A

B. TECH. PROJECT REPORT

on

# Cyclone Intensity Estimation Using Deep Learning Technique

Submitted in partial fulfillment of the requirements for the degree of

**Bachelor of Technology** in **Information Technology**

By


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Under the guidance of

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**Academic Year 2023 – 24**

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**Academic Year 2023 – 24**

## ***CERTIFICATE***

This is to certify that the B.TECH. Project Report Entitled

**Cyclone Intensity Estimation Using Deep Learning Technique**

Submitted by

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is a record of bonafide work carried out by him/her, under our guidance, in partial fulfillment of the requirement for the award of Degree of Bachelor of Technology (Information Technology) at Shri Vile Parle Kelawani Mandal's Institute Of Technology, Dhule under the Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra. This work is done during semester VIII of Academic year 2023-24.

Date:
Place: SVKM's IOT, Dhule

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# DECLRATION

We declare that this written submission represents ideas in our own words and where other's ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

| | Signatures |
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| Mr. Abhinash Kailash Joshi | _________________ |
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# ACKNOWLEDGMENTS

We have immense pleasure in expressing our interest and deepest sense of gratitude towards our project guide **Prof. Mangesh Balpande** for the assistance, valuable guidance and co-operation in carrying out this project successfully. It is a privilege for us to have been associated with **Prof. Mangesh Balpande**, our Project Guide, during our Project Phase 1 work. We have greatly benefited from his valuable suggestion and ideas. It is with great pleasure that we express our deep sense of gratitude to him for his valuable guidance, constant encouragement and patience throughout this work. We express our gratitude and are thankful to all people who have contributed in their way in making this final year project phase 1 success. Particularly we want to thank **Prof. Rubi Mandal**, Project Coordinator for our department for making this process seamless for us and arranging everything so perfectly. I take this opportunity to thank all the classmates for their company during the course work and for the useful discussion, I had with them. We take this opportunity to express our heartfelt gratitude towards the Department of Information Technology of Shri Vile Parle Kelvani Mandal's Institute of Technology, Dhule Head of Department, **Dr Bhushan Chaudhar**i and **Dr. Nilesh Salunke**, Principal of Shri Vile Parle Kelvani Mandal's Institute of Technology, Dhule, that gave us an opportunity for the presentation of our project phase 1 in the esteemed organization and for providing the required facilities in completing this project. We are greatly thankful to our parents, friends and other faculty members for their motivation, guidance and help whenever needed.

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## LIST OF ABBREVIATIONS

| | |
|---|---|
| MVT | Model View TEMPLATE |
| MVC | Model View Controller |
| DRY | User Interface |
| ORM | Object Relational Mapping |
| ADT | Advanced Devork Technique |
| DAVT | Deviation Angle Variance Technique |
| ELU | Exponential Linear Unit |

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# ABSTRACT

The estimation of cyclone intensity is a crucial component of tropical weather forecasting, traditionally relying on intricate numerical models. However, recent strides in deep learning offer a promising avenue for refining the precision of these predictions. This abstract delves into the application of deep learning methodologies for cyclone intensity estimation. Specifically, Convolutional Neural Networks (CNNs) is harnessed to analyse extensive datasets encompassing satellite imagery, atmospheric pressure, and other pertinent parameters. These deep learning models exhibit notable proficiency in discerning intricate patterns and correlations within the data, consequently enabling more precise and timely forecasts of cyclone intensity. The integration of transfer learning bolsters the model's adaptability to diverse environmental conditions, contributing to heightened generalization capabilities. The research assesses the efficacy of the proposed deep learning approach in comparison to traditional methods, showcasing superior accuracy and efficiency. Notably, the incorporation of real-time data feeds amplifies the model's responsiveness to evolving cyclonic conditions. In essence, this investigation underscores the transformative potential of deep learning in advancing cyclone intensity estimation, promising more effective strategies for disaster preparedness and response.

**Keywords-** Deep learning, Convolutional Neural Network, Satellite imagery.

# 1.INTRODUCTION

Coastal regions worldwide confront significant risks from potent tropical cyclones, underscoring the vital importance of accurate analysis of cyclone images and enhanced intensity prediction. Conventional methods for estimating cyclone intensity often struggle to attain precision, particularly in the face of dynamic weather patterns. In response, machine learning techniques emerge as promising solutions, approaching cyclone intensity estimation as a classification challenge. Various methods, encompassing Multiple Logistic Regression, Support Vector Machine, and Back-Propagation Neural Network, have demonstrated success in managing diverse multispectral cyclone images. Notably, the Convolutional Neural Network (CNN) stands out as a robust classifier, exhibiting substantial progress in various visual tasks and proving effective in estimating cyclone intensity from infrared images [4]. Despite these strides, both CNNs and many existing supervised techniques encounter a common hurdle: their dependence on extensive training datasets. This challenge is further exacerbated by the limited availability of accurately labelled samples, especially for cyclone intensity estimation using multispectral images from China's No. 4 meteorological satellite (FY-4), launched in December 2016. The intricate features within these images' present challenges for unsupervised methods, solely driven by data, to achieve satisfactory classification accuracy. Recognizing the unique complexities of the problem, a nuanced approach becomes imperative. Purely supervised or unsupervised methods alone prove suboptimal for cyclone intensity estimation, particularly given the scarcity of labelled data. However, the vast collection of unlabelled images holds substantial promise due to their rich information. This situation introduces an opportunity for semi supervised classification, where both labelled and unlabelled data collaborate to address the intricacies of cyclone intensity estimation. A tropical cyclone is a rapidly rotating storm system characterised by a low-pressure centre, a closed low-level atmospheric circulation, strong winds, and a spiral arrangement of thunderstorms that produces heavy rain and squalls. Depending on the location and strength, a tropical cyclone is called by different names, including hurricane, typhoon, tropical depression, tropical storm, cyclonic storm, or simply cyclone. A hurricane is a strong tropical cyclone that occurs in the Atlantic Ocean or north eastern Pacific Ocean, and a typhoon occurs in the north western Pacific Ocean. In the Indian Ocean, South Pacific, or (rarely) South Atlantic, comparable storms are referred to as "tropical cyclones", and such storms in the Indian Ocean can also be called "severe cyclonic storms". "Tropical" refers to the geographical origin of these systems, which form almost exclusively over tropical seas. "Cyclone" refers to their winds moving in a circle, whirling round their central clear eye, with their surface winds blowing counter clockwise in the Northern Hemisphere and clockwise in the Southern Hemisphere. The opposite direction of circulation is due to the Coriolis effect. Tropical cyclones typically form over large bodies of relatively warm water [16]. They derive their energy through the evaporation of water from the ocean surface, which ultimately condenses into clouds and rain when moist air rises and cools to saturation. This energy source differs from that of mid-latitude cyclonic storms, such as nor'easters and European windstorms, which are powered primarily by horizontal temperature contrasts. Tropical cyclones are typically between 100 and 2,000 km (62 and 1,243 mi) in diameter. Every year tropical cyclones affect various regions of the globe including the Gulf Coast of North America, Australia, India, and Bangladesh.

## 1.1 How do they form?

In the tropics there is a broad zone of low pressure which stretches either side of the equator. The winds on the north side of this zone blow from the north-east (the north-east trades) and on the southern side blow from the south-east (south-east trades). Within this area of low pressure, the air is heated over the warm tropical ocean. This air rises in discrete parcels, causing thundery showers to form. These showers usually come and go, but from time to time, they group together into large clusters of thunderstorms. This creates a flow of very warm, moist, rapidly rising air, leading to the development of a centre of low pressure, or depression, at the surface. There are various trigger mechanisms required to transform these cloud clusters into a tropical cyclone. These trigger mechanisms depend on several conditions being 'right' at the same time. The most influential factors are:

1. A source of warm, moist air derived from tropical oceans with sea surface temperatures normally in the region of, or in excess, of 27 °C
2. Winds near the ocean surface blowing from different directions converging and causing air to rise and storm clouds to form winds which do not vary greatly with height - known as low wind shear.

This allows the storm clouds to rise vertically to high levels, sufficient distance from the equator to provide spin or twist. The Coriolis force caused by the rotation of the Earth helps the spin of this column of rising air. The development of the surface depression causes an increase in the strength of the trade winds. The spiralling winds accelerate inwards and upwards, releasing heat and moisture as they do so

## 1.2 Motivation Behind Project

Investigating car emission monitoring and control via IoT is essential and compelling given the current era's growing concerns about public health and environmental sustainability. Vehicle emissions are a major source of air pollution, which has an effect on air quality and puts respiratory health at risk. This problem goes beyond personal health to include more general environmental issues, such as climate change brought on by greenhouse gas emissions [5]. Global regulatory agencies are implementing strict emission regulations, which call for real-time monitoring to guarantee adherence and prevent fines. In addition, there is a growing need for creative solutions as people become more conscious of the negative effects that automobile emissions have on the environment. In addition to addressing the urgent need for emission control, utilizing IoT technology opens the door to more intelligent urban planning, data-driven policy creation, and global cooperation in the fight for a better, cleaner, and sustainable future. In this case, IoT integration is not only a significant technological achievement but also a critical step in reducing the harmful consequences that vehicle emissions have on our world and its people

## 1.3 Aim and Objective(s) of the work

The central goal of this project is to create a precise and dependable system for estimating cyclone intensity. By harnessing advanced computational techniques and meteorological data, the objective is to improve our comprehension of cyclones and, in turn, enhance the accuracy of predictions regarding their intensity. The project's core objectives revolve around developing a robust cyclone intensity estimation system. Beginning with thorough data collection and pre-processing, the project aims to identify key features influencing cyclone intensity, incorporating advanced machine learning algorithms for accurate predictions. Integration of remote sensing technologies, user-friendly visualization tools, and real-time monitoring for early warnings are key components. Documentation of methodologies and continuous improvement mechanisms, including user feedback and adaptation to evolving meteorological patterns, ensures the effectiveness and longevity of the developed system

## 1.4 Scope of the topic

The scope of project on cyclone intensity estimation involves the comprehensive development of a system that leverages advanced computational techniques and meteorological data. Key components include data collection, pre-processing, and the identification of critical features influencing cyclone intensity [8]. The project extends to the creation and optimization of machine learning algorithms tailored for cyclone intensity prediction, with a consideration for additional data sources such as satellite imagery. Practical applications include the integration of remote sensing technologies for enhanced data accuracy, the development of a user-friendly interface for visualizing predicted cyclone intensity, and the implementation of a real-time monitoring and early warning system. Documentation is a critical aspect, ensuring transparency in methodologies and facilitating understanding for users, meteorologists, and researchers. The continuous improvement aspect of the project involves mechanisms for adapting the system to evolving meteorological patterns and incorporating user feedback. Overall, the scope of your project spans multiple domains, from data science and machine learning to remote sensing technology integration and real-world applications in disaster preparedness.

