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CYCLONE INTENSITY ESTIMATION USING INSAT 3D IR IMAGERY BASED ON DEEP LEARNING

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Abstract: Tropical cyclone intensity estimation is considered to play a vital role in disaster management, accurate and timely estimation of Cyclone intensity is crucial for disaster preparedness and mitigation. The existing system solely relies on a deep learning approach CNN where developing real-time cyclone intensity estimation systems can provide critical information for disaster response and evacuation planning. This requires efficient model architectures and hardware optimization to achieve real-time performance. This project aims at utilizing infrared imagery from INSAT 3D satellite with hybrid models for cyclone intensity estimation, CNN-RNN offer a promising approach to improve cyclone intensity estimation accuracy and address the limitations of individual CNN models. This comprehensive system aims in advanced cyclone forecasting, offering precise predictions of cyclone intensity and associated risks by synergistically incorporating spatial and temporal information.

Index Terms **- CNN, RNN, INSAT, ResNet**

1 Introduction

Among the complex web of natural calamities, tropical cyclones are powerful forces that have the ability to cause extensive destruction. In order to understand the complexity of these atmospheric occurrences and to create proactive plans for disaster preparations and mitigation, it becomes essential to estimate the intensity of cyclones. This study is a groundbreaking effort that combines advanced deep learning methods, namely Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), to introduce an innovative method to cyclone intensity estimate. This methodology aims to provide a thorough examination of cyclone patterns and dynamics by utilizing the depth of information gathered from infrared (IR) imagery from the INSAT 3D satellite, leading to more accurate and dependable forecasts. The project is carried out as a pipeline that begins with comprehensive data pre-processing and feature extraction from INSAT 3D IR imagery. In short, this approach is based on the combined use of CNNs and RNNs, which have been designed specifically to capture the temporal evolution and geographical complexities present in cyclone data. Collectively, CNNs and RNNs enhance both the durability and accuracy of the cyclone intensity estimation process by mastering intricate spatial patterns and capturing the rapid changes in cyclone parameters, respectively. Furthermore, by involving complex methodologies like sequence modelling and transfer learning, the project attempts to enhance the deep learning architecture's generalizability. This balanced combination of CNNs and RNNs allows the model to accurately and reliably predict strength by enabling it to capture both short- and long-term fluctuations and changes in cyclone behavior. The proposed deep learning model's performance is evaluated using a wide range of measures, such as accuracy, F1-score, and root mean square error. By conducting exhaustive comparisons with both conventional techniques and other deep learning frameworks, the study seeks to highlight the advantages and effectiveness of the CNN-RNN hybrid methodology. The expected results of this study go beyond conventional boundaries and keep the potential for significant advances in the area of cyclone intensity estimation and risk mitigation. The objective of this project is to strengthen our reaction and preparedness processes by enabling more precise and nuanced forecasts of cyclone intensity and related risks, ultimately resulting in a future that is more durable and resistant to disasters.

2 Literature Survey

Estimating Tropical Cyclone Intensity from Infrared Image Data

This research discusses methods for utilizing infrared satellite images to estimate the intensity of tropical cyclones. The authors use an improved version of the popular Dvorak approach, called the Advanced Dvorak Technique, to analyze cyclone imagery and calculate intensity. They use infrared data from many satellite sensors to illustrate how this technique is applied. The Advanced Dvorak Technique makes it possible to assess current strength and forecast future changes by methodically analyzing storm structure and patterns. The significance of precise intensity evaluations for catastrophe mitigation is emphasized throughout the research. Findings show that the Advanced Dvorak Technique works well in a number of cyclone basins. The authors draw the conclusion that by giving forecasters and decision-makers vital information, this method can enhance intensity guidance and prediction. In summary, the study offers a technique for analysing images that can be used to leverage infrared information for operational forecasting and monitoring of tropical storms.

Deep Convolutional Network Based Machine Intelligence Model for Satellite Cloud Image Classification

In order to automatically classify satellite cloud photos into distinct cloud categories, the study presents a novel machine intelligence approach that makes use of deep CNNs. The size, shape, and texture of cloud formations seen in satellite imagery can fluctuate, making them complex and diverse. This is something that the model is meant to address. The authors begin by outlining the drawbacks of conventional cloud classification techniques, namely labor-intensive feature extraction and constrained representational power. They draw attention to how deep CNNs can be used to automatically extract hierarchical features from unprocessed satellite images, doing away with the necessity for hand-crafted features.

