WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Deep Learning Based Cyclone Intensity Estimation Using INSAT-3D IR Imagery

Prof. V. D. Punjabi, Kavita Vilas Borane, Sejal Anil Sarnaik, Kalyani Nilkanth Patil, Roshani Gokul Patil

R. C. Patel Institute of Technology, Shirpur

ABSTRACT-

This article-based survey report is based on a review of cyclone intensity prediction using INSAT-3D satellite imagery. Natural disasters are unplanned events that can possibly disrupt the environment at any time or location. Natural catastrophes can affect a society's citizens and damage the environment, including earthquakes, cyclones, floods, tsunamis, wildfires, landslides, and volcanic eruptions, among other catastrophes. Avalanches, heat waves, and other common natural disasters are only a few. Gigantic air systems called cyclones swirl around a powerful centre of low air pressure. They spin in opposite directions, depending on whether they find themselves in the Northern or Southern Hemisphere. Cyclones are generally massive storms with powerful winds and heavy rainfall. Tropical cyclones, also known as typhoons or hurricanes, are cyclonic storms originating over warm tropical seas and are exceedingly potent, causing significant damage and displaying tremendous force. India boasts a multitude of geostationary satellites, and one of them is named INSAT. The Indian National Satellite System, or INSAT, was launched by ISRO as a multipurpose geostationary satellite to address India's needs for communications and broadcasting, as well as search and rescue missions. The INSAT 3D satellite precisely records cyclones and their growth by measuring the brightness temperatures of numerous IR channels, temperature and humidity profiles, atmospheric stability indices and parameters, precipitate water, geo-potential height, and many other characteristics. The identification of previously observed anomalies and unknown regularities in the existence of cyclone intensity. This could make it easier for people to understand how tropical storm intensity changes. We are employing satellite photos to find the tropical cyclone because of this idea. The system provides an automated method for cyclone estimation using hurricane satellite data and deep learning research. The current system's ability to estimate the severity of tropical cyclones takes longer to complete. The purpose of this study is to evaluate the cyclone's intensity using the generated image series.

***Keywords*-Deep Learning Convolutional Neural Network; Intensity Prediction; Machine Learning; Estimation; INSAT 3D IR Imagery; Less timing complexity.**

I. INTRODUCTION

One of the riskiest categories of natural catastrophes, cyclones can cause immense destruction. The centre of a cyclone is called the eye, and once an eye forms, the severity and intensity usually increase. The images captured by the geostationary satellites are of extraordinarily high quality. There are several uses for weather, including studying wildfires, forming clouds, and determining the direction of atmospheric winds. The eye of the cyclone, which is the cyclone's centre, as well as the intensity and other characteristics, are determined by additional examination of these obtained satellite photos. Cyclone intensity estimation is essential for disaster management activities. Every time the cyclone's eye experiences a significant alteration, the cyclone's intensity changes.

It is essential to identify the storm as early as possible and predict its maximum strength to provide early warning of these tropical cyclones for their efficient management, taking into account the size of the ocean basin and the social and economic vulnerability of that specific region. In this study, we seek to describe the many observed characteristics in the evolution of a cyclone, especially during the rapid intensification (RI) stage, using satellite data produced by the INSAT-3D imager [2]. Numerous supervised and unsupervised techniques are used in the classification of infrared pictures by Cyclone. To find anomalies under statistical methodology, modern deep-learning approaches are frequently applied.

Deep learning approaches have unequivocally emerged as the gold standard for handling unstructured data and delivering exceptional detection accuracy, all while requiring minimal processing time when it comes to classifying satellite data. Their reliability and prowess are indisputable. Moreover, developing state-of-the-art deep pedagogical models no longer demands prior expertise. Within the Deep Convolutional Neural Network (DCNN), the input, output, and hidden layers stand as independent pillars, each intricately connected to convoluted processes responsible for recognising intricate visual characteristics. In essence, deep learning techniques shine brightly, consistently delivering exceptional results, even with the most complex and unstructured datasets, and they do so with remarkable efficiency.

Nearly 90% of the damage is attributed to powerful winds causing seawater inundation, as indicated by studies. The model presented here is utilized by the Multilayer Perceptron (MLP) to train and test the feature values of TC images. MLPs, which are feedforward artificial neural network subsets, follow a supervised learning approach and consist of at least one hidden layer along with input and output layers. Each node in the MLP, except for the input nodes, is represented as a neuron with a nonlinear activation function. The backpropagation algorithm, a supervised learning method, is employed for training and testing models [1].

The primary method used by operational forecasters to estimate tropical cyclone intensity in the absence of direct aircraft readings is an adaptation of the Dvorak methodology, which was established in the 1970s using satellite images. These methods make use of brightness temperatures obtained from infrared satellite measurements as well as human visual evaluation of cloud field features, including the outer rainband curvature and inner core symmetry. The subjectivity of human storm strength classification based on cloud features is one of the known weaknesses of Dvorak-based approaches. With this method, two skilled analysts can simultaneously determine differing strength estimates for the same storm. While the precision of Dvorak-based estimates can agree to within 0.5 Tropical Number (T-Number; the intensity classification scale used by the Dvorak technique), there can be differences in wind speed estimates for hurricane-forced storms of up to 12 knots (hence abbreviated as kts) or roughly 6 ms^{-1}. Additionally, anecdotal data suggests that significant variations can occasionally be observed when comparing estimates from several agencies and in situations involving complicated cloud structures. The following NHC advice on Tropical Storm Ophelia, October 10, 2017 UTC 1500, is an example of a difficult case: T3.0/45 kts from the Tropical Analysis and Forecast Branch (TAFB) to T4.0/65 kts from the National Oceanic and Atmospheric Administration/National Environmental Satellite, Data, and Information Service Satellite Analysis Branch (SAB) are the range of Dvorak intensity estimates. The estimates are provided by the University of Wisconsin Cooperative Institute for Meteorological Satellite Studies (UW-CIMSS). The initial intensity, which is based on an average of the scatterometer winds and all other available intensity estimations, will stay at 45 kts for the time being [3].

