flooding, or strong winds. [15] They can take preventive measures such as harvesting crops early or securing livestock to minimize losses.

6) Maritime Safety: Cyclone forecasts are crucial for maritime safety, as they help ships and boats to avoid dangerous conditions at sea. [16] Mariners can adjust their routes or seek safe harbour based on the forecasted track and intensity of the cyclone.

VI. CONCLUSION

The development of the diagnostic tropical cyclone intensity estimation system represents a significant advancement in leveraging deep learning techniques for objective and automated intensity assessment. Through the systematic integration of satellite imagery, machine learning models, and real-time data processing, the system enables accurate and timely predictions of cyclone intensity levels, crucial for disaster preparedness and response efforts. By following the machine learning lifecycle and implementing a robust methodology, we have successfully addressed the challenges associated with traditional intensity estimation methods, such as subjectivity and reliance on empirical thresholds. The trained convolutional neural network (CNN) model demonstrates promising performance, as evidenced by metrics such as Mean Absolute Error (MAE) and Root Mean Squared

Error (RMSE), ensuring reliable intensity estimations for cyclones in the Atlantic and Eastern Pacific basins.

Additionally, the deployment of the production system facilitates seamless integration with existing forecasting systems and decision support tools, empowering meteorological agencies and disaster management authorities with valuable insights for informed decision-making. Continuous monitoring and maintenance mechanisms ensure the system's reliability and effectiveness in operational settings, contributing to enhanced disaster resilience and mitigation strategies.

VII. FUTURE SCOPE

Foster cross-disciplinary collaborations between meteorologists, climatologists, social scientists, and technology experts to co-create ini tive solutions that integrate scientific expertise with technological advancements and community insights for effective cyclone intensity estimation and disaster management.

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