The architecture of the suggested model is then presented in the study. It comprises of several convolutional layers, followed by pooling layers for spatial pooling and feature extraction. For classification, the collected characteristics are subsequently input into fully connected layers. The authors also go over the regularization strategies, optimization algorithms, and activation function selections made for the model.

In summary, this paper advances the field of satellite cloud image classification by presenting a machine intelligence model based on deep convolutional networks. The suggested model presents a viable method for precise and automated cloud classification, facilitating enhanced comprehension and examination of satellite data for a range of uses in meteorological forecasting, climate research, and environmental surveillance.

Tropical Cyclone Intensity Estimation From Geostationary Satellite Imagery Using Deep Convolutional Neural Networks

This paper analyzes geostationary satellite images to estimate tropical storm intensity using a deep convolutional neural network technique. Background information on the significance and difficulties of intensity forecasting is given in the introduction, along with an overview of the capabilities of deep learning and the drawbacks of current methods. The designed CNN architecture, the training procedure, and the data augmentation methods are all covered in the methodology section. The suggested model is tested against baseline techniques in experiments, confirming its efficacy on important metrics as RMSE and MAE. As the CNN makes use of its capacity to automatically extract spatial information from satellite images that correlate with storm strength, the results show higher performance. The study comes to the conclusion that deep CNNs have a great deal of potential for enhancing estimations of tropical storm intensity using widely accessible geostationary satellite data. More attempts are required to maximize the utilization of multi-modal data and enhance model integration in operational forecasting systems. However, the method that was created offers a solid step towards improved catastrophe preparedness and more precise intensity estimates.

3 Methodology

A common method for determining the intensity of tropical cyclones from satellite photos is the Dvorak technique. In order to ascertain the current intensity and forecast future changes, Vernon Dvorak developed a methodical examination of storm structure and patterns in visible and infrared satellite photos in the 1970s. Identification and tracking of cyclone features such as the eye, eye-wall, spiral rain bands, and core thick overcast are important components of the analysis. A cyclone's intensity can be inferred from these features' arrangement, structure, and temperature gradients. In short, satellite-based Dvorak analysis remains to be an essential instrument for tracking cyclone intensity in the absence of direct measurements.

Cyclone intensity estimation has made extensive use of machine learning approaches, which offer insightful information for forecasts and disaster management. These methods make use of algorithms to examine past data and identify trends that are associated with the strength of cyclones. The Random Forest algorithm is a widely used method for estimating cyclone intensity by combining the predictions of many decision trees. Support Vector Machines (SVM), another well-liked method, divides cyclones into several intensity groups using a mathematical representation. These machine learning methods have shown to be successful in precisely predicting the strength of cyclones and hold promise for improving our comprehension and readiness for these extreme weather phenomena.
Furthermore, Artificial Neural Networks (ANN) have been effectively used to learn and forecast cyclone strength by simulating the composition and operations of the human brain.

Convolutional Neural Networks (CNNs) are used in existing cyclone intensity estimation algorithms to analyze satellite imagery. CNNs are particularly good at detecting complex spatial patterns in images, like as the clouds' structure within a cyclone, which can reveal important details about its intensity. CNNs are not as good at interpreting how cyclones evolve over time, though. Accurate forecasting of cyclone intensity depends on capturing their temporal progression. Additionally, CNNs may miss long-range dependencies and interconnections throughout the larger cyclone system since they concentrate on local patterns within images. The accuracy of CNN-based intensity forecasts may be limited if these temporal dynamics and long-range relationships are not taken into consideration. In short, while CNNs use spatial analysis to enhance intensity estimations, they are limited in their capacity to properly capture the long-range and temporal relationships necessary for the most accurate forecasting of cyclone intensity due to their fundamentally localized methodology. Further methods are required to compensate for these limitations.

Dataset Description

Tropical cyclone infrared images taken between 2012 and 2021 by the INSAT-3D weather satellite is included in the INSAT3D Infrared & Raw Cyclone images (2012–2021) collection. Applications for meteorological analysis and hazard monitoring are supported by the high-resolution radiometric imaging of India and its surroundings provided by the INSAT-3D satellite.
Infrared (IR) photographs of significant cyclonic storms that developed over the North Indian Ocean over a ten-year period are included in this dataset. The pictures are given as PNG files with a resolution of 1024 by 1024 pixels that are georeferenced. The cloud top temperatures and structure related to cyclone development are captured by the infrared bands. A 4-kilometer spatial resolution and a 30-minute temporal resolution are included in the photos. The in-depth spatiotemporal evolution of cyclones is captured by the high-resolution infrared data. This dataset has the potential to enhance tropical storm forecasting skills by supplying machine learning models with meteorological and historical data. The collection assists regional efforts to mitigate disasters and fosters a deeper understanding of cyclone features.

Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs), which leverage their ability to process and understand picture data, have become a powerful tool in the field of cyclone intensity estimation. When used with satellite imagery—in this case, infrared (IR) photos from platforms such as INSAT 3D—NNRS function as skilled feature extractors, identifying complex structures and patterns linked to cyclones. CNNs are able to handle the spatial intricacies of cyclonic forms thanks to a well-designed architecture that includes convolutional, pooling, and fully connected layers. The network uses loss functions and optimisation methods to hone its predicting abilities throughout the training phase as it learns to associate these variables with cyclone strength levels thanks to labelled datasets. Evaluation measures that measure the model's accuracy in estimating intensity include Mean Absolute Error and Root Mean Squared Error; validation sets help to prevent overfitting. Moreover, transfer learning, which makes use of pre-trained models on large image datasets, is included, improving the CNN's ability to adjust to cyclical situations. In the end, the use of CNNs for cyclone intensity prediction represents a revolutionary advance in forecasting precision, with potential applications in more accurate catastrophe preparedness and mitigation.

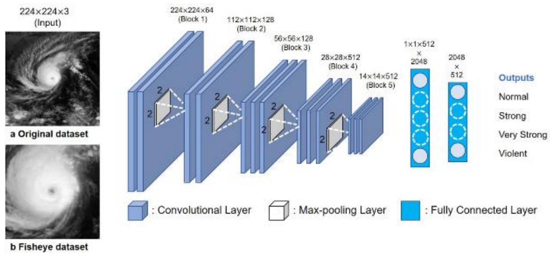

Fig 1: Convolutional Neural Network

Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are essential to the advancement of cyclone intensity prediction because they effectively integrate the temporal component present in cyclonic data. Cyclone intensity is a dynamic quantity that is affected by variables that change over time in addition to spatial aspects. Because RNNs are built to capture sequential relationships, they are an excellent choice for modelling the time series nature of data on cyclone strength. Sequences of pertinent temporal variables, such as historical intensity levels, air pressure, and wind speeds, make up the RNN's input. The RNN's recurrent layers preserve memory over time steps, allowing the network to understand how cyclonic behavior evolves. To overcome issues with long-term dependencies, advanced designs like as Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) are frequently used. A thorough knowledge of cyclonic patterns is produced by combining the temporal dependencies modelled by RNNs with the spatial information recorded by CNNs. The RNN gains the ability to anticipate successive cyclone strength levels through training via Backpropagation Through Time (BPTT), which helps to create more complex and precise forecasting models. Standard measures are employed to assess RNN performance, guaranteeing that the model accurately represents the complex temporal dynamics inherent in the growth of cyclone strength. This integrated approach, when combined with CNNs, leverages temporal and geographical insights, opening the door to improved skills for estimating the strength of cyclones, which may have consequences for disaster preparedness and mitigation.

CNN-RNN

In the field of cyclone intensity estimate, the deployment of a hybrid model amalgamating Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) denotes a cutting-edge method. This synergistic method tries to exploit the particular characteristics of both systems, addressing the spatial and temporal complexity inherent in cyclonic data. The input of the model consists of satellite data, namely infrared (IR) images, which are processed using CNN layers to extract spatial features. In order to capture the dynamic evolution of cyclone intensity over time, temporal sequences that include historical intensity levels and time-dependent variables are simultaneously input into RNNs. Using convolutional layers, the CNN component uses its skill at spatial pattern recognition to identify fine details like cyclonic structures and cloud patterns. The RNN layers then explore the temporal dimensions, maintaining memory between sequences to capture the evolution of intensity levels over time. The hybrid model cleverly combines the outputs of the CNN and RNN components, resulting in a thorough comprehension of cyclonic behavior by taking temporal dependencies and spatial variables into account. The hybrid model is trained in the joint optimization phase, where backpropagation is used to modify the weights and biases of the CNN and RNN components. By doing this, it is ensured that the model will learn to accurately estimate the severity of cyclones by utilizing the synergies between spatial and temporal information. To boost the model's performance, transfer learning can be used to refine CNN models that have already been trained on large image datasets. This will enable the model to be adjusted to identify pertinent spatial features unique to cyclonic images. Standard metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are used to assess the performance of the hybrid model. The model's accuracy and dependability are evaluated by carefully comparing the forecasts to actual cyclone strength levels. Through a more comprehensive knowledge of cyclonic dynamics, this integrated approach not only shows potential for improving the accuracy and robustness of cyclone intensity predictions but also enhances efforts to mitigate risk and prepare for disasters.