II. PROBLEM STATEMENT

Even in their initial phases, tropical cyclones present a formidable risk to both human life and property. The diverse range of threats associated with these weather phenomena is extensive, with each possessing the capacity to inflict significant harm on individuals and their surroundings. The convergence of storm surges, tornadoes, flash floods, powerful winds, and thunderstorms amplifies the potential for fatalities and property damage. The intertwining of these hazards during the early development of a tropical cyclone emphasizes the urgency of comprehensive preparedness and mitigation measures. Proactive strategies, such as robust early warning systems, well-orchestrated evacuation plans, and stringent building codes, play a pivotal role in minimizing the impact on lives and property. Governments, communities, and individuals in cyclone-prone regions must collaborate to enhance resilience and effectively mitigate the multifaceted risks posed by tropical cyclones.

III. RELATED WORK

Along with current portals that offer real-time information on tropical cyclones, some related work on wind speed estimation from satellite photos is presented here. Convolutional neural networks, the foundation of our deep learning model, are also briefly discussed.

1. Dvorak Technique

The Dvorak method, a cornerstone in cloud pattern recognition, traces its origins to a model illuminating the intricate dynamics of tropical cyclone formation and dissipation. Developed and rigorously tested in 1969 for monitoring storms in the western North Pacific, this method relies on satellite imagery sourced from polar satellites. The orbital paths of these satellites meticulously document the evolution of tropical storms, encompassing typhoons, cyclones, and hurricanes. Through the analysis of thermal photographs capturing the sea's conditions during the day and visible spectrum images taken at night, the Dvorak method discerns patterns within the observed storm structure, serving as a key technology in pinpointing and measuring storm intensity, including the identification of storm eyes, offering critical data for evaluating the potential for intensification.

However, it is crucial to emphasize that the Dvorak method primarily functions as a tool for assessing storm intensity, diverging from direct predictions or measurements of factors such as wind speed or pressure. Instead, it relies on satellite imagery to provide valuable insights into the storm's structural nuances. Beyond its meteorological utility, the Dvorak method sheds light on the integral role of community engagement in disaster preparedness. The proximity of communities to authorities is paramount, and local residents emerge as indispensable contributors to the evacuation planning process. Their firsthand knowledge of the region, coupled with the analytical prowess of the Dvorak method, forms the backbone of a holistic and collaborative strategy to mitigate the far-reaching impact of tropical cyclones. This amalgamation of advanced technology and grassroots involvement reinforces the importance of adopting a multifaceted approach in confronting the complex challenges posed by severe weather events [3].

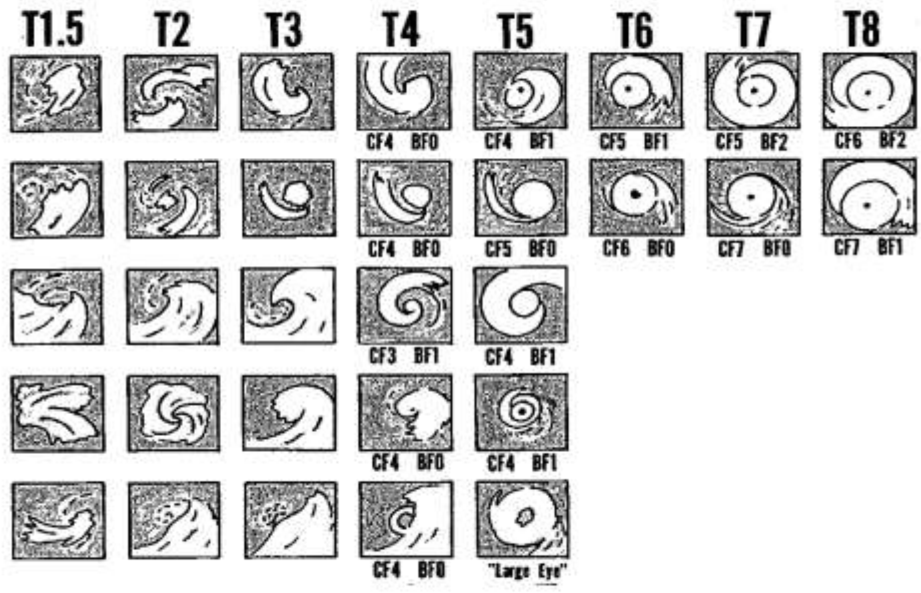


Fig. 1: Dvorak's illustration of common development patterns and corresponding intensities [5].

2. Advanced Dvorak Technique

Developed by Olander and Velden as an evolution of the manual Dvorak technique, the Advanced Dvorak Approach (ADT) represents a pivotal advancement in tropical cyclone intensity estimation. ADT employs an automated algorithm that analyzes satellite images, generating a T-number output. This automated process has undergone refinement with the integration of additional data sources, including passive microwave data, aircraft observations, and improved tropical cyclone centering, all of which play indispensable roles in enhancing its accuracy. Despite its superior performance compared to the human Dvorak method, ADT faces challenges with smaller storms characterized by irregular cloud distribution, resulting in diminished model efficacy. Nevertheless, the incorporation of empirical thresholds acts as a constraint, limiting the extent to which cyclone strength can fluctuate over time. The continual refinement and augmentation of ADT underscore its significance as a sophisticated tool in the realm of tropical cyclone monitoring, contributing to more precise and automated assessments of cyclone intensity [5].