## 2.LITERATURE SURVEY

The CNN-TC employs adaptable CNN architecture to accurately gauge tropical cyclone intensity. It crafts specific CNN models for predicting cyclone formation based on diverse satellite factors. This innovative approach enhances prediction precision and adapts to varying conditions, revolutionizing cyclone forecasting. Reference [1] employs the Multilayer Perceptron (MLP) algorithm to predict cyclone intensity, using image-based geometric traits of tropical cyclones (TC). The Dvorak technique extracts significant features from satellite TC images. These features train the MLP model, enabling it to effectively estimate TC intensity based on learned patterns from the data. [4] This approach involves developing and deploying models for manufacturing after evaluating them against CAM-recognized functions and Dvorak T-wide variety images. The models are trained on local servers to minimize training costs. Once trained, they're integrated into the manufacturing system. The user interface for interacting with these models is built using React and Redux, known for their dynamic interface design and efficient state management. An analytical assessment and skill evaluation study is conducted over a thirty-minute timeframe, focusing on various levels of design and efficient state management. An analytical assessment and skill evaluation study is conducted over a thirty-minute timeframe, focusing on various levels of cyclone attributes such as intensity and structure. This evaluation involves measuring the model's performance and its ability to make accurate predictions within this specific timeframe. Different aspects of cyclone behaviour are taken into consideration during this analysis.[9] The model introduced in the context focuses on Very High-Resolution (VHR) remote sensing images. Its primary contribution lies in enhancing the precision of object detection and instance segmentation. Notably, this model incorporates a technique to compute the two-order integral, significantly elevating its accuracy levels. The Dvorak technique for calculating cyclone intensity has been used for a long time, but it relies on human judgment, which can be inconsistent and make it hard to use on big datasets. Convolutional Neural Networks (CNNs) combined with INSAT 3D images offer a solution to automate the process of cyclone intensity assessment. By leveraging these technologies, the system becomes proficient in autonomously recognizing patterns within the images that correspond to cyclone strength. This eliminates the necessity for human interpretation, ensuring a uniform approach across diverse datasets. The Dvorak technique for calculating cyclone intensity has been used for a long time, but it relies on human judgment, which can be inconsistent and make it hard to use on big datasets. Convolutional Neural Networks (CNNs) combined with INSAT 3D images offer a solution to automate the process of cyclone intensity assessment. By leveraging these technologies, the system becomes proficient in autonomously recognizing patterns within the images that correspond to cyclone strength. This eliminates the necessity for human interpretation, ensuring a uniform approach across diverse datasets. An advantageous aspect of CNNs is their immunity to fluctuations in image quality and atmospheric conditions. This robustness contributes to their reliability, which surpasses that of the traditional Dvorak technique. As a result, CNNs, along with the utilization of INSAT 3D images, yield more precise and dependable estimations of cyclone intensity. An advantageous aspect of CNNs is their immunity to fluctuations in image quality and atmospheric conditions. This robustness contributes to their reliability, which surpasses that of the traditional Dvorak technique. As a result, CNNs, along with the utilization of INSAT 3D images, yield more precise and dependable estimations of cyclone intensity. In [1] Multilayer perceptron (MLP) algorithm is used. By using this algorithm, authors predicted the intensity of cyclones. Image based geometric properties of Tropical Cyclone (TC) are the key factors for the approach given in this research. TC intensity is estimated based on the images obtained from satellites using Dvorak technique. Properties or feature values of cyclone images are trained and tested by the model proposed in this research through a multilayer perceptron. In [2] the CNN-TC is able to determine the intensity by making changes to the CNN and the ability to design different models of CNN for prediction of the formation of tropical cyclone on the basis of different factors and images from satellite. The proposed model in [3] discusses about models that are substantially evaluated and systematically transferred to manufacturing via comparing CAM-recognized functions to Dvorak T-wide variety pictures. The version is trained using neighbourhood servers to avoid the excessive fee of necessities for the duration of training. After the training of the model, it's uploaded to the production system. The website advanced the usage of React and Redux technology for the view and state management. In [4] analytical and rating of skill study is performed each over a thirty-minute scale with admiration to different degrees of cyclone characteristics like intensity framework. The proposed model in [5] explains about VHR remote sensing images, it helped in increasing accuracy of detection of object and instance segmentation. It can calculate the two-order integral for good accuracy. The Dvorak technique for calculating cyclone intensity has been used for a long time, but it relies on human judgment, which can be inconsistent and make it hard to use on big datasets. CNNs and INSAT 3D images can solve this by automating the process and learning to identify patterns in the images that indicate cyclone intensity. This removes the need for humans to interpret the images and ensures that the technique is consistent across different datasets. Also, CNNs are not affected by variations in image quality or atmospheric conditions, making them more reliable than the Dvorak technique. Ultimately, CNNs and INSAT 3D images help us get more accurate and consistent estimates of cyclone intensity [13].

## 2.1 Literature Survey Table

| Reference No. /Paper Title | Year | Issues Found | Parameters / Tools Used | Work Description |
|---|---|---|---|---|
| [4] Tropical cyclone intensity detection by geometric features of cyclone images and multilayer perceptron Chinmoy Kar, Ashirvad Kumar & Sreeparna Banerjee Published: 26 August 2019 volume 1, Article number: 1099 (2019) | 2019 | Ethical concerns related to data collection or analysis. | MATLAB, OpenCV, and scikit-image in Python. deep learning frameworks multilayer perceptron's, include TensorFlow and Porch. | The system classifies cyclone intensities based on wind speed, employs ensemble learning for improved accuracy, and integrates the model into an Android application for real-time intensity prediction. |
| [5] Intensity Estimation of Tropical Cyclone using Different Satellite Imagery and Random Forest Classifier Chinmoy Kar; Sreeparna Banerjee 2022 IEEE Region 10 Symposium (TENSYMP)Year: | 2022 | The research paper lacks CNN-based Approaches Drawback Limited Application of Feature Extraction Strategy Limited Information on Dataset | Programming Language: Octave (for feature extraction) Classification Tool: Weka (for classification) Two-layer Perceptron Model (TLPM): A model based on a two-layer perceptron | The work is conducted using Octave for feature extraction and Weka for classification, and the results are discussed in the context of other established models, showcasing the |

| | | | | |
|---|---|---|---|---|
| 2022 \| Conference Paper \| Publisher: IEEE | | | Gray Level Co-occurrence Matrix and SVM Classifier (GLCM+SVM) | potential of the proposed methodology in enhancing cyclone intensity estimation |
| [16] Chong Wang, Gang Zheng* contributed in "Tropical Cyclone Intensity Estimation from Geostationary Satellite Imagery Using Deep Convolutional Neural Networks presented in IEEE Transactions on Geoscience and Remote Sensing (Volume: 60)2021 | 2021 | The paper provides accuracy metrics for the proposed multilayer perceptron (MLP) model but does not delve into a detailed analysis of false positives, false negatives, or other relevant metrics. | Octave GNU was used for feature extraction using image processing techniques in the project. | The work includes the use of Octave GNU for feature extraction and Weka for implementing and evaluating the MLP model. The results indicate an 84% accuracy in classifying TC images, showcasing the potential of the image-centric approach for predicting TC intensity. |
| [17] Chen, Zhao; Yu, Xinxiang; Chen, Guangcheng; Zhou, Jun Feng, "A Semi Supervised Deep Learning Framework for Tropical Cyclone | 2019 | The complexity of cyclone image features in multispectral images (MSIs) could pose a challenge for accurate | Convolutional Neural Networks (CNNs), Principal Component Analysis (PCA), Semi supervised Learning | The proposed methodology uses sensors and Arduino technology to control vehicle pollutants. When emission levels |

| | | | | |
|---|---|---|---|---|
| Intensity Estimation" presented in Conference: 2019 10th International Workshop on the Analysis of Multitemporal Remote Sensing Images (Multitap) | | classification. This complexity might make it difficult for traditional methods to achieve desirable results. | Framework | exceed a threshold, an alarm is triggered and data is sent to the IBM Watson IoT platform via a GSM module, allowing the Pollution Control Board to monitor and reduce emissions. |

Fig 2.1: Literature Table

# 3.PROBLEM STATEMENT

This project involves crafting a specialized Convolutional Neural Network (CNN) for the precise estimation of Tropical Cyclone intensity, utilizing half-hourly INSAT-3D infrared images. The CNN is intricately designed to recognize complex patterns and spatial relationships within the imagery, providing a solution with high temporal resolution for accurate intensity predictions. In addition, a user-friendly web application has been developed to facilitate the intuitive visualization of INSAT-3D data, making it more accessible to meteorologists, researchers, and the general public. This cohesive approach represents a significant advancement in harnessing cutting-edge technology for the timely and accurate forecasting of tropical cyclones, ultimately contributing to enhanced disaster preparedness and mitigation efforts [8].

## 3.1 Project Requirement Specification

3.1.1Tensorflow/Keras

TensorFlow and Keras are powerful open-source machine learning frameworks that have become integral tools in the field of deep learning. TensorFlow, developed by the Google Brain team, is a comprehensive machine learning library that provides a flexible platform for building and deploying various machine learning models. It is particularly renowned for its support of deep neural networks and offers functionalities for tasks ranging from image and speech recognition to natural language processing. On the other hand, Keras serves as a high-level neural networks API that runs on top of TensorFlow, making it accessible and user-friendly. Keras simplifies the process of building neural network architectures by offering a clean and intuitive interface. Its modular design allows users to rapidly prototype and experiment with different model architectures, enabling efficient development and testing. The seamless integration between TensorFlow and Keras combines the computational power of TensorFlow with the user-friendly interface of Keras, creating a versatile and robust ecosystem for deep learning research, development, and deployment. This combination facilitates the implementation of complex neural network structures with ease, making it a preferred choice for both beginners and seasoned machine learning practitioners in the development of advanced deep learning models.

3.1.2 ReactJS:

ReactJS, developed and maintained by Facebook, is a widely used JavaScript library for building user interfaces, particularly for single-page applications where seamless and dynamic user experiences are essential [14]. Renowned for its efficiency and declarative syntax, react allows developers to create interactive and reusable UI components. The core concept of React is the virtual DOM (Document Object Model), a lightweight representation of the actual DOM. React efficiently updates the virtual DOM in response to user interactions, and then selectively updates the actual DOM, minimizing unnecessary re-rendering for enhanced performance. Reacts component-based architecture promotes a modular and maintainable code structure, enabling developers to build complex applications by composing small, self-contained components. Reacts unidirectional data flow and state management further contribute to predictable and scalable development. Additionally, reacts ecosystem includes tools like Redux for state management and React Router for navigation, enhancing its capabilities for building robust and scalable web applications. With its emphasis on simplicity, reusability, and performance optimization, react has become a cornerstone in modern front-end development, widely adopted by developers and organizations for creating responsive and engaging user interfaces.

3.1.3 Map box API:

Map box API is a comprehensive and versatile geospatial platform that provides developers with a wide array of tools and services to integrate dynamic and interactive maps into their applications. Developed by Map box, this API offers functionalities for creating visually stunning and customizable maps, incorporating various layers of geographic data such as satellite imagery, terrain, streets, and custom datasets. One of the notable strengths of the Map box API is its ability to support vector tiles, allowing for efficient rendering of complex map data on the client-side, resulting in faster loading times and a smoother user experience. The API is well-documented and supports popular web technologies, including JavaScript and RESTful APIs, making it accessible for developers across different platforms [6]. The flexibility of the Map box API is evident in its support for diverse applications, ranging from mobile and web applications to augmented reality and location-based services. Developers can leverage Map box’s rich set of SDKs (Software Development Kits) for various platforms, including Map box GL JS for web applications, Map box Maps SDK for Android and iOS for mobile applications, and Map box Unity SDK for game development. Furthermore, Map box API goes beyond basic mapping services by offering advanced features such as geocoding (converting addresses into geographic coordinates) and routing (finding optimal paths between locations). It also allows for the creation of custom map styles to match the branding or thematic requirements of specific applications [9]. The platform's commitment to open-source technologies and collaboration is reflected in its community-driven development and continuous updates. It provides developers with tools to contribute to OpenStreetMap, enhancing the accuracy and richness of map data globally. Map box API's robust capabilities, ease of integration, and focus on customization make it a popular choice for developers seeking powerful geospatial solutions in their applications, whether for visualizing geographic data, facilitating location-based services, or creating immersive mapping experiences across various digital platforms.

### 3.1.4 Django Framework

Django is a high-level, open-source web framework for building robust and scalable web applications using the Python programming language. Developed with a focus on simplicity, efficiency, and the "Don't Repeat Yourself" (DRY) principle, Django provides a comprehensive set of tools and conventions that streamline the development process. At its core, Django follows the Model-View-Controller (MVC) architectural pattern, but it refers to it as Model-View-Template (MVT), emphasizing the importa5+nce of templates in handling the user interface. Django offers an integrated and batteries-included approach, incorporating a wide range of built-in features such as an Object-Relational Mapping (ORM) system for database interactions, an admin panel for effortless content management, and a powerful URL routing system. Its security features include protection against common web vulnerabilities, making it a secure choice for web development. Django's modularity is evident in its use of reusable applications, allowing developers to create independent components that can be easily integrated into different projects. The framework encourages the adoption of best practices through its emphasis on clean and maintainable code, automatic administration interfaces, and robust testing tools [9].

Moreover, Django embraces the concept of "loose coupling" by allowing developers to choose and use only the components they need. This flexibility, combined with a vibrant and supportive community, has contributed to Django's popularity and its widespread adoption for applications of various sizes and complexities, from simple websites to large-scale, data-intensive platforms. Overall, Django stands out as a versatile and developer-friendly framework that accelerates the web development process while maintaining a high standard of code quality and security. PostgreSQL, often referred to as "Postgres," is a powerful, open-source relational database management system (RDBMS) known for its robustness, extensibility, and adherence to SQL standards. Developed by a vibrant and dedicated open-source community, PostgreSQL provides a reliable and scalable solution for managing and querying structured data. One of its notable strengths lies in its support for advanced data types, including arrays, store (a key-value store), and JSONB (binary JSON), making it suitable for handling complex and diverse data structures [3].

### 3.1.5 PostgreSQL

PostgreSQL excels in ACID (Atomicity, Consistency, Isolation, Durability) compliance, ensuring data integrity and reliability, even in the face of system failures. Its extensibility is evident in the support for custom functions, operators, and procedural languages, allowing developers to tailor the database to specific application requirements. Additionally, PostgreSQL supports both synchronous and asynchronous replication, facilitating high availability and fault tolerance. The versatility of PostgreSQL extends to its support for spatial data through the Postages extension, enabling the storage and analysis of geographic information. Furthermore, its full-text search capabilities, transactional DDL (Data Definition Language), and support for concurrent access make it a robust choice for applications with demanding requirements. The community-driven development of PostgreSQL has resulted in a rich ecosystem of extensions, plugins, and tools that enhance its functionality. Its commitment to standards compliance and continuous improvement is reflected in frequent updates that introduce new features, performance enhancements, and security patches. PostgreSQL is widely adopted across industries for applications ranging from small-scale projects to enterprise-level systems. Its permissive open-source license, combined with its reliability and feature-rich nature, makes it an attractive option for developers and organizations seeking a powerful and extensible database solution. In summary, PostgreSQL stands as a versatile, feature-rich, and community-driven relational database management system that excels in managing complex data scenarios while providing a strong foundation for scalable and reliable applications. Visual Studio Code, commonly known as Viscose, is a free and open-source code editor developed by Microsoft. Renowned for its versatility, efficiency, and extensive support for various programming languages, Viscose has become a popular choice among developers for a wide range of software development tasks. Its lightweight yet powerful design strikes a balance between simplicity and functionality, making it suitable for both beginners and experienced developers.