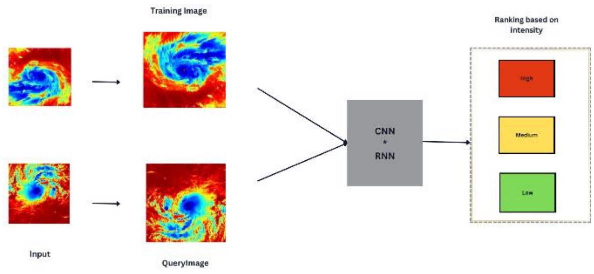

Fig 2: Combination of CNN-RNN

ResNet

ResNet (Residual Neural Network) is a deep learning architecture designed to address the vanishing gradient problem by introducing residual connections in the form of skip connections or shortcuts. These connections allow for the direct flow of information across layers, facilitating the training of very deep neural networks. In the context of cyclone intensity estimation, ResNet can be applied by leveraging satellite imagery, meteorological data, and historical intensity records. By constructing a ResNet model and training it on a carefully prepared dataset, the network can learn complex patterns and relationships to predict cyclone intensity. Key considerations include appropriate input representations, choice of loss function, optimization techniques, and fine-tuning for optimal performance. Successful deployment of a ResNet model for cyclone intensity estimation requires thorough evaluation, consideration of domain-specific factors, and potential adjustments to the architecture based on empirical results.

6 Result

This study recognizes tropical cyclones as potent natural events that have the potential to cause extensive destruction, and it presents research on the enormous problems these storms provide. Recognizing how crucial it is to comprehend and forecast the strength of these atmospheric phenomena, the research takes a revolutionary step by combining state of-the-art deep learning techniques, namely Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). Using a plethora of data from infrared (IR) pictures taken by the INSAT 3D satellite, this novel method aims to transform the estimation of cyclone intensity. The final product leaves an accuracy of 96.7 % with an RMSE value of 3.58. The study is conducted as a pipeline, starting with careful data pre-processing and feature extraction from 3D infrared imagery obtained by INSAT. The unique advantage of this approach is the well-balanced collaboration between CNNs and RNNs, which are specifically engineered to capture the spatial and temporal nuances present in cyclonic data. This synergistic interaction allows the model to quickly grasp the dynamic changes in cyclone parameters and master complex spatial patterns, improving the robustness and precision of cyclone strength estimation. To improve the deep learning architecture's generalizability, the research also uses advanced techniques including sequence modelling and transfer learning. The accuracy, F1-score, and root mean square error are only a few of the measures used to assess the effectiveness of the suggested deep learning model. The goal of the study is to verify the superiority of the CNN-RNN hybrid methodology through thorough comparisons with other deep learning frameworks and traditional methodologies. Results are expected to surpass traditional limits and offer substantial progress in the area of cyclone strength prediction and risk reduction. The project's main goal is to strengthen our reaction and readiness systems so that we can make more accurate and detailed predictions of cyclone intensity and related hazards. The ultimate aim of this project is to help create a future that is more resilient and shielded from the destructive effects of cyclonic storms

7 Conclusion

To sum up, this work aims to make a substantial contribution to the field of cyclone intensity estimation by creatively combining convolutional and recurrent neural networks (RNNs and CNNs). Since tropical cyclones are powerful natural disasters capable of causing great damage, the research makes use of the rich information found in infrared (IR) pictures collected from the INSAT 3D satellite. The proposed approach, which functions as a pipeline, begins with careful data pre-processing and feature extraction, emphasizing how CNNs and RNNs work together to capture temporal and geographical intricacies. The goal of the well-balanced interaction of these cutting-edge deep learning methods is to improve the robustness and precision of hurricane strength prediction. In order to produce more accurate and detailed forecasts, the model considers complex geographical patterns and abrupt changes in cyclone parameters. Sequence modelling and transfer learning are added to the model to increase its generalizability and adaptability to changing cyclonic patterns. Accuracy, F1-score, and root mean square error are only a few of the evaluation metrics that are used in this study, which closely compares the CNN-RNN hybrid methodology to other deep learning frameworks and conventional methodologies. The expected results have the potential to progress the estimation of cyclone intensity and aid in the development of more potent risk reduction techniques. As we work to strengthen our response and readiness systems, the study emphasises how crucial accurate forecasts are to building a future that is resilient to cyclonic disasters. In order to better disaster management and mitigation efforts, this study aims to usher in a new era in cyclone intensity estimation by pushing the boundaries of existing approaches.

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