3. Convolutional Neural Network

Convolutional neural networks are an artificial neural network type that has revolutionised computer vision and image processing. It is extensively employed in many different applications, including face identification, image segmentation, and object recognition. The biological organisation of the human brain's visual cortex serves as the foundation for CNN architecture. The input layer, convolutional layer, pooling layer, and fully connected layer are among the layers that make up this system. The convolutional layer applies a set of filters to the raw data that is obtained by the input layer in the form of an image. The filters are used to identify different aspects of the image, like corners, edges, and shapes. The pooling layer is subsequently applied to the convolutional layer's output, reducing its dimensionality and improving its computing efficiency. The filters, which are essentially tiny matrices, are convolved with the input image to form a feature map. The activation of a specific feature at a specific spot in the image is represented by the feature map. During the training phase, CNN learns the best combination of filters to apply in order to identify different features in a picture. Reducing the difference in inaccuracy between the expected and actual output is a key component of the learning process. CNN is a potent machine learning method that has transformed image processing and computer vision. It has been a popular option for many applications due to its capacity to extract intricate features from unprocessed data [6].

IV. DATASET

The pictures of Tropical cyclone as a dataset is captured by the satellites INSAT 3D photos taken over the Indian Ocean by the INSAT-3D satellite's visible and infrared channels are part of a 24-hour time series with a half hour interval. The four imager channels which are considered are: First one is Visible which is covering 0.55- 0.75 m, second is Short-Wave Infrared, next is Mid-wave Infrared and finally Water Vapor which is covering around 6.5-7.1 m. VIS and NIR channels have a spatial resolution of 1 km, MIR, TIR1 and TIR2 channels of 4 km, and WV channels of 8 km. During pre-processing, satellite-captured photos are converted from the .tif(Tag Image File) format to the.jpg format, which eventually yields output images. In the pre-processing of the data the tool known as Quantum Geographic Information System will be used to determine the study region for the satellite picture, and it will also be used to do the shape file operation and crop only the tropical cyclone-centered study area. We will apply the fish-eye effect to the resultant cropped image to make it more noticeable for the convolutional neural network model to process. Based on knots in satellite pictures, tropical cyclones in India can be categorized into seven categories:

- Low Depression -The knots in the range (17-27 KT)

- Severe depression – The knots in the range (28-33 KT) Vol-9 Issue-1 2023 IJARIIE-ISSN(O)-2395-4396 19285 ijariie.com 1697
- Tropical Storm - The knots in the range (34-47 KT)
- Significant Tropical Storm - The knots in the range (48-63)
- Strong Tropical Storm- The knots in the range (64-89 KT)
- Very Strong Tropical Storm- The knots in the range (90-119)
- (>120 KT) Super Tropical Storm for simple access to the cyclone data

Each satellite picture sample has a linked HDF (Hierarchical Data Format) meta datafile that can be easily converted to comma-separated values file format using the python tool called Rasterio (example: set = rasterio.open('traningimage.tif')).Our convolutional neural network model would then receive the transformed image input and begin training [6].

V. METHODOLOGY

The diagnostic tropical cyclone intensity estimation system is developed and deployed in accordance with the end-to-end machine learning lifecycle. The machine learning lifecycle is a systematic iterative process of training, testing, and deploying a model in order to develop an optimised model suitable for ingestion into a production system and consumption by the intended end-users.

1. Machine Learning Lifecycle

The machine learning journey is a comprehensive process that begins with identifying the problem, followed by data collection and analysis. The next step involves creating a model and evaluating its performance. However, the journey doesn't end here. Many projects conclude once they demonstrate an improvement in the model's accuracy, but there are two crucial stages that are often overlooked. The first is a thorough examination of the decision-making process of the model, which is essential to understand its functioning and reliability. The second is deploying the model in a live environment where it can handle new data, a step that truly tests the model's effectiveness and adaptability. In our paper, we emphasize the importance of these often-neglected stages and advocate for a holistic approach to machine learning, using the complete process as a roadmap for developing our production system.

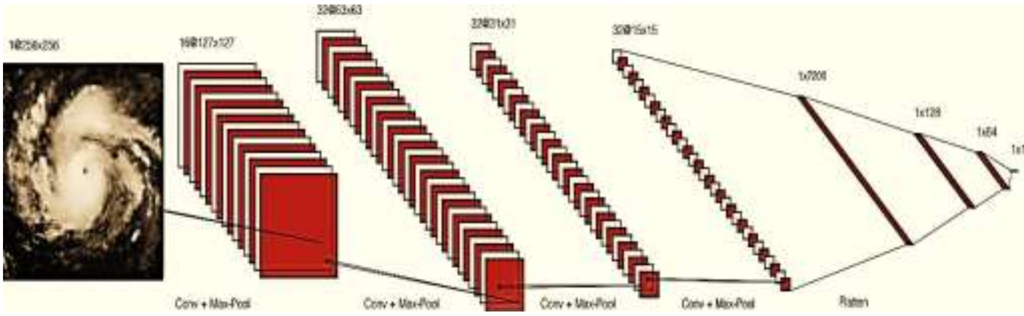


Fig. 2: CNN model architecture used for wind speed estimation [4].

The infrared (IR) pictures that comprise our data are convolutioned in the convolutional layer prior to being sent to the subsequent layer. Two distinct CNN models will be used: one for estimating tropical storm strength and the other for classifying it. The outputs of a subset of neurons from the preceding layer are combined into a single layer in the next layer, known as the max pooling layer. Every neuron in the layer below is connected to every other neuron in the layer above by the final, fully connected layer. The fully linked layers will additionally undergo L2 regularization of 0.01. Additionally, we will employ call-back techniques such as early pausing and dropout layers at a rate of 0.5 to keep the model from being overfit [8].