### 3.1.6 Viscose

One of the standout features of Viscose is its rich set of extensions, which are available through the Visual Studio Code Marketplace. These extensions enhance the editor's capabilities, providing support for additional languages, integrating with version control systems, offering debugging tools, and customizing the user interface to suit individual preferences. The extension ecosystem, combined with a vibrant and active community, contributes to the editor's adaptability to diverse development workflows [19]. Viscose’s built-in IntelliSense, a powerful code completion and suggestion engine, aids developers in writing code more efficiently. The editor also integrates seamlessly with Git for version control, allowing developers to manage their codebase directly within the editor. Its integrated terminal provides a convenient environment for executing commands and scripts without leaving the editor, streamlining the development workflow Additionally, Viscose supports a wide range of customization options, enabling users to tailor the editor to their preferences. The "Command Palette" feature allows quick access to a plethora of commands, and the editor's split-screen and tabbed interface provides an efficient way to navigate and work with multiple files simultaneously. The commitment to cross-platform compatibility is another notable aspect of Viscose. It is available for Windows, macOS, and Linux, ensuring a consistent and familiar experience across different operating systems. Furthermore, frequent updates from the Microsoft team and an open-source community contribute to the continuous improvement and refinement of the editor. In summary, Visual Studio Code has positioned itself as a leading code editor in the software development landscape, offering a potent combination of features, extensibility, and a user-friendly interface. Its adaptability to diverse programming languages and development scenarios, coupled with a robust extension ecosystem, has solidified its place as a go-to choose for developers seeking a versatile and efficient coding environment. The development initiative for a deep Convolutional Neural Network (CNN) dedicated to estimating Tropical Cyclone intensity, coupled with the creation of a web application for visualizing imagery, encompasses a multifaceted array of functional and non-functional prerequisites. Functionally, the project mandates the establishment of a robust framework for data acquisition and pre-processing, ensuring the meticulous curation of half-hourly INSAT-3D IR images sourced from reputable meteorological outlets. The CNN model development phase necessitates the formulation of an intricate architecture, tailored for optimal feature extraction from these images, coupled with a rigorous training regimen utilizing historical data and a systematic validation protocol. The web application, a pivotal component, must feature an intuitive user interface facilitating image uploads, real-time intensity predictions, and seamless integration with the trained CNN model [20]. Visualization elements are paramount, encompassing not only intensity representations but also geospatial overlays to enhance situational comprehension. On the non-functional spectrum, paramount is the imperative of peak performance, demanding an elevated level of accuracy from the CNN model and swift responsiveness from the web application. Reliability considerations span the robust handling of diverse image datasets and scenarios, coupled with the assurance of consistent system availability. Security protocols must be implemented to safeguard user data privacy and avert unauthorized alterations to the CNN model. Scalability emerges as a critical parameter, mandated to accommodate an expanding user base and effectively manage escalating volumes of INSAT-3D IR image data. An emphasis on an enriched user experience is embedded in the need for an intuitive interface.

Compliance with meteorological standards is a sine qua non, while comprehensive documentation, including exhaustive user manuals and rigorous testing protocols, stands as an imperative for the effective deployment and operation of this intricate system. In synthesis, these myriad functional and non-functional stipulations form the indispensable framework for the triumphant development and operationalization of an integrated system for Tropical Cyclone intensity estimation and imagery visualization [4].

# 4.RELATED WORK

## 4.1 Dvorak Method

The Dvorak Technique is a widely used method for estimating the intensity of tropical cyclones based on satellite imagery. Dvorak technique are considered the gold standard for satellite image-based tropical cyclone intensity estimation among tropical meteorologists. The main concept of the Dvorak technique is that the shape and coverage of the cloud field determine the intensity of the cyclone. Features such as the length and curvature of the storm's outer rainbands are analysed to arrive at a particular T-number [2]. But Dvorak Technique has some drawbacks of its own, because the Dvorak technique relies on human interpretation of features in a tropical cyclone cloud field, two well-trained analysts can assign different intensity estimates. Additionally, subtle differences in T-number can result in differences in maximum wind speed by 12 knots or more at hurricane intensities. The Dvorak technique (developed between 1969 and 1984 by Vernon Dvorak) is a widely used system to estimate tropical cyclone intensity (which includes tropical depression, tropical storm, and hurricane/typhoon/intense tropical cyclone intensities) based solely on visible and infrared satellite images [7]. Within the Dvorak satellite strength estimate for tropical cyclones, there are several visual patterns that a cyclone may take on which define the upper and lower bounds on its intensity. The primary patterns used are curved band pattern (T1.0-T4.5), shear pattern (T1.5–T3.5), central dense overcast (CDO) pattern (T2.5–T5.0), central cold cover (CCC) pattern, banding eye pattern (T4.0–T4.5), and eye pattern (T4.5–T8.0).

Both the central dense overcast and embedded eye pattern use the size of the CDO. The CDO pattern intensities start at T2.5, equivalent to minimal tropical storm intensity (40 mph, 65 km/h). The shape of the central dense overcast is also considered. The eye pattern utilizes the coldness of the cloud tops within the surrounding mass of thunderstorms and contrasts it with the temperature within the eye itself. The larger the temperature difference is, the stronger the tropical cyclone [4]. Once a pattern is identified, the storm features (such as length and curvature of banding features) are further analysed to arrive at a particular T-number. The CCC pattern indicates little development is occurring, despite the cold cloud tops associated with the quickly evolving feature [18].

## 4.2 Advanced Dvorak Technique (ADT)

The Advanced Dvorak Technique (ADT) is an enhanced version of the original Dvorak Technique for estimating the intensity of tropical cyclones. ADT takes into account a wider range of storm features, including cloud top temperature, storm size, and asymmetry of the storm's structure. It also uses microwave satellite data to provide a more accurate estimate of the storm's centre and overall intensity. While the ADT improves upon the manual Dvorak technique, model performance struggles on weaker storms that tend to have a more disorganized cloud distribution and empirical thresholds are retained to constrain the change in cyclone intensity with time. The Advanced Dvorak Technique (ADT) utilizes longwave-infrared, temperature measurements from geostationary satellites to estimate tropical cyclone (TC) intensity. The ADT is based upon the operational Dvorak Technique developed by Vern Dvorak of NOAA over 30 years ago [8]. This step-by-step technique relies upon the user to determine a primary cloud pattern and measure various TC cloud top parameters in order to derive an initial intensity estimate. Various rules regarding TC development and intensity change over time are employed to guide the user in the scene selection process and govern the rate in intensity change over a given time period. The Dvorak Technique continues to be the standard method for estimating TC intensity where aircraft reconnaissance is not available (all tropical regions outside the North Atlantic and Caribbean Sea), however it has several important limitations and flaws. The primary issue centres upon the inherent subjectivity of the storm centre selection and scene type determination procedures. Secondly, learning the Dvorak Technique and its regional nuances and adjustments can take a significant time to master. Finally, the technique was developed more or less empirically by Dvorak and his colleagues, without the aid of computer analysis, to determine statistical relationships between various environmental parameters and intensity [3]. The ADT (and its predecessors the ODT and AODT) sought to alleviate many of the limitations found within the Dvorak Technique and previous objective algorithms based upon methods outlined by Dvorak. The ADT currently utilizes an objective storm centre determination scheme and cloud pattern determination logic to remove the subjectivity aspect from the intensity estimation process. It also can be applied to all phases of the TC lifecycle; something that previous objective schemes could not do. Finally, the ADT makes use of statistical analysis results obtained from a 10+ year sample of North Atlantic storms, along with a significant sample of West and East Pacific storms, covering the entire spectrum of TC intensities to derive a regression-based intensity value estimate for various phases of the TC lifecycle. The ADT is a powerful but easy-to-use TC intensity estimation guidance tool possessing an accuracy on par with estimates obtained by experienced TC forecasters using the Dvorak Technique [4].

### 4.3 Deviation-Angle Variance Technique (DAVT)

DAVT works by analysing the deviation angles between the microwave emissions of the storm and a reference background. The technique compares the variance of these deviation angles over time to estimate the rate of change of the storm's intensity. This technique has two main limitations: (I) it requires images with properly marked tropical cyclone centres and (ii) it uses different models and fitting parameters for tropical cyclones in different regions [7].

### 4.4 Convolutional neural networks (CNN)

Convolutional neural networks (CNNs) have been used for many different computer vision tasks ranging from image classification to object detection and even visual saliency detection. In this method, the CNN is trained on a large dataset of satellite images of tropical cyclones with known intensity values. The CNN learns to recognize patterns in the images that are indicative of higher wind speeds and more intense storms. Once the CNN is trained, it can be used to predict the intensity of new tropical cyclones based on satellite imagery [2].

One of the advantages of CNN-based intensity estimation is that it can provide accurate results even in cases where other methods may not be effective, such as storms with unusual structures or rapidly changing intensities. CNN is a powerful tool for pattern recognition, which has developed in recent years, attracting widespread attention [18]. The CNN architecture mainly includes convolution layers, pooling layers, fully connected (FC) layers, and SoftMax layer, as indicated in the graphical illustration of the architecture of vanilla CNN The convolutional layers first extract features from the input images. The pooling layers help reduce computation and control overfitting. The role of the fully connected layers. The convolutional layers first extract features from the input images. The pooling layers help reduce computation and control overfitting. The role of the fully connected layers is to pull the feature maps extracted from the convolutional layer or the pooling layer into a vector, and obtain the category label through the SoftMax layer. As indicated by the vanilla CNN can be directly applied to cyclone intensity estimation, with cyclone images as the input and intensity categories as the output. Neural networks are a subset of machine learning, and they are at the heart of deep learning algorithms. They are comprised of node layers, containing an input layer, one or more hidden layers, and an output layer. Each node connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network [15]. Otherwise, no data is passed along to the next layer of the network. While we primarily focused on feedforward networks in that article, there are various types of neural nets, which are used for different use cases and data types. For example, recurrent neural networks are commonly used for natural language processing and speech recognition whereas convolutional neural networks (Convent’s or CNNs) are more often utilized for classification and computer vision tasks. Prior to CNNs, manual, time-consuming feature extraction methods were used to identify objects in images. However, convolutional neural networks now provide a more scalable approach to image classification and object recognition tasks, leveraging principles from linear algebra, specifically matrix multiplication, to identify patterns within an image. That said, they can be computationally demanding, requiring graphical processing units (GPUs) to train models [11].