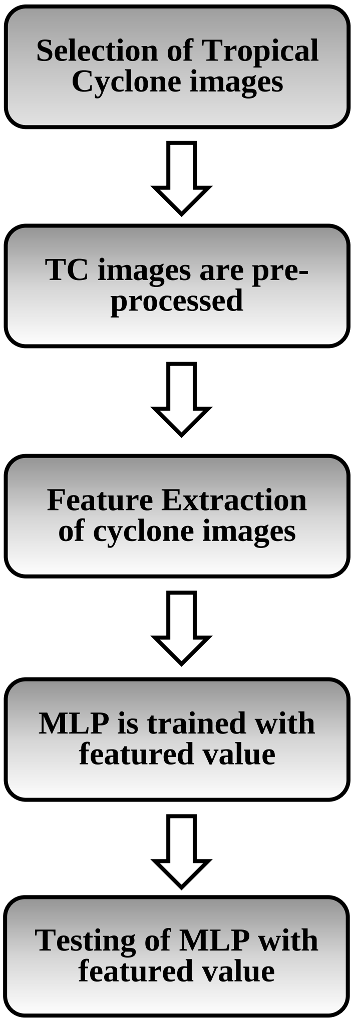


Fig. 3: Task for Project [9].

2. Object Segmentation

Object segmentation can be accomplished through a variety of methods, including thresholding, clustering, and edge detection. Deep learning-based segmentation methods, such as convolutional neural networks (CNNs), can also be used to recognize and classify objects in an image. Once the objects in the image have been segmented and identified, the deep learning model can be trained to classify the cyclone's intensity based on characteristics such as its size, shape, and cloud patterns. Object segmentation algorithms divide an image into groups of pixels or regions. The goal of partitioning is to better understand what the image represents. Sets of pixels may represent objects in the image that are relevant to a particular application [11].

3. K-Means

In the pursuit of creating a deep learning-based solution for the categorization of cyclone intensity, the methodology embraced not only object segmentation but also leveraged k-means clustering as a fundamental component. K-means clustering, a versatile machine learning algorithm played a crucial role in the segmentation and classification of images within this context. Its functionality involves grouping data points into k clusters based on their similarities, a process particularly adept at identifying patterns and structures within datasets. In the specific realm of image segmentation, k-means clustering becomes a potent tool for discerning and isolating various regions within an image that correspond to distinct objects or features. By applying this algorithm to cyclone imagery, the methodology enhances the precision of cyclone intensity categorization, showcasing the adaptability and efficacy of k-means clustering within the broader framework of deep learning applications for meteorological analysis.

4. CNN + LSTM

CNN+LSTM is a neural network architecture that combines convolutional neural networks (CNNs) and networks with long short-term memory (LSTM). CNNs are frequently used for image classification, whereas LSTMs are used for sequential data analysis. A CNN+LSTM model can be used to analyse the different regions identified through k-means clustering and extract relevant features that can be used to classify the intensity of the cyclone over time in the context of cyclone intensity estimation. The model's CNN component can be used to analyse the spatial features of the various regions within the satellite image, while the LSTM component can be used to analyse the temporal features of the cyclone's development. The different regions of the satellite image can be fed into the CNN component of the model to extract spatial features when using a CNN+LSTM model [11].

VI. DESIGN DETAILS

In the intricate journey of crafting a cyclone intensity estimation model, the initial step involves judiciously acquiring INSAT-3D IR imagery data from reputable sources like the Indian Meteorological Department (IMD). This foundational data then undergoes meticulous preprocessing, wherein relevant attributes are extracted, and spatial and temporal alignment is ensured. The subsequent pivotal stage involves feature engineering, wherein the model identifies and computes crucial features, such as cloud temperature gradients and moisture convergence, from the raw data, enhancing its ability to discern patterns and characteristics associated with cyclone intensity.

As the process transitions to the modeling phase, a conscientious selection of a suitable machine learning algorithm for regression tasks takes center stage. Options ranging from traditional linear regression and decision trees to more sophisticated approaches like random forests or convolutional neural networks (CNNs) are considered. Ensemble techniques are explored as well, aiming to harness the collective power of multiple models for heightened accuracy. The model training phase is characterized by the meticulous optimization of hyperparameters through techniques like cross-validation, ensuring the model's robustness and generalizability. Upon successful training, the model is deployed in a production environment, where an intuitive interface is created for seamless input and cyclone intensity estimation. Rigorous testing with unseen data serves as a litmus test, affirming the model's accuracy and reliability in real-world scenarios [15].

The model's journey doesn't conclude with deployment; instead, it enters a phase of ongoing monitoring and maintenance. Real-time performance checks, periodic updates, and retraining efforts are undertaken to adapt to evolving data patterns and cyclone characteristics. An often-underestimated yet crucial aspect of the entire process lies in comprehensive documentation. This entails detailing data sources, preprocessing methodologies, feature engineering intricacies, model selection rationale, and deployment strategies. Such documentation not only aids in current project understanding but also serves as a valuable resource for future replication and improvement, contributing to the collective knowledge base in cyclone intensity estimation modeling.

VII. RESULT DISCUSSIONS

Deep learning is used to analyse typhoon satellite imagery in our project (CNN). In the National Hurricane centre outlook, keep an eye out for "investment zones," or areas where tropical cyclones may form and begin wind speed estimation operations. To compare estimated wind speeds to operational forecasts, plot estimated wind speeds and additional data on a map. The primary goal of this project is to provide the larger scientific community with an understandable interpretation of model results.

Fig. 4: Home Page.

This is homepage of our website, where you'll find three prominent icons that lead to distinct features. The first icon, labeled "Archive," directs you to a repository where all predicted image intensities are saved and stored. The second icon, "Insert Your Image," guides you to the intensity estimator page, where you can assess and analyze the intensity of any given image. The third icon, the "Live Weather Map," takes you to a dynamic map showcasing real-time weather conditions, including live locations, atmospheric pressure, and temperature data. You can explore these features to make the most of our platform's capabilities.

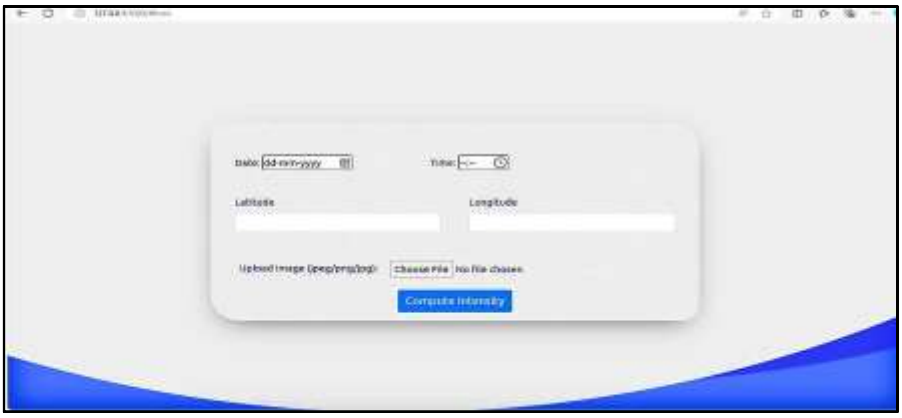


Fig. 5: Estimation Page.

This is our estimation page, also known as the form section, designed for submitting images to our model for intensity computation. This section not only computes the intensity of the image but also seamlessly transmits the input data to our archive database for future reference. On this page, you'll find several options. Firstly, there's a date input where you must provide the correct date, time, latitude, and longitude of the cyclone you are assessing. This information is crucial for accurate archival storage for future references. Downwards you'll encounter the "Choose File" option, allowing you to upload the specific image for intensity computation. Once you've selected the image, a simple click on the "Compute Intensity" button initiates the process, providing you with the intensity of the cyclone. This user-friendly interface ensures a streamlined experience in estimating cyclone intensities and archiving the relevant data for further analysis.

Fig. 6: Intensity Estimation Page.

This is the Intensity Estimation Page after intensity estimation. Once the cyclone intensity has been successfully calculated, a popup box will appear on the screen, presenting the estimated intensity of the cyclone. Additionally, below the "Choose File" option, you will find a message displaying the computed intensity in knots. To view this information, simply enter the correct and necessary details, and the page will promptly reveal the estimated intensity of the cyclone, providing a clear and informative user experience.

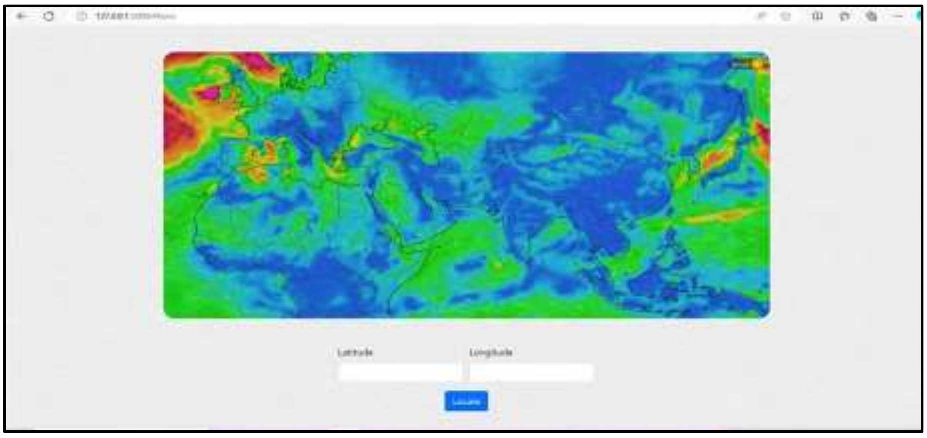
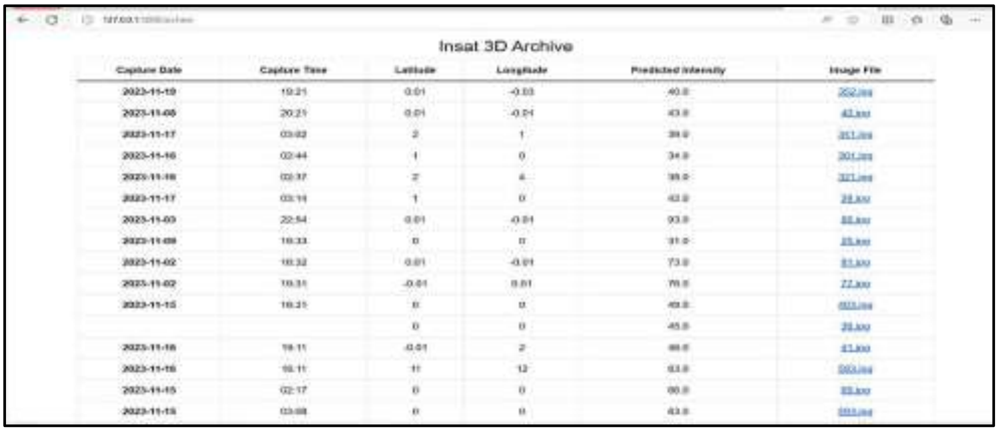


Fig. 7: Live Weather Map.

Presenting our Live Weather Map, crafted with the powerful Windy API. This dynamic map showcases real-time wind patterns and seamlessly redirects to coordinates received as input. In the event of a cyclone, areas with strong wind patterns are prominently highlighted. To explore a specific location, simply input the longitude and latitude of your desired destination. Upon clicking "Locate," the map will instantly redirect to that location, unveiling detailed insights into the prevailing wind patterns. Not only does the map display the intensity and direction of the winds, but it also provides temperature data for the selected location, offering a comprehensive overview of the weather conditions. Enter the coordinates, click "Locate," and delve into the live weather experience.