# 5. PROPOSED ARCHITECTURE

## 5.1 System Proposed Architecture

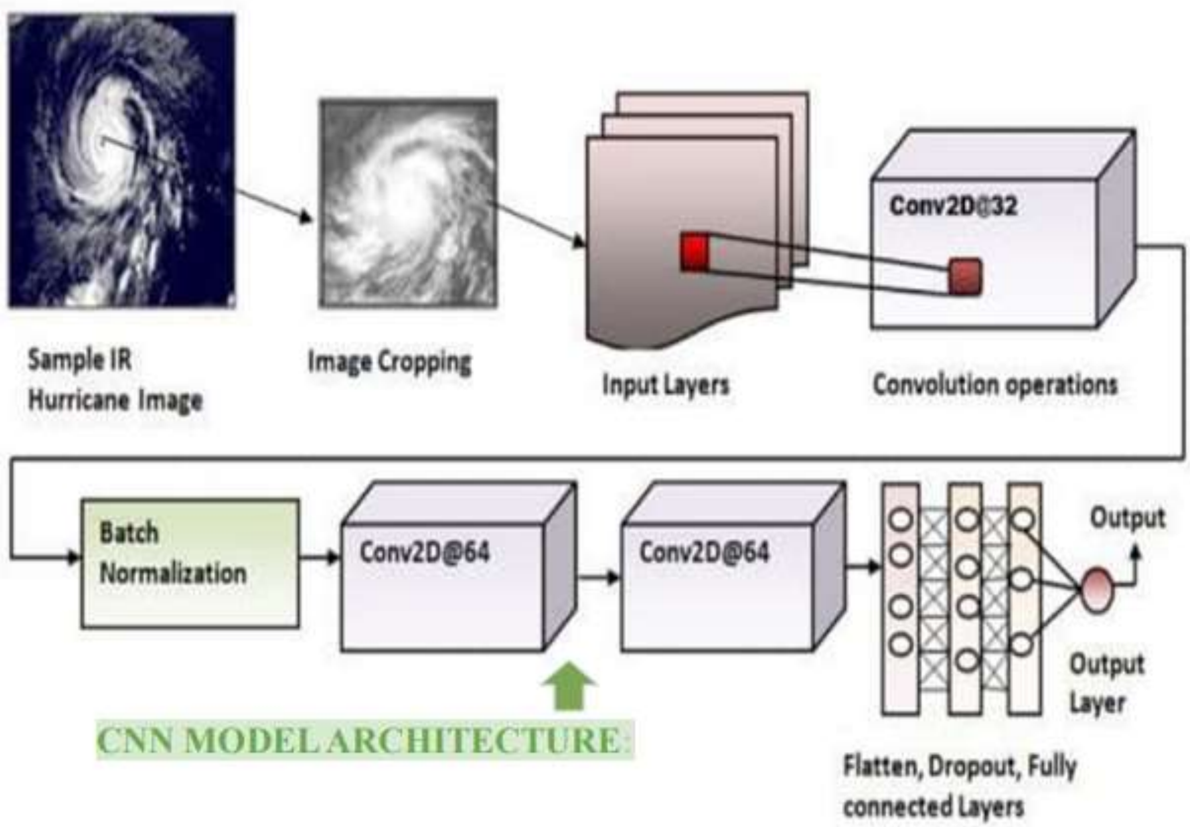



Fig 5.1: Architecture of CNN Model

In the implementation of the model firstly it takes an image and after processing the input it is passed through the deep learning CNN architecture in the case of intensity estimation, imagery data of satellite is often used, which consists of a series of images of the cyclone taken over time [12]. Therefore, the problem can be viewed as an image classification task, where each image represents a different stage of the cyclone's development, and the goal is to accurately classify the cyclone based on these features and assign it to the appropriate intensity category, which can then be used for various purposes, such as predicting its potential impact on an area and informing emergency response efforts. CNNs are well-suited to this type of task because they are designed to extract features from images in ordered manner, using a series of convolutional layers that learn increasingly complex representations of the image data. This allows the CNN to capture the spatial relationships and patterns in the image data that are relevant to the task at hand [4]. Therefore, CNNs are a suitable choice for tropical cyclone intensity estimation, as they can effectively handle the image data and learn the relevant features and patterns needed to classify the cyclone into different intensity categories based on the image data. The CNN architecture works as mentioned in the flowchart. Convolutional neural network (CNN) is used in image processing that is designed to process pixel data [15]. After the images are passed, the images will be processed, and the datasets are loaded with a batch size of 16. A mean absolute error loss function is commonly used to calculate the difference between predicted and actual values. The activation function REL is often applied to the hidden layer, while a linear function is used for the final layer activation function. These techniques can help improve the accuracy of machine learning models. Rectified Linear Units (REL) function is given as f(x) = max (0, x) (1) x is input to the layer. Loss function used here is Mean Squared Error: $MSE = 1/n \sum (yi - \hat{y}i)\ n\ i$=1 (2) Where, MSE: Mean Squared Error n: Number of data points Yi: observed values mi: predicted values other formulas used for the comparison of CNN architectures are Mean Absolute Error: MAE= 1 $n \sum |yi - \hat{y}|\ n\ i$=1 (3) MAE: Mean Absolute Error n: Number of data points Yi: observed values mi: predicted values |I=1 ton|: absolute value of the difference between actual and predicted values Root Mean Squared Error: $RMSE = \sqrt{MSE} = \sqrt{1/n} \sum (yi - \hat{y}i\ )\ n\ i$=1 (4) RMSE: Root Mean Squared Error n: Number of data points Yi: observed values mi: predicted values R2 score: $R2 = 1 - \sum(yi - \hat{y})\ 2\ \sum(yi - \bar{y})\ 2$ (5) RMSE: Root Mean Squared Error n: Number of data points Yi: observed values mi: predicted values Σ: sum of values |I=1 ton|: absolute value of the difference between actual and predicted values[9].

### 5.1.1 InceptionV3:

Inception-v3 is a type of convolutional neural network that consists of 48 layers. The ImageNet consists of a trained variant network that was created in advance and trained on thousands of images. Several animals, a keyboard, a mouse, and a pencil are among the 1000 different item categories that the pretrained network can classify photographs into. As a result, the network now includes comprehensive feature representations for a range of photos. The input image for the network is 299 by 299 pixels in size [19].

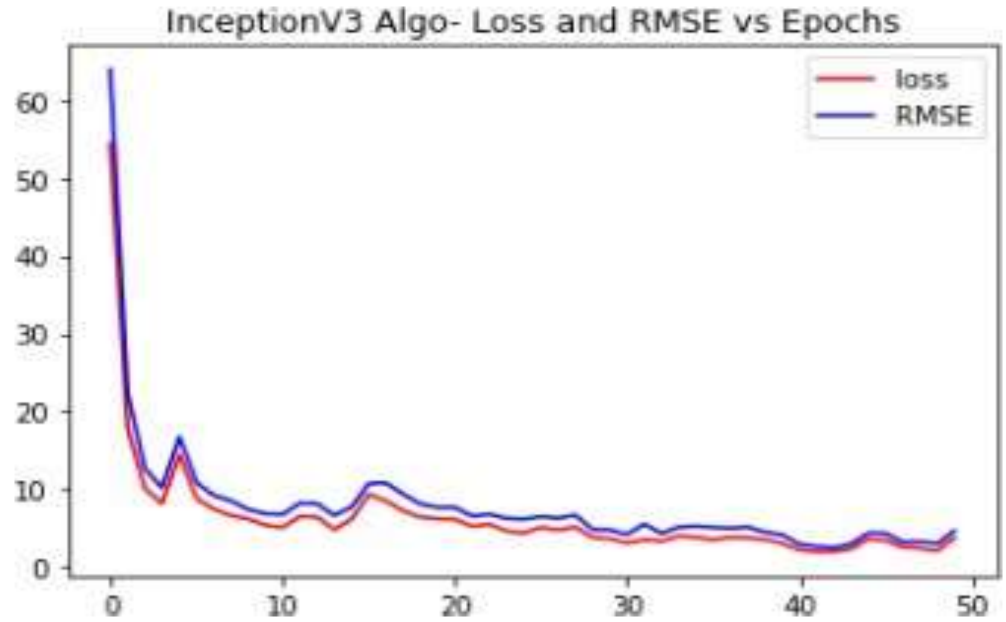



Fig. 5.1.1 Graph of Loss and RMSE vs epochs in Inception V3

5.1.2 VGG16:

As a 16-layer transfer learning architecture with only CNN as its foundation, VGG16 is relatively comparable to earlier architectures, however the configuration is a little different. For this architecture, the input image with a standard dimension of 224 x 224 x 3, where 3 stands for the RGB channel has been used [20]. As a 16-layer transfer learning architecture with only CNN as its foundation, VGG16 is relatively comparable to earlier architectures, however the configuration is a little different. For this architecture, the input image with a standard dimension of 224 x 224 x 3, where 3 stands for the RGB channel has been used [20]. Of all the configurations, VGG16 was identified to be the best performing model on the ImageNet dataset. Let's review the actual architecture of this configuration. The input to any of the network configurations is considered to be a fixed size 224 x 224 image with three channels – R, G, and B. The only pre-processing done is normalizing the RGB values for every pixel. This is achieved by subtracting the mean value from every pixel. Image is passed through the first stack of 2 convolution layers of the very small receptive size of 3 x 3, followed by REL activations. Each of these two layers contains 64 filters. The convolution stride is fixed at 1 pixel, and the padding is 1 pixel. This configuration preserves the spatial resolution, and the size of the output activation map is the same as the input image dimensions. The activation maps are then passed through spatial max pooling over a 2 x 2-pixel window, with a stride of 2 pixels. This halves the size of the activations [2]. Thus, the size of the activations at the end of the first stack is 112 x 112 x 64. The activations then flow through a similar second stack, but with 128 filters as against 64 in the first one. Consequently, the size after the second stack becomes 56 x 56 x 128. This is followed by the third stack with three convolutional layers and a max pool layer. The no. of filters applied here are 256, making the output size of the stack 28 x 28 x 256. This is followed by two stacks of three convolutional layers, with each containing 512 filters. The output at the end of both these stacks will be 7 x 7 x 512.

The stacks of convolutional layers are followed by three fully connected layers with a flattening layer in-between. The first two have 4,096 neurons each, and the last fully connected layer serves as the output layer and has 1,000 neurons corresponding to the 1,000 possible classes for the ImageNet dataset. The output layer is followed by the SoftMax activation layer used for categorical classification [16].

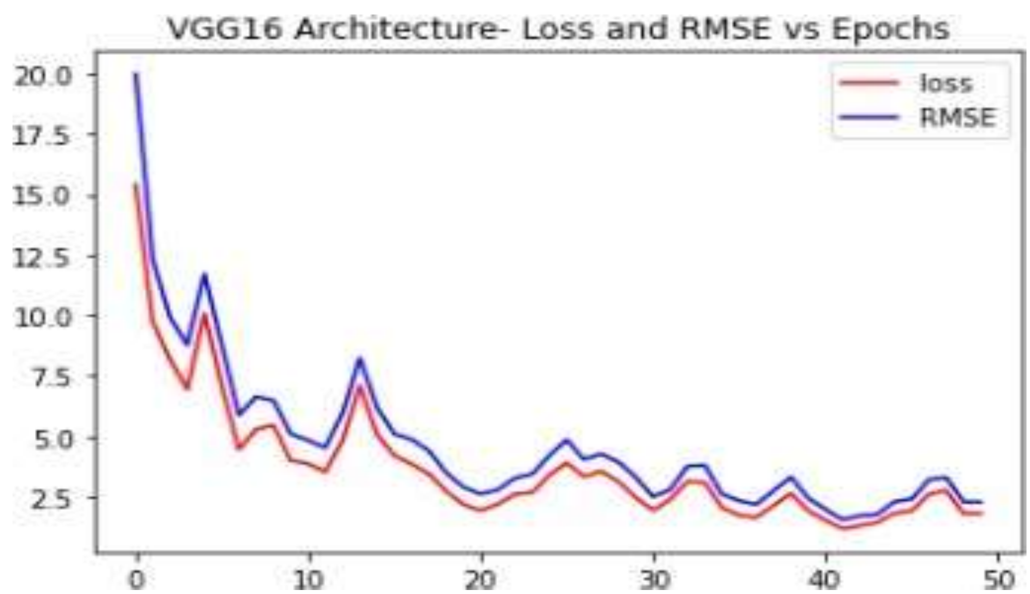



Fig. 5.1.2 Graph of Loss and RMSE vs Epochs

5.1.3 InceptionV3:

Inception-v3 is a type of convolutional neural network that consists of 48 layers. The ImageNet consists of a trained variant network that was created in advance and trained on thousands of images. Several animals, a keyboard, a mouse, and a pencil are among the 1000 different item categories that the pretrained network can classify photographs into. As a result, the network now includes comprehensive feature representations for a range of photos. The input image for the network is 299 by 299 pixels in size [19]. Inception v3[1][2] is a convolutional neural network for assisting in image analysis and object detection, and got its start as a module for Google Net. It is the third edition of Google's Inception Convolutional Neural Network, originally introduced during the ImageNet Recognition Challenge. The design of Inceptionv3 was intended to allow deeper networks while also keeping the number of parameters from growing too large: it has "under 25 million parameters", compared against 60 million for Alex Net [1]. Just as ImageNet can be thought of as a database of classified visual objects, Inception helps classification of objects [3] in the world of computer vision. The Inceptionv3 architecture has been reused in many different applications, often used "pre-trained" from ImageNet. One such use is in life sciences, where it aids in the research of leukaemia.[4]. The original name (Inception) was codenamed this way after a popular "'we need to go deeper' internet meme" went viral, quoting a phrase from the Inception film of Christopher Nolan.[1]

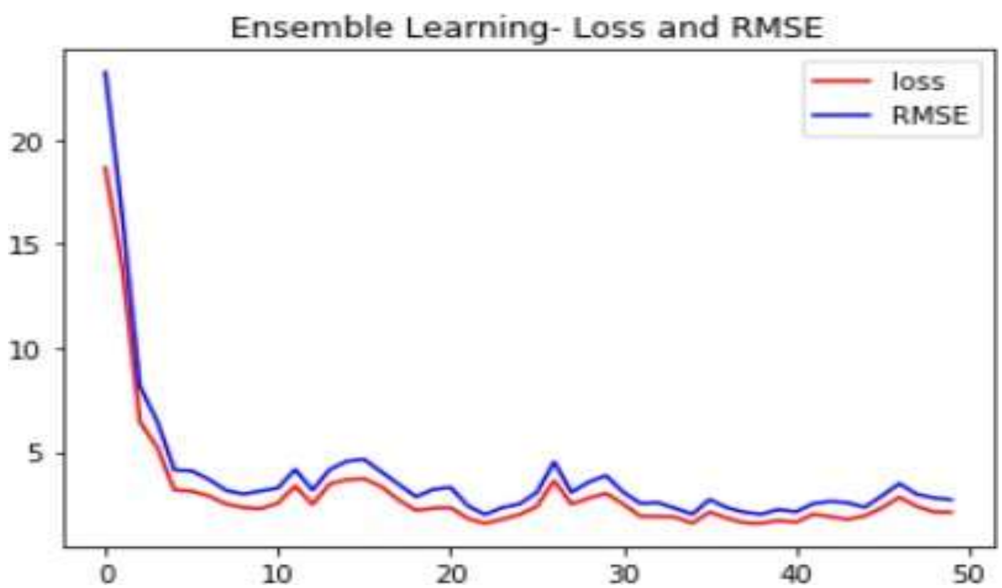



Fig. 5.1.3 - Graph of Ensemble Learning Loss and RMSE

5.2 Data accumulation and design:

The dataset is satellite imagery obtained from hursat-b1. The satellite imagery is downloaded from Noa’s national centres for environmental information (nice) archive and NASA’s website for the year 2016 to 2020. The netted library is used to read the downloaded dataset. The advantages of using this dataset are that the centre of each hurricane was in the middle of each image. To label this dataset, best track data from the hurdat2 database provided by the national hurricane centre is used. It contains records of all known hurricanes in the Atlantic and pacific basins, as well as their wind speeds at 6-hour intervals. Visualization of the two random satellite images is shown in figure,

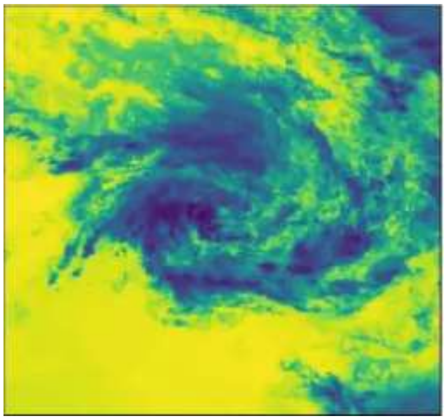


Fig. 5.2 – (a)IR Image

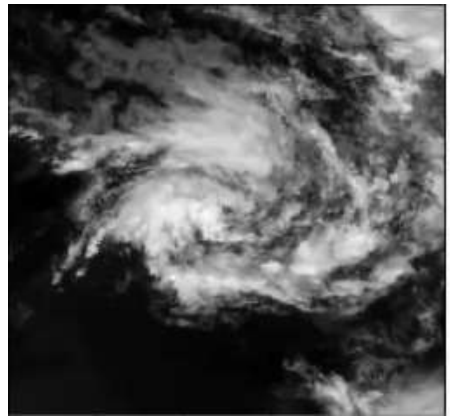


Fig. 5.2.1 - (b) Gray image

The International Best Track Archive for Climate Stewardship (Ibra's) dataset was developed by the NOAA National Climatic Data Center, which took the initial step of synthesizing and merging best track data from all official Tropical Cyclone Warning Centers (TCWCs) and the WMO Regional Specialized Meteorological Centers (RSMCs) who are responsible for developing and archiving best track data worldwide [16]. In recognizing the deficiency in global tropical cyclone data, and the lack of a public ally available dataset, the Ibra's dataset was produced, which, for the first time, combines existing best track data from over 10 international forecast centers. The dataset contains the position, maximum sustained winds, minimum central pressure, and storm nature for every tropical cyclone globally at 6-hr intervals in UTC. Statistics from the merge are also provided (such as number of centers tracking the storm, range in pressure, median wind speed, etc.). The dataset period is from 1848 to the present with dataset updates performed annually in August. The dataset is archived as Ibra's files but can be accessed via a variety of user-friendly formats to facilitate data analysis, including Ibra's, Shapefile, and CSV formatted files. The update to version 3 data includes new data sources, bug fixes, shapefile-support, discontinued support of ASCII and new variables [9].

## 5.3 Pre-processing of the data

The most valuable information about a hurricane's intensity is near the center. So, the satellite images are cropped to remove the outer part of the hurricane from the image. The satellite images are read using the netted library and converted to array by NumPy library. The images are cropped to a 50-by-50-pixel square at the center. Sample of a cropped image is shown below

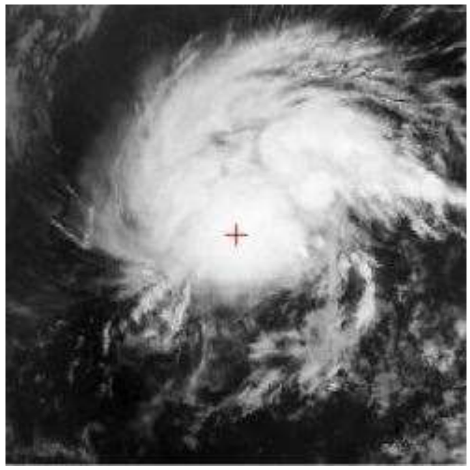


Fig 5.3 – Grey scale image

## 5.4 Convolution Layer

Central to the convolutional neural network is the convolutional layer that gives the network its name. This layer performs an operation called a "*convolution* ". In the context of a convolutional neural network, a convolution is a linear operation that involves the multiplication of a set of weights with the input, much like a traditional neural network. Given that the technique was designed for two-dimensional input, the multiplication is performed between an array of input data and a two-dimensional array of weights, called a filter or a kernel. After applying the convolution operation, the output image is produced from equation M is the Shape of output, N is input image shape, K filters, P is padding and S is Stride. Each convolution layer finalizes the feature vector based on activation functions like Rely, Sigmoid, Tanh and Leaky Rely.

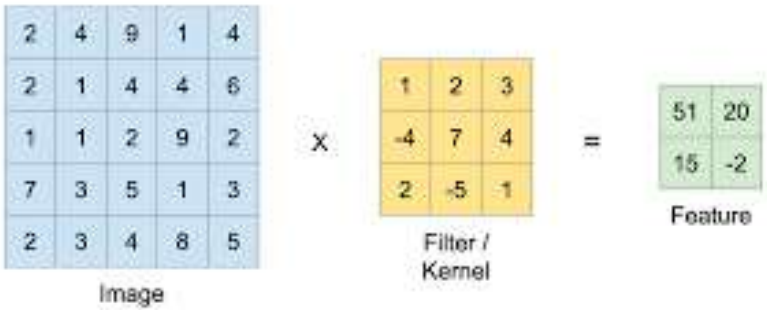



Fig 5.4 – Basic CNN architecture

The convolutional layer is a fundamental building block in convolutional neural networks (CNNs), a class of deep learning architectures specifically designed for processing grid-like data such as images. The convolutional layer plays a pivotal role in feature extraction by applying a set of learnable filters (also known as kernels) to the input data. Each filter scans through the input, performing a convolution operation to detect local patterns, edges, textures, or more complex features. This operation involves element-wise multiplication of the filter weights with the input data, followed by the summation of the results to produce a single value in the output feature map. The spatial arrangement of these filters allows the network to capture hierarchical and spatial hierarchies of features, learning representations from low-level to high-level features. Striding, a key concept in convolutional layers, determines the step size with which the filters move across the input data. Additionally, padding can be applied to the input to ensure that the spatial dimensions of the feature map are preserved. These mechanisms allow convolutional layers to maintain spatial information and reduce the spatial dimensions gradually, facilitating the network's ability to capture hierarchical features efficiently. Pooling layers often follow convolutional layers to down sample the feature maps, reducing computational complexity and enhancing translation invariance. Common pooling operations include max pooling and average pooling, which select the maximum or average value, respectively, from a specific region in the feature map. The learnable parameters in the convolutional layer, represented by filter weights, are optimized during training using backpropagation and gradient descent, enabling the network to automatically learn and adapt to discern relevant patterns from the input data. Convolutional layers are foundational in image recognition, object detection, and other computer vision tasks due to their ability to capture spatial hierarchies and translational invariance, making them indispensable components in the success of CNN architectures.

**5.5 Activation function:**

In a neural network, the activation function is responsible for transforming the summed weighted input from the node into the activation of the node or output for that input. For this model, we have used the REL activation function. REL stands for rectified linear activation unit and is considered one of the few milestones in the deep learning revolution In Rectified Linear Unit layer (Rely), the pixels value obtained from the convolution layer are converted into either 0 or 1. If any pixel containing any shade of important information, then it is converted into 1 else it is converted into 0. REL is defined as. An activation function is a critical component in artificial neural networks, serving as the mathematical operation applied to the output of each neuron or node in a neural network layer. The primary purpose of an activation function is to introduce non-linearity into the network, allowing it to learn complex patterns and relationships within data. In essence, activation functions determine the output of a neural network node, providing a threshold or decision point for the information flow through the network. One of the most commonly used activation functions is the Rectified Linear Unit (REL) [6]. The REL activation function replaces all negative input values with zero and leaves positive values unchanged. Its simplicity and efficiency have contributed to its widespread adoption, promoting faster convergence during training and mitigating the vanishing gradient problem. Sigmoid and hyperbolic tangent (tanh) are other classic activation functions used in certain scenarios. The sigmoid function squashes input values to a range between 0 and 1, making it suitable for binary classification tasks where outputs need to be interpreted as probabilities. Tanh, on the other hand, maps input values to a range between -1 and 1, offering stronger gradients and helping mitigate issues related to the zero-centered nature of the data. More recently, advanced activation functions like the Parametric Rectified Linear Unit (PReLU) and Exponential Linear Unit (ELU) have gained popularity. PReLU introduces a learnable parameter to REL, allowing the network to adapt the slope of the negative side during training. ELU, similar to REL, prevents the vanishing gradient problem and also allows negative values with a smooth transition, contributing to better learning representations. Choosing the appropriate activation function depends on the specific characteristics of the data and the nature of the task at hand. The activation function plays a crucial role in shaping the neural network's ability to learn and generalize patterns from the input data, and the ongoing research in this field continues to yield innovative activation functions that enhance the capabilities of neural networks in various domains, from image and speech recognition to natural language processing [3]

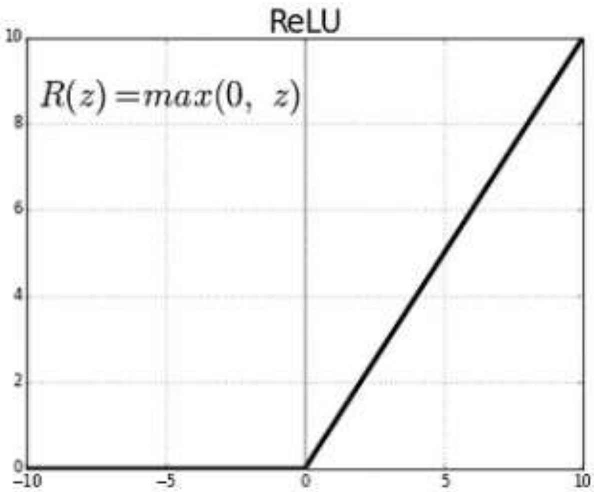



Fig. 5.5 – RELU (Activation Function)

**5.6 Pooling layer:**

The pooling layer compresses the dimension of the input image. A filter is selected and it is applied to the dimension matrix obtained from the convolution layer. The max pooling operation selects the maximum element from the region of the feature map covered by the filter. Max pool layer of pool size 2-by-2 are used after the conv2D layers. The pooling layer is a critical component in convolutional neural networks (CNNs), functioning as a down sampling operation applied to the feature maps generated by the preceding convolutional layers. This layer aims to reduce the spatial dimensions of the input while retaining essential information, thereby decreasing computational complexity and enhancing the network's ability to generalize across different spatial locations. Max pooling and average pooling are the most commonly employed pooling operations, both involving the partitioning of the input feature map into non-overlapping regions and computing a single representative value for each region. In max pooling, the maximum value within each region is retained, emphasizing the most prominent features, while average pooling computes the average value, providing a smoother down sampling effect [11] The pooling layer contributes to achieving translation invariance, allowing the network to recognize features irrespective of their precise spatial location within the input. Moreover, pooling helps control overfitting by reducing the spatial resolution, focusing on the most salient features, and preventing the network from becoming overly sensitive to minor variations. The strategic placement of pooling layers in CNN architectures, typically after convolutional layers, aids in progressively reducing the spatial dimensions while preserving the relevant features, enabling the network to capture hierarchical patterns efficiently and facilitating the extraction of abstract representations critical for tasks such as image recognition and object detection.

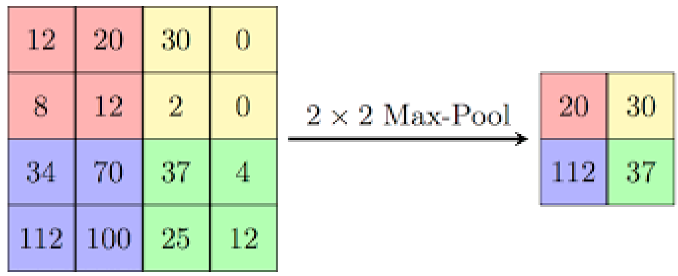



Fig 5.6 Max Pooling Layer

**5.7 Model Architecture**

The input layer is followed by Conv2D layer. The first Conv2D layer is trained with 32 filters, 50x50px input shape and with stride of 1x1. Batch normalization layer is also used after the first Conv2D layer to normalize the data which is then followed by the max pool layer. All in all, 3 Conv2D layers are used followed by max pool layer the output of which is flattened and is fed to the Fully connected dense layer (FCN), also 3 “FCN “are used the output of which is our estimated intensity. “REL” is used as the activation function in Conv2D and “FCN” layers. A basic CNN model architecture is represented below [3].

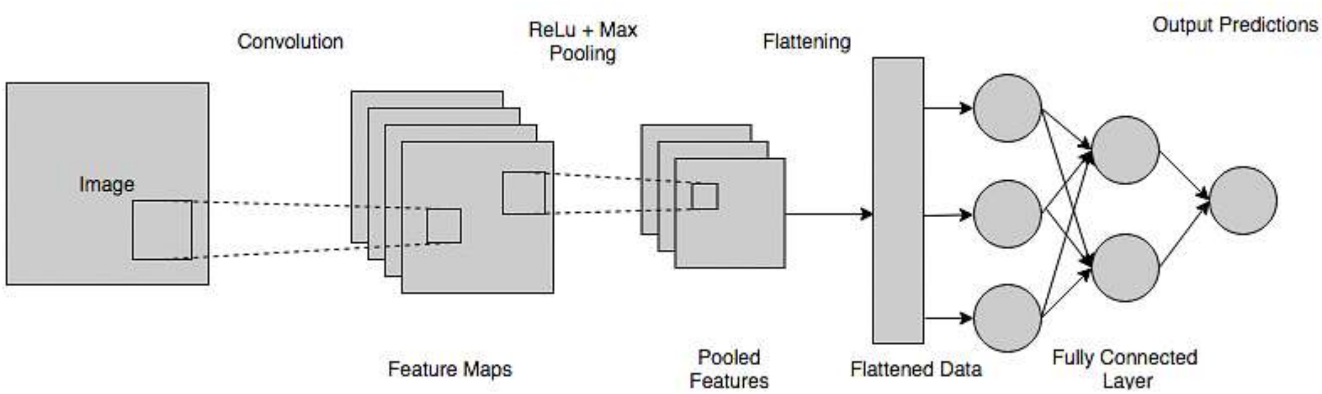



Fig 5.7.1 - Convolutional Neural Network

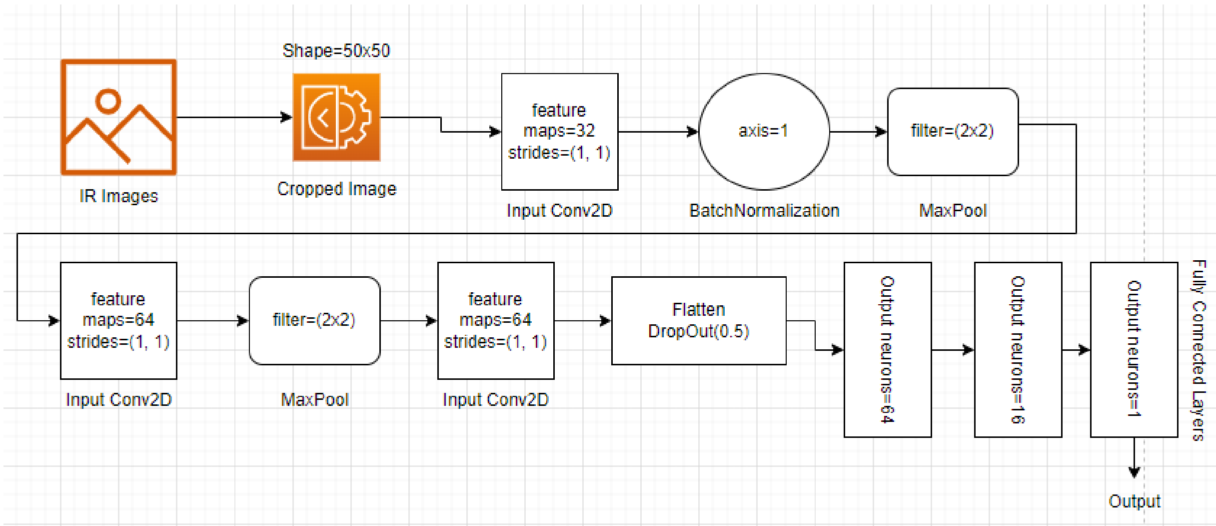



Fig 5.7.2 – Proposed Architecture

### 5.8 Model Training:

For the proposed model, we have used a batch size of 64 and trained the CNN model over 100 epochs. The CNN model was trained using a batch size of 32 and an initial learning rate of 0.001. RMSprop is used as the optimizer to optimize the model. The model was implemented using Python 3.9 and Keras with a TensorFlow backend. Optimizer plays a vital role in training. While training the network, the optimizer adjusts each neuron's weights to reduce each epoch's loss. This model is tested on different optimizers like Respro, SGD (Stochastic gradient descent), Adam, Dugard and Ad delta RMSprop increases the learning rate and our algorithm could take larger steps in the horizontal direction converging faster. The following equations show how the gradients are calculated for the RMSprop and gradient descent with momentum. The value of momentum is denoted by beta and is usually set to 0.9. For evaluating loss, Mean Squared Error (MSE) is used as a metric. To calculate the MSE, we take the difference between the model's predictions and the ground truth, square it, and average it out across the whole dataset. The MSE will never be negative, since we are always squaring the errors. The MSE is formally defined by the following equation:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad \ldots\ldots (1)$$

## 5.9 Use Case Diagram

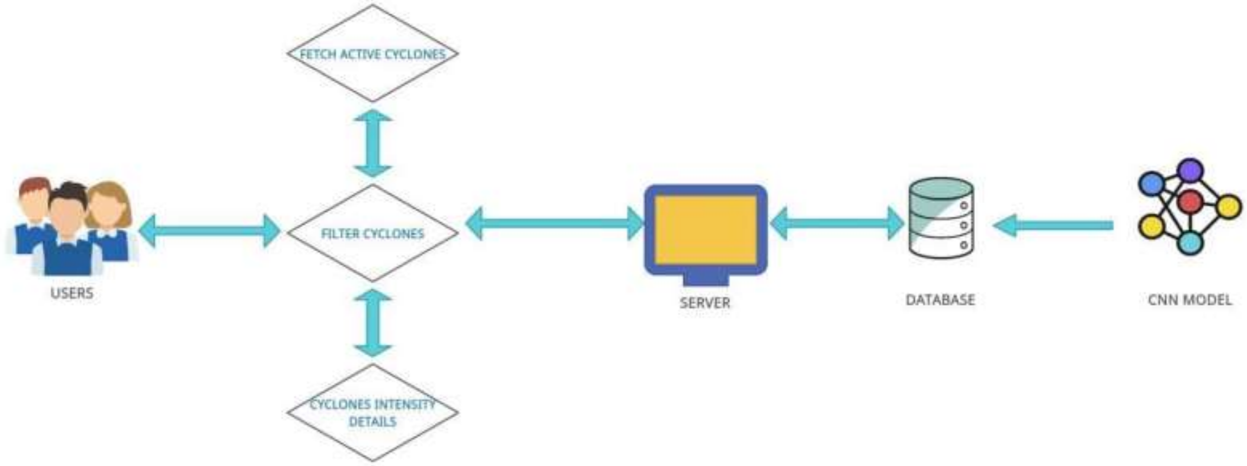



Fig 5.9 -Use Case Diagram

In the provided use case scenario, several main topics are covered to illustrate the practical application and significance of the project involving the development of a deep Convolutional Neural Network (CNN) for Tropical Cyclone intensity estimation and the creation of a web application for imagery visualization. These main topics include:

5.9.1 Early Detection and Monitoring:

Data Input: Highlighting the initial step where meteorological agencies gather half-hourly satellite images, emphasizing the importance of real-time and high-frequency data acquisition for monitoring evolving atmospheric conditions. In the context of developing a deep Convolutional Neural Network (CNN) for Tropical Cyclone intensity estimation utilizing half-hourly INSAT-3D IR images, the stage of Early Detection and Monitoring plays a pivotal role in enhancing our ability to anticipate and respond to potential cyclonic threats. As meteorological agencies gather a continuous stream of half-hourly INSAT-3D IR images, this phase involves the systematic acquisition and pre-processing of this data to form the foundational input for the CNN model [6]. The early detection mechanism relies on the model's capability to discern intricate patterns and features within these images that are indicative of cyclone development and intensity. The temporal granularity of half-hourly images allows for a real-time monitoring system, enabling the model to capture the evolving atmospheric conditions associated with the cyclone. The CNN, designed with the capacity to extract meaningful spatial and temporal features, becomes an indispensable tool for recognizing the subtle but crucial indicators of cyclone formation. This phase is characterized by the seamless integration of cutting-edge image processing techniques and deep learning methodologies. The CNN, with its ability to automatically learn and adapt to complex patterns, becomes a sophisticated tool for discerning subtle changes in cloud patterns, temperature variations, and other atmospheric features that signify cyclonic activity. The Early Detection and Monitoring stage is not just about identifying a cyclone's presence but also about continuously tracking and understanding its development over time. Furthermore, the deployment of a web application for visualization amplifies the impact of this early detection system. Meteorologists and relevant authorities can access the web interface to visually interpret the CNN's predictions and gain immediate insights into the evolving cyclonic conditions. The visualization aspect becomes crucial for decision-making, allowing experts to assess the real-time intensity estimates and take proactive measures, such as issuing timely warnings, planning evacuations, and mobilizing resources for disaster preparedness and response. In essence, the Early Detection and Monitoring phase, facilitated by the integration of deep learning techniques and web-based visualization, empowers meteorological agencies, disaster response teams, and communities to stay ahead of cyclonic events. By harnessing the capabilities of a CNN on half-hourly INSAT-3D IR images, this phase lays the groundwork for a more responsive and informed approach to cyclone intensity estimation, contributing significantly to disaster risk reduction and management [19].

5.9.2 Intensity Estimation:

Model Prediction: Focusing on the core function of the CNN model, explaining how it processes the input images to estimate the intensity of the tropical cyclone.

Visualization: Emphasizing the role of the web application in providing a user-friendly interface for visualizing the predicted intensity levels, making the complex data more accessible.

5.9.3 Decision-Making for Disaster Management:

5.9.3.1 Accessible Information:

Underlining the practical utility of the system, describing how meteorologists and disaster response teams access real-time intensity predictions through the web application. Timely Alerts: Stressing the critical impact of accurate predictions on decision-making, specifically in issuing timely warnings and evacuation orders to minimize potential harm. In the context of developing a deep Convolutional Neural Network (CNN) for Tropical Cyclone intensity estimation and the concurrent creation of a web application for imagery visualization, the stage of "Decision-Making for Disaster Management" assumes a critical role in enhancing preparedness and response efforts. As the CNN model processes half-hourly INSAT-3D IR images, it generates real-time intensity predictions, providing meteorologists and disaster response teams with valuable insights for informed decision-making. The accuracy of these predictions becomes paramount in issuing timely warnings and alerts to vulnerable regions, enabling the orchestration of evacuation plans and the allocation of emergency resources [14]. The web application acts as a central hub for decision-makers to access and interpret these real-time intensity estimates visually. By leveraging the visualization features, including geospatial overlays and historical data analysis, decision-makers can assess the trajectory and potential impact of the tropical cyclone [18]. This information becomes instrumental in orchestrating targeted responses, deploying resources strategically, and ensuring that communities in the cyclone's path are adequately informed and protected. The integration of technology, specifically the CNN model and the visualization capabilities of the web application, enhances the decision-making process by providing a data-driven, real-time understanding of the cyclone's evolving intensity and potential risks. Ultimately, this integrated approach contributes to more effective disaster management, minimizing the impact of tropical cyclones and safeguarding lives and infrastructure.

5.9.4 Public Awareness and Preparedness:

5.9.4.1 User-Friendly Interface: Discussing the inclusive nature of the web application, catering not only to experts but also to the general public with a design that is intuitive and easy to use.

Visual Representation: Demonstrating how visual representations provided by the application empower coastal residents to comprehend the potential severity of the cyclone, fostering proactive preparedness measures [20]. In the context of developing a deep Convolutional Neural Network (CNN) for Tropical Cyclone intensity estimation and the concurrent creation of a web application for imagery visualization, the facet of "Public Awareness and Preparedness" holds paramount significance. The integration of the CNN model and the web application serves as a crucial tool in disseminating real-time information to the public, fostering heightened awareness and preparedness in the face of impending tropical cyclones. The user-friendly interface of the web application becomes a conduit for the general public to access and interpret complex meteorological data through visual representations generated by the CNN model. These visualizations, encompassing predicted cyclone intensities and geospatial overlays, empower coastal residents and communities to grasp the potential severity of the approaching cyclone, facilitating informed decision-making. The real-time nature of the intensity predictions, coupled with the accessibility of the web application, ensures that individuals can stay updated on the evolving situation. This timely and accurate information becomes instrumental in promoting proactive preparedness measures, such as evacuation planning and securing essential resources. The web application serves as a centralized hub for users to not only understand the current state of the cyclone but also to access historical data and trends, aiding in comprehensive risk assessment. Through this integrated system, public awareness is elevated, and communities are better equipped to respond effectively to the dynamic nature of tropical cyclones. The visual nature of the information, made possible by the CNN model and the web application, facilitates clear communication of the potential impact, fostering a sense of urgency and responsibility among residents in vulnerable areas. In essence, the development of the CNN model and the associated web application contributes significantly to enhancing public awareness, facilitating preparedness initiatives, and ultimately bolstering the resilience of communities in the face of tropical cyclones [5].

5.9.5 Post-Event Analysis:

Historical Data Analysis: Transitioning to the post-event phase, highlighting how the system facilitates the analysis of historical data, enabling a retrospective examination of the model's accuracy.

Improvement Feedback: Concluding with a forward-looking perspective, suggesting that insights from post-event analysis inform continuous refinement and improvement of the CNN model for future cyclone intensity estimations [16]. In the context of the development of a deep Convolutional Neural Network (CNN) for Tropical Cyclone intensity estimation and the accompanying web application for imagery visualization, the stage of Post-Event Analysis holds significant importance. This phase involves a retrospective examination of the model's performance and the historical data collected during and after tropical cyclone events. Meteorologists and researchers utilize the web application to delve into the accuracy of intensity predictions made by the CNN model in comparison to the actual observed intensities during the cyclonic events. Post-Event Analysis serves multiple purposes, including assessing the model's predictive capabilities under different cyclone scenarios, identifying any discrepancies between predicted and actual intensities, and extracting insights to enhance the model's accuracy for future estimations. This analysis aids in understanding the strengths and limitations of the CNN model, shedding light on its performance in varying environmental conditions and cyclone characteristics. Furthermore, the web application facilitates the visualization of historical INSAT-3D IR images alongside the model's predictions and actual intensity data. This visual representation allows meteorologists to comprehensively evaluate the model's ability to capture the intricacies of cyclone dynamics, such as rapid intensification or weakening, and provides a valuable tool for refining the model's parameters and architecture. Post-Event Analysis not only serves as a tool for model improvement but also contributes to the broader scientific understanding of tropical cyclones. By scrutinizing the historical data in conjunction with the model's predictions, researchers can derive insights into the factors influencing cyclone intensity changes, contributing to advancements in meteorological knowledge The iterative nature of Post-Event Analysis ensures a continuous feedback loop, where findings from each cyclone event contribute to refining the CNN model, enhancing its robustness and adaptability to diverse cyclonic conditions. Ultimately, this phase plays a pivotal role in the continuous improvement of the tropical cyclone intensity estimation system, promoting its reliability and effectiveness in supporting real-time decision-making and disaster preparedness efforts [6].

## 5.10 Flow Diagram

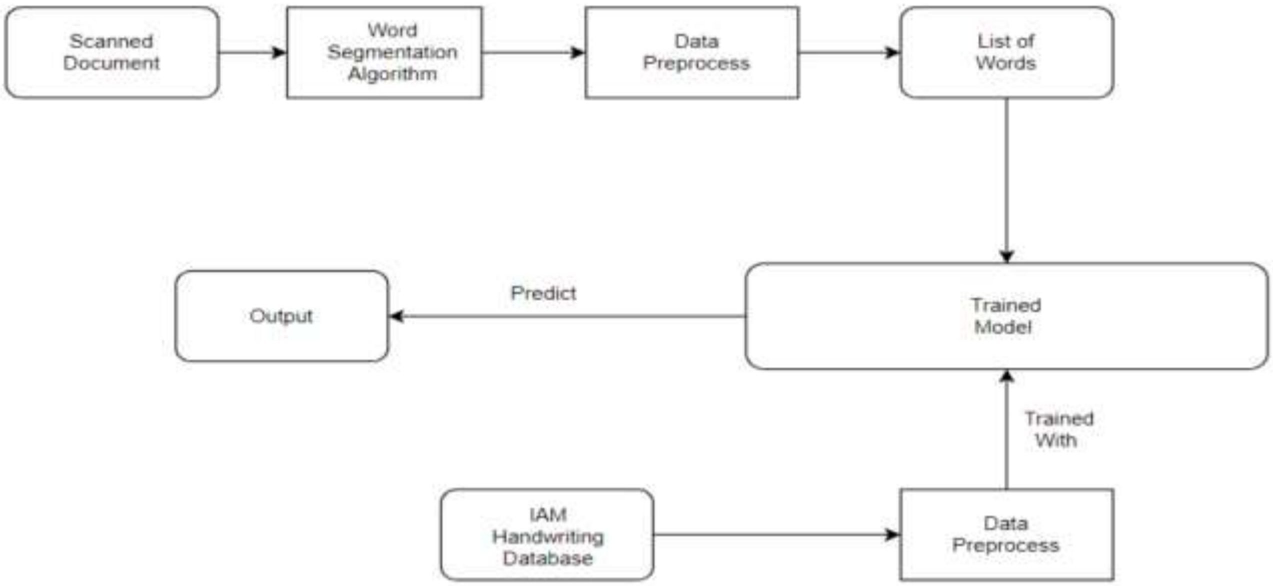



Fig 5.10 - Flow Diagram

Creating a comprehensive flow diagram for the development and utilization of a deep Convolutional Neural Network (CNN) for Tropical Cyclone intensity estimation and a web application for imagery visualization involves several interconnected steps. Below is an outline of a flow diagram capturing the key processes and interactions in this scenario:

### 5.10.1 Data Acquisition and Pre-processing:

The initial phase of the project, Data Acquisition and Pre-processing, is pivotal for establishing a robust foundation for subsequent model development. In this stage, the focus is on procuring half-hourly INSAT-3D IR images, which serve as the primary dataset for capturing the evolving atmospheric conditions associated with tropical cyclones. This critical dataset is sourced from meteorological agencies and reliable data providers. Once obtained, the data undergoes a meticulous pre-processing pipeline to enhance its quality and suitability for training the Convolutional Neural Network (CNN). The pre-processing steps include standardization processes to normalize the data and improve image quality [12]. Additionally, the pipeline addresses data integrity by handling missing values, identifying outliers, and ensuring temporal alignment for creating a consistent dataset. The overarching goal is to optimize the quality of the input data, mitigating potential challenges that may arise from inconsistencies or artifacts in the acquired images. This rigorous pre-processing sets the stage for a more accurate and reliable CNN model, laying the groundwork for successful tropical cyclone intensity estimation.

### 5.10.2 CNN Model Development:

The CNN Model Development phase is a core component of the project, where the architecture of a Convolutional Neural Network is meticulously designed and trained to estimate tropical cyclone intensity. This stage involves a deep exploration of suitable CNN architectures tailored to the intricacies of INSAT-3D IR images. The design considerations include optimizing the network for effective feature extraction, critical for discerning patterns indicative of cyclone intensity. Subsequently, the model undergoes a training process using historical INSAT-3D IR image data, enabling it to learn the complex relationships between image features and cyclone intensity levels. A crucial aspect of this phase is the implementation of validation mechanisms to assess the model's performance and ensure its robustness. Iterative refinement and fine-tuning are carried out to enhance the model's accuracy and generalization capabilities. The outcome is a well-trained CNN model poised to effectively analyse and predict tropical cyclone intensity based on real-time or historical INSAT-3D IR images, forming a fundamental component of the integrated system for disaster preparedness and response [18].

### 5.10.3 Application Design and Development:

In the Web Application Design and Development phase, the project transitions towards creating an intuitive and user-friendly interface to facilitate the interaction between end-users and the developed Convolutional Neural Network (CNN) model. The focus here is on designing a visually appealing and accessible interface that allows users to seamlessly upload half-hourly INSAT-3D IR images for intensity predictions. The interface includes functionalities for real-time visualization of predictions, historical data analysis, and geospatial representations. A key aspect is the integration of features that enable users, including meteorologists, disaster response teams, and the general public, to easily interpret and interact with the intensity estimates generated by the CNN model. This phase also involves incorporating elements for user input validation, ensuring the reliability and security of data uploaded to the system. The end goal is to create a comprehensive web application that not only serves as a practical tool for decision-makers but is also accessible and informative for the broader community, contributing to enhanced awareness and preparedness for tropical cyclones.

5.10.4 User Integration of CNN Model with Web Application:

The Integration of the CNN Model with the Web Application marks a pivotal step in operationalizing the system for tropical cyclone intensity estimation and visualization. In this phase, the developed CNN model is seamlessly interconnected with the user interface of the web application, forging a cohesive and efficient system. This integration ensures smooth communication between the model and the application, facilitating the exchange of data necessary for real-time predictions. The web application becomes the user-facing gateway through which users can interact with the model, uploading INSAT-3D IR images and obtaining intensity predictions [9]. This integration layer is designed to handle data processing, ensuring that user inputs are efficiently fed into the CNN model, and predictions are seamlessly communicated back to the application for visualization. The overarching objective is to create a user-friendly, responsive interface that harnesses the predictive power of the CNN model, making the system accessible and valuable to meteorologists, disaster response teams, and the general public in understanding and responding to tropical cyclones.

5.10.4 User Interaction and Input:

The User Interaction and Input phase plays a pivotal role in the operational deployment of the system, facilitating a seamless interaction between users and the integrated platform for tropical cyclone intensity estimation. In this phase, users, including meteorologists, disaster response teams, and the general public, actively engage with the web application's user-friendly interface. Through this interface, users have the capability to upload INSAT-3D IR images, providing the crucial input required for the CNN model to perform intensity predictions. The design of the user interface is paramount, ensuring intuitive navigation and clear guidance for users to effectively interact with the system. This phase establishes a direct link between the end-users and the core functionality of the system, enabling a collaborative and informed approach to cyclone monitoring. It empowers meteorologists and response teams to make timely decisions based on the model's predictions, while the accessibility of the platform allows the broader public to stay informed and take proactive measures in response to impending cyclonic events.

### 5.10.5 Real-Time Intensity Estimation:

The Real-Time Intensity Estimation phase is a pivotal component of the project, involving the utilization of the trained Convolutional Neural Network (CNN) to provide immediate and accurate predictions of tropical cyclone intensity based on the half-hourly INSAT-3D IR images. In this stage, the web application interacts with the CNN model to trigger the real-time prediction process. Users upload the most recent INSAT-3D IR images through the intuitive web interface, initiating the model's analysis. The CNN processes the uploaded images, extracting crucial features indicative of cyclone intensity. Subsequently, the model generates intensity estimates, offering timely insights into the evolving conditions of the tropical cyclone. The real-time predictions, seamlessly integrated into the web application, serve as a valuable resource for meteorologists, disaster response teams, and decision-makers, enabling them to make informed choices and take prompt actions in response to the dynamically changing atmospheric conditions associated with the cyclone. This phase is instrumental in enhancing the system's responsiveness and utility, contributing to more effective disaster preparedness and response efforts in real-time scenarios.

### 5.10.6 Decision-Making and Alerts:

In the context of the development of a deep Convolutional Neural Network (CNN) for Tropical Cyclone intensity estimation and the accompanying web application, the stage of "Decision-Making and Alerts" is crucial for facilitating timely and informed responses to potential cyclonic threats. Meteorologists and disaster response teams leverage the web application's real-time intensity predictions, accessing the platform to make critical decisions aimed at minimizing the impact of the cyclone [5]. As the CNN model processes half-hourly INSAT-3D IR images and provides up-to-date intensity estimates, decision-makers are empowered to issue timely warnings and alerts to the affected regions. These alerts serve as a pivotal mechanism for public safety, enabling the implementation of evacuation plans, deployment of emergency resources, and the coordination of disaster response efforts. The accuracy and immediacy of the intensity predictions play a pivotal role in the effectiveness of these decisions, highlighting the significance of the integration between the CNN model and the web application in providing actionable insights for decision-makers during the critical phases of cyclone monitoring and response.

# 6. FEASIBILITY STUDY

## 6.1 Economic Viability

Evaluating the economic viability of a project focused on cyclone intensity estimation requires a thorough examination of costs and benefits. Development, implementation, and operational expenses constitute the project's costs, while benefits arise from heightened accuracy leading to minimized damages, streamlined resource allocation, and improved efficiency in disaster response. A favourable return on investment, scalability, diverse funding sources, market potential, and societal impacts collectively contribute to economic viability. Affordability, efficiency in disaster response costs, public trust, and the project's role in bolstering economic resilience are pivotal factors in determining its economic feasibility.

## 6.2 Technical Feasibility

The technical feasibility of a cyclone intensity estimation project depends on the practicality and effectiveness of the proposed method or technology. Clear articulation of the project's methodology and technology, along with an in-depth explanation of the scientific principles and algorithms employed, is crucial. Consideration of data requirements, encompassing sources and quality, is essential, as is the evaluation of computational resources and compatibility with existing hardware and software systems. Seamless integration with current meteorological systems, scalability to different regions, and adaptability to changes in cyclone patterns are key factors. Rigorous model validation and testing, coupled with long-term sustainability in terms of operational maintenance and resource needs, contribute to the technical viability of the project. The availability of skilled personnel and requisite training, adherence to regulatory standards, and a thorough risk assessment with mitigation strategies further ensure the project's technical feasibility. This comprehensive evaluation aims to establish a scientifically sound, operationally practical, and sustainable cyclone intensity estimation method.

## 6.3 Behavioural Feasibility

The project's behaviour should be characterized by accurate and precise estimates, demonstrating resilience to uncertainties and adaptability to evolving conditions. Scalability ensures relevance across different operational scales, while real-time responsiveness is crucial for effective disaster response. Consistency, interoperability with existing systems, and a commitment to continuous improvement contribute to positive project behaviour. Resource efficiency is essential, optimizing computational resources and personnel. Overall, a project with favourable behavioural feasibility is practical, user-friendly, and effectively addresses the challenges of cyclone intensity estimation.

## 6.4 Time Feasibility

Ensuring the time feasibility of a cyclone intensity estimation project is paramount, requiring a careful assessment of whether the project can be successfully completed within predefined timeframes. Key considerations involve aligning development, implementation, and testing phases with realistic schedules. A well-thought-out timeline is crucial for the timely delivery of precise cyclone intensity estimates, ultimately enhancing the project's efficacy. Efficient resource allocation, thorough planning, and strict adherence to deadlines are imperative to meet time feasibility requirements, enabling the project to contribute promptly to the enhancement of disaster preparedness and response capabilities.

## 6.5 Resource Feasibility

6.5.1 Data Sources:

Various data sources, including satellite imagery, weather stations, and historical meteorological data, are crucial for input into the cyclone intensity estimation model.

6.5.2 Software and Algorithms:

The project relies on specialized software and algorithms designed for cyclone intensity estimation. These tools are essential for data processing, analysis, and generating accurate intensity predictions.

6.5.3 Testing and Validation Tools:

Tools and protocols for testing and validating the accuracy and reliability of the cyclone intensity estimation model are essential. This ensures that the project meets scientific standards and produces dependable results.

6.5.4 Training Programs:

Programs for training meteorological personnel and end-users on how to use the cyclone intensity estimation system effectively. Training ensures that stakeholders can interpret and act upon the information provided by the project.

6.5.4 Remote Sensing Tools:

Instruments and software used in remote sensing, like MODIS (Moderate Resolution Imaging Spectroradiometer), assist in gathering information about sea surface temperatures, cloud patterns, and other relevant data for cyclone analysis

# 7.IMPEMENTATION

**7.1 prototype follows:**

• Intensity estimation by the CNN model which is then stored in a database with other relevant data about the cyclone.

• The user then can access this information from the website. The simple and interactive User Interface of the website allow users to filter cyclones. The filtered cyclones are then visualized on the map and upon clicking on one, user can access different information about the cyclones on the cyclone detail card. Graphical comparisons of estimated intensities are also represented on the card.

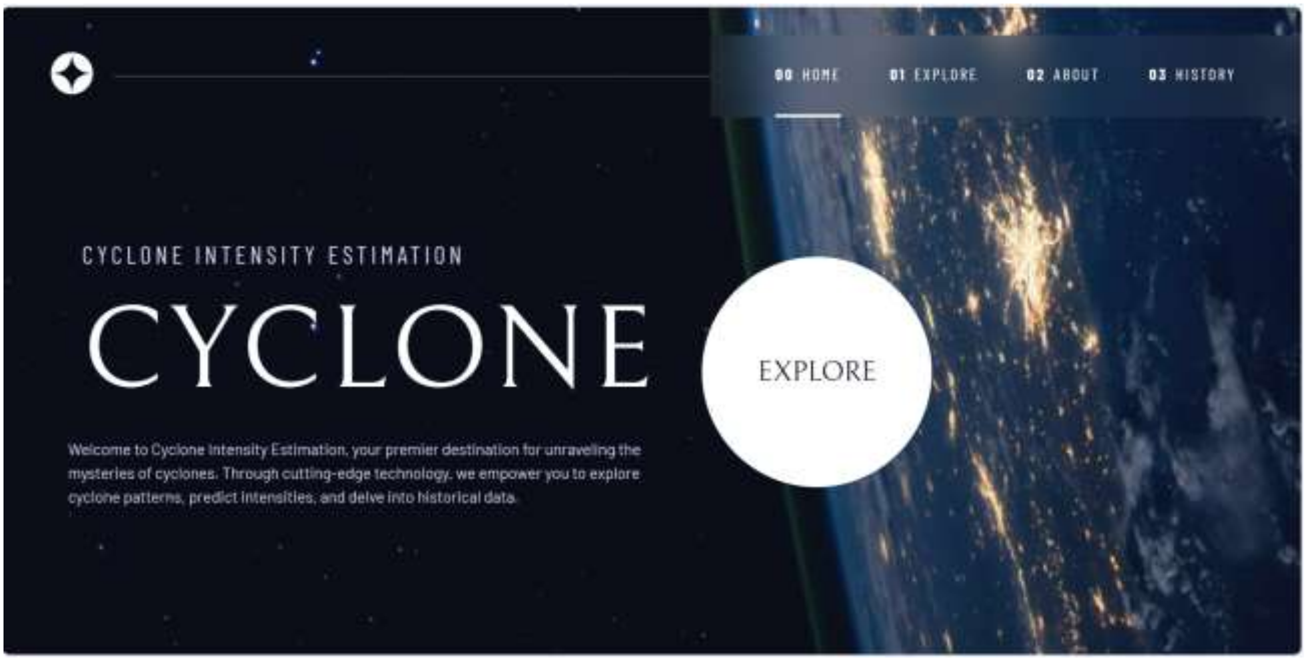



Fig 7.1 Home Interface

• Users can also access live cyclones on the map with their estimated intensities.

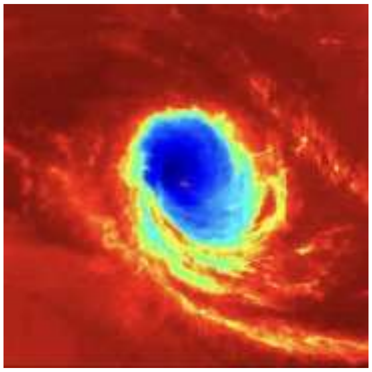
• Different map layers can be imposed on the map for scientific purposes.

# 8.EXPERIMENTATION AND RESULT

The VGG16 Algorithm Model correctly analyses and predicts the wind speed with the mean squared error of 1.8935 and the loss is 1.2124. The intensity and other characteristics, such as the regions affected, are predicted by the model. Additionally, it indicates which of the previously mentioned categories, from 0 to 7, the cyclone falls within. It becomes helpful for the public if there are any active cyclones whether it may be too harsh or too low on the basis of which they can take necessary action. After applying various algorithms using transfer learning and assembling all them and comparing the values from above table the minimum loss of 1.1173 comes for VGG16 and after that Exception come out to be 1.3408 of loss. After integrating all the algorithms ensemble learning shows the loss 1.5124 and RMSE 1.8236 provided to distinguish between the header and body text in a document, users can utilize the options available in a dropdown menu. From below figure, the various images are shown with their true output and predicted values by the model. The model is then further integrated with the android app where the cyclone intensity and its category are predicted.

Table 2: Classification based on wind speed

| Sr no. | Algorithm | Loss | RMSE | MAE | MSE | R2 Score |
|---|---|---|---|---|---|---|
| 1 | Inception V3 | 1.7421 | 2.1434 | 1.7802 | 5.0453 | 0.6345 |
| 2 | VGG16 | 1.2124 | 1.4320 | 1.2985 | 1.8935 | 0.8567 |
| 3 | Ensemble Learning | 1.6156 | 1.7846 | 1.2984 | 3.4985 | 0.8469 |



Output Intensity Value :79
Predicted intensity Value: 85 KN
Fig.8.1: Category 2

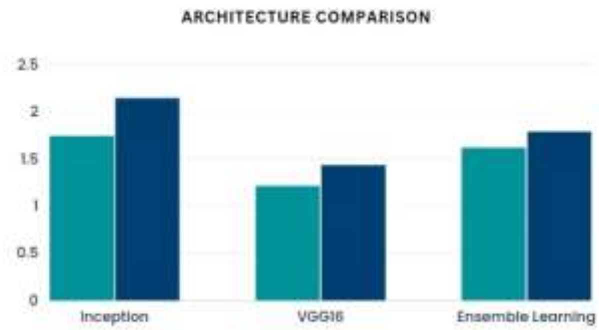



Fig.8.2 Comparison of Loss and RMSE in different CNN architectures

Our newly developed interface for cyclone intensity estimation offers a seamless user experience with intuitive navigation. The "Explore" tab serves as a gateway to delve into comprehensive data sets, allowing users to analyse historical patterns, track real-time updates, and gain valuable insights into cyclone behaviour. Meanwhile, the "About" section provides concise yet informative details regarding the methodology employed, ensuring transparency and fostering trust in the accuracy of our estimations. With the "Home" tab serving as the central hub, users can effortlessly navigate between functionalities, empowering them to make informed decisions in the face of natural disasters.

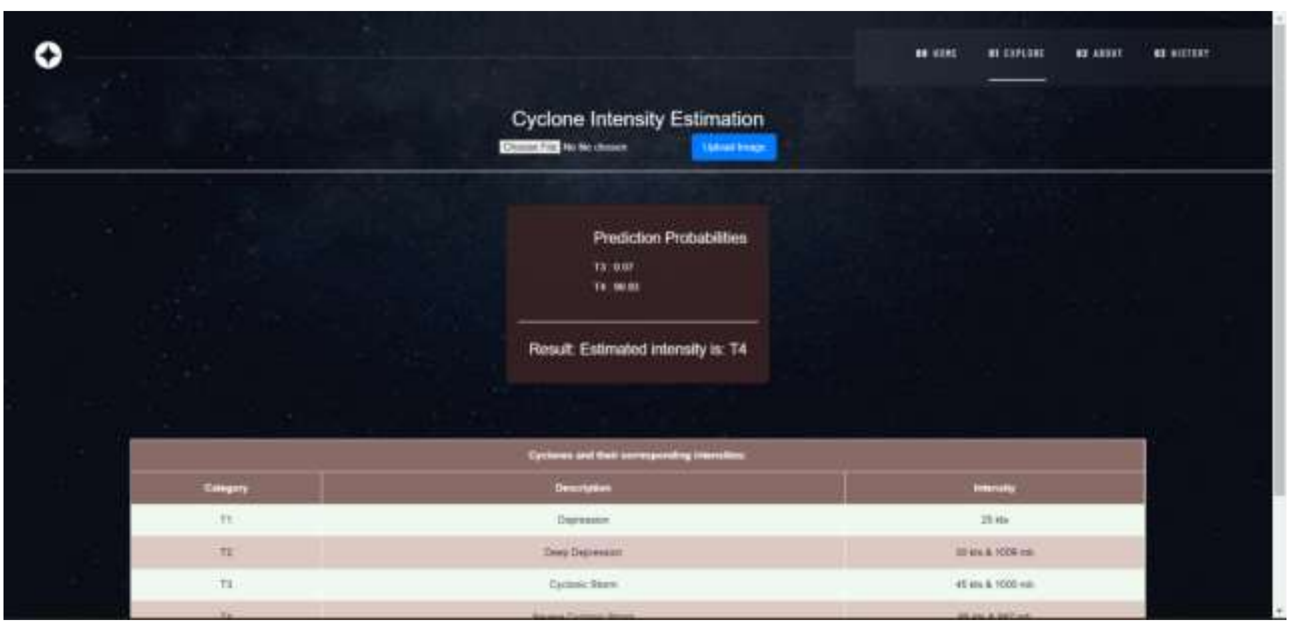



Fig 8.3– Explore page

In our interface, the "Explore" tab serves as the gateway for users to engage with our cyclone intensity estimation system. This innovative feature allows users to input images, which are then processed using advanced image recognition algorithms to extract relevant data on cyclone intensity. Through seamless integration of image analysis technology, users can obtain real-time or historical intensity estimates with just a few clicks, enabling swift and accurate decision-making in the face of cyclonic events. Whether tracking current storms or analysing past occurrences, the "Explore" tab provides a user-friendly interface that empowers users to harness the power of image-based data for cyclone intensity estimation