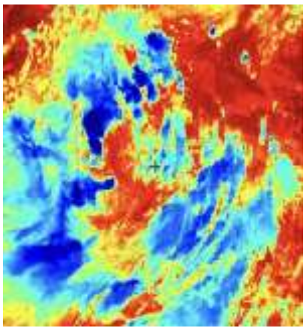
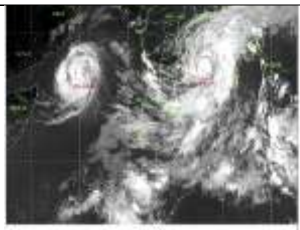
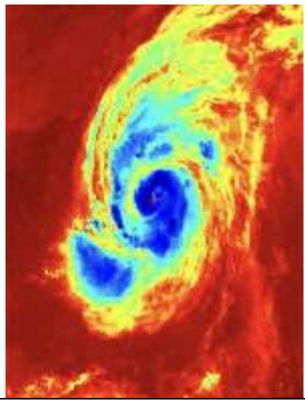
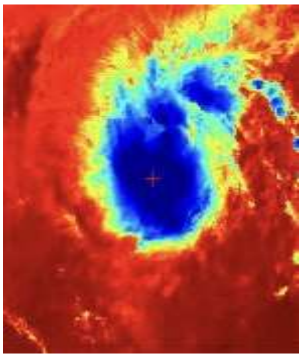
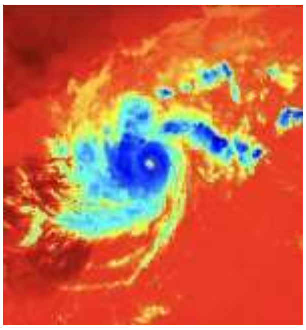
Insat 3D Archive

Capture Date	Capture Time	Latitude	Longitude	Predicted Intensity	Image File
2023-11-19	19:21	0.01	-0.03	40.0	252.jpg
2023-11-08	20:21	0.01	-0.01	43.0	42.jpg
2023-11-17	03:02	2	1	39.0	351.jpg
2023-11-16	02:44	1	0	34.0	301.jpg
2023-11-16	02:37	2	4	35.0	321.jpg
2023-11-17	03:14	1	0	42.0	28.jpg
2023-11-03	22:54	0.01	-0.01	93.0	88.jpg
2023-11-09	18:33	0	0	31.0	25.jpg
2023-11-02	18:32	0.01	-0.01	73.0	81.jpg
2023-11-02	18:31	-0.01	0.01	78.0	77.jpg
2023-11-15	18:21	0	0	49.0	603.jpg
		0	0	45.0	39.jpg
2023-11-16	19:11	-0.01	2	46.0	41.jpg
2023-11-16	18:11	11	12	63.0	503.jpg
2023-11-15	02:17	0	0	80.0	83.jpg
2023-11-15	03:08	0	0	43.0	553.jpg

Fig. 8: INSAT 3D Archive Page.

INSAT-3D Archive Page, an immersive space where you can explore and review all the stored data from previous uploads. The Archive Table provides a comprehensive overview of the information stored in our database. Displayed in the table are key details such as the capture image, date, time, latitude, and longitude. Additionally, you'll find the projected intensity for each entry, offering a historical perspective on various events. For a more visual understanding, the uploaded images associated with each entry are also available, ensuring a complete reference for future analyses. Dive into the wealth of information within the Archive Table as we continue to build a valuable repository for your reference and research needs.

VIII. COMPARITIVE STUDY

Name of Cyclone	INSAT-3D IR Image	BT Calibrated Image	Intensity predicted by our system	Intensity	Reference Link
Cyclonic Storm Daye (20 Sep 2018)			35 Knots	35 Knots	https://en.wikipedia.org/wiki/2018_North_Indian_Ocean_cyclone_season
TC Luban (10 Oct 2018)			45 to 75 knots	63 knots	https://www.sciencedirect.com/science/article/pii/S2225603221000059#:~:text=On%20the%20other%20hand%2C%20the,kts%20(CWD%2C%202018a).
Cyclonic Storm Pawan (6 Dec 2019)			30 Knots	34 Knots	https://en.wikipedia.org/wiki/2019_North_Indian_Ocean_cyclone_season
Nivar (22 Nov 2020)			35 to 64 Knots	42 Knots	https://en.wikipedia.org/wiki/Cyclone_Nivar

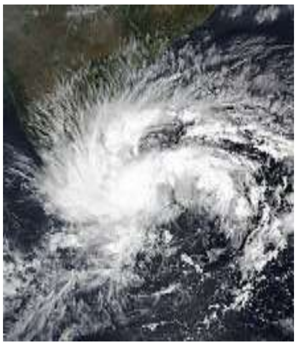
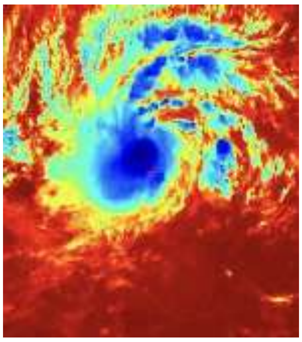
Cyclone Burevi (3 Dec 2020)			32 to 45 Knots	34 knots	https://en.wikipedia.org/wiki/Cyclone_Burevi

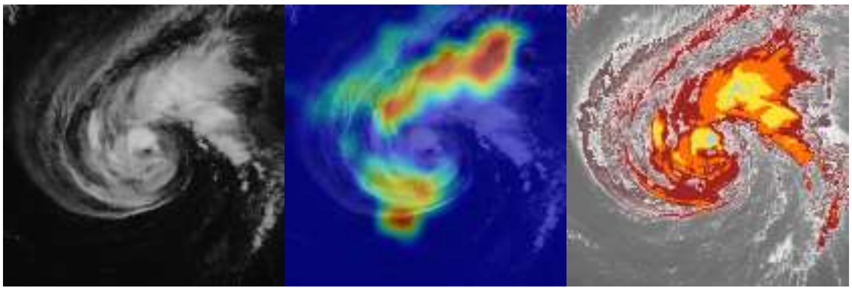
Table 1: Comparative Studies of Intensities.

IX. RESULT DISCUSSIONS

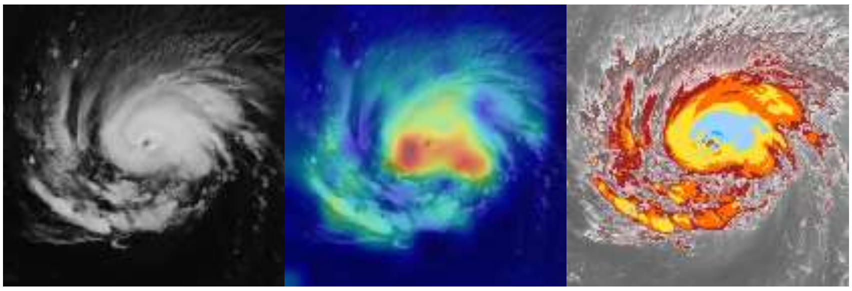
A common issue raised by experts in certain fields about machine learning is that it's often tough to figure out how a model comes to decisions. This lack of clarity creates a trust gap between those who specialize in machine learning and experts in physical sciences, making it challenging to apply these models in real-world systems. To address this concern, we employ methods to uncover how our model, specifically the convolutional neural network (CNN), calculates cyclone intensities. This helps us evaluate our model and ensures that it's not only effective but also understandable, aiming to build trust and encourage the practical use of these models, especially in areas like predicting cyclone intensities.

X. FUTURE WORK

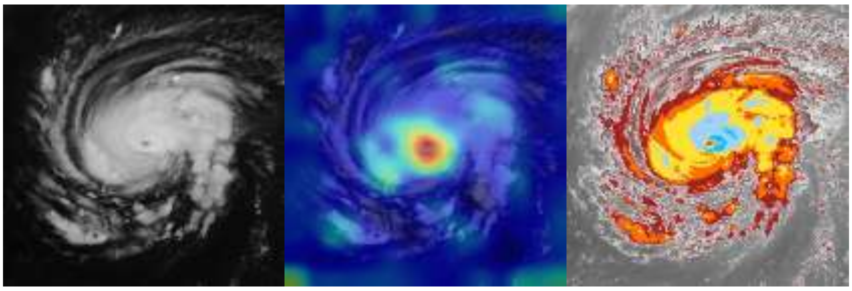
In the coming years, there's room for exploring different areas of research, like figuring out how to predict the wind speed of less intense tropical cyclones using passive microwave data. Another exciting possibility for future studies could involve taking a close look at a particular storm to see how well our models do when the storm rapidly strengthens or changes its structure. By delving into these topics, we can enhance our understanding of tropical cyclones and improve the accuracy of our models in predicting their behavior, making it more helpful for people in areas prone to these storms.



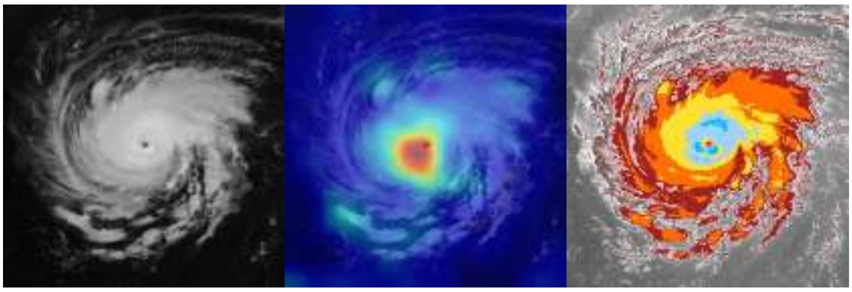
(a) GOES: TS (b) CAM: TS (c) *TB* : TS



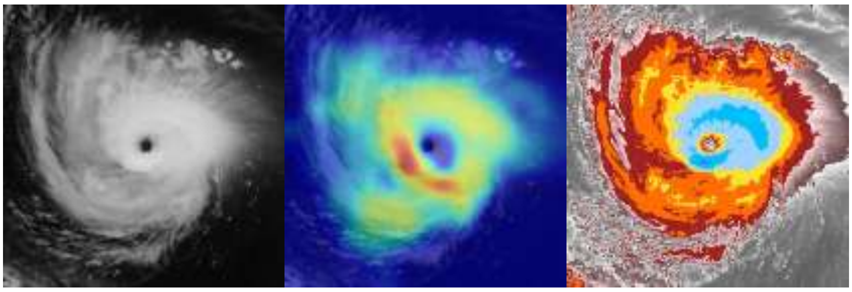
(d) GOES: Cat 1 (e) CAM: Cat 1 (f) *TB* : Cat 1



(g) GOES: Cat 2 (h) CAM: Cat 2 (i) *TB* : Cat 2



(j) GOES: Cat 3 (k) CAM: Cat 3 (l) *TB* : Cat 3



(m) GOES: Cat 4 (n) CAM: Cat 4 (o) *TB* : Cat 4

Fig. 9: Hurricane Florence evaluation samples at different categories [12].

XI. CONCLUSION

The integration of deep learning techniques with INSAT-3D IR imagery for cyclone intensity estimation represents a significant advancement in predictive capabilities. This project have created a deep learning-based solution for estimating and classifying tropical cyclone intensity. The proposed solution makes use of geometric features in cyclone images, a multilayer perceptron, and a convolutional neural network model for intensity estimation and classification. The evaluation results demonstrated the developed solution's effectiveness in accurately estimating the intensity of tropical cyclones and categorising them. This current method for estimating tropical cyclone intensity is difficult, and anomalies have been observed in the past. To address this, the proposed system employs deep learning research and hurricane satellite data to provide an automated cyclone estimation technique. The system aims to reduce timing complexity of cyclone estimation and increase the efficiency of the process. Overall, the proposed system has the potential to improve the accuracy and reliability of cyclone intensity estimation, potentially aiding in the reduction of chaos and abnormalities caused by tropical cyclones.

ACKNOWLEDGEMENTS

No volume of words is enough to express my gratitude towards my guide, Prof. V. D. Punjabi, Assistant Professor in Computer Engineering Department, who has been very concerned and has aided for all the material essential for the preparation of this work. He has helped me to explore this vast topic in an organized manner and provided me with all the ideas on how to work towards a research oriented venture.

I wish to express my sincere gratitude towards Project Coordinator Prof. Dr. S. S. Sonawane for his timely suggestions and instructions.

I am also thankful to Prof. Dr. N. N. Patil, Head–Department of Computer Engineering, for the motivation and inspiration that triggered me for the project work.

I am thankful to Prof. Dr. J. B. Patil, Director–R. C. Patel Institute of Technology, Shirpur for the support and encouragement.

XII. REFERENCES

[1] Abijina K C, B G Shreyas, Bhargavi, Dhanush Gowda S(2023) Cyclone Intensity Estimation Using INSAT-3D IR Imaginary using Deep Learning IJARIIE – ISSN Vol-9(Issue-1) 1695-1699.

[2] WEI TIAN1,2,3(Member, IEEE), WEI HUANG1 (2016) A CNN-Based Hybrid Model for Tropical Cyclone Intensity Estimation in Meteorological Industry researchgate.net Vol-4(Issue-1)

[3] Tropical Cyclone Intensity Estimation Using a Deep Convolutional Neural Network," IEEE Transactions on Image Processing, vol. 27(2), pp. 692–702, 2018. R. Pradhan, R. Aygun, M. Maskey, R. Ramachandran, and D. Cecil.

[4] Hurricane Weather Research and Forecasting Model [online] Available at: Hurricane Weather Research and Forecasting Model - Wikipedia [Accessed 6 May 2023].

[5] Method for analysing and predicting tropical cyclone intensity from satellite images, V. Dvorak. NOAA Technical Memo, NESS 36, 15 pages, 14 February 1972.

[6] "Tropical Cyclone Intensity Estimation Using a Deep Convolutional Neural Network," IEEE Transactions on Image Processing, vol. 27(2), pp. 692–702, 2018. R. Pradhan, R. Aygun, M. Maskey, R. Ramachandran, and D. Cecil.

[7] What Is Python Used For? A Beginner's Guide [online] Available at: https://www.coursera.org/articles/what-is-python-used-for-a-beginners-guide-to-using-python [Accessed 7 May 2023].

[8] Lee, J. Im, D Cha, H. Park, and S. Sim, "Tropical Cyclone Intensity Estimation Using Multi-Dimensional Convolutional Neural Networks from Cecstationary Satellite Data," Remote Sensing, vel 12, pp. 108, 2014.

[9] Requirements Analysis [online] Available at: Software Engineering Requirements Analysis - javatpoint [Accessed 10 May 2023]. [11] Convolutional Neural Network [online] Available at: Convolutional Neural Network Definition | DeepAI [Accessed 10 May 2023].

[10] Tropical Cyclone Intensity Estimation Using a Deep Convolutional Neural Network," IEEE Transactions on Image Processing, vol. 27(2), p. 697 702, 2018 R. Prathon, R Aygur, M. Maskey, B. Ramachandran, and Cacil Long-term hurricane risk assessment and anticipated damage to residential structures, Z. Huang, D. Rosowsky, and P. Sparks, Reliability 61

[11] Eum, H., et al. (2020). Convolutional neural networks for estimating tropical cyclone intensity using passive microwave observations. Remote Sensing, 12(15), 2383.

[12] Deepti: Deep-Learning-Based Tropical Cyclone Intensity Estimation System [online] Available at: Deepti: Deep-Learning-Based Tropical Cyclone Intensity Estimation System | IEEE Journals & Magazine | IEEE Xplore [Accessed 10 May 2023]

[13] Stewardship System for NOAA's Comprehensive Large Array Data. The 15th of December, 2019.

[14] Machine Learning Lifecycle for Earth Science Application: A Practical Insight into Production Deployment, IEEE International Geoscience and Remote Sensing Symposium, Yokohama, Japan, pp. 10043–10046, 2019. M. Maskey, R. Ramachandra, I. Gurung, B. Freitag, J.J. Miller, M. Ramasubramanian, D. Bollinger, R. Mestre, D. Cecil, A. Molthan, and C. Hain.

[15]Weather, Climate, and Society, vol. 3, pp. 261-268, 2011. K. Emanuel, "Global Warming Effects on U.S. Hurricane Damage." 4) A method for analysing and predicting tropical cyclone intensity from satellite images, V. Dvorak. NOAA Technical Memo, NESS 36, 15 pages, 14 February 1972.

[16]"Tropical Cyclone Intensity Estimation Using a Deep Convolutional Neural Network," IEEE Transactions on Image Processing, vol. 27(2), pp. 692–702, 2018. R. Pradhan, R. Aygun, M. Maskey, R. Ramachandran, and D. Cecil.

[17]Long-term hurricane risk assessment and anticipated damage to residential structures, Z. Huang, D. Rosowsky, and P. Sparks, Reliability Engineering & System Safety, vol. 74, pp. 239–249. 2001.

[18]C. Landsea and J. Franklin, "Atlantic Hurricane Database Uncertainty and Presentation of a New Database Format," Monthly Weather Review, Vol. 141, pp. 3576-3592.

[19]J. Lee, J. Im, D. Cha, H. Park, and S. Sim, "Tropical Cyclone Intensity Estimation Using Multi-Dimensional Convolutional Neural Networks from Geostationary Satellite Data," Remote Sensing, vol. 12, pp. 108, 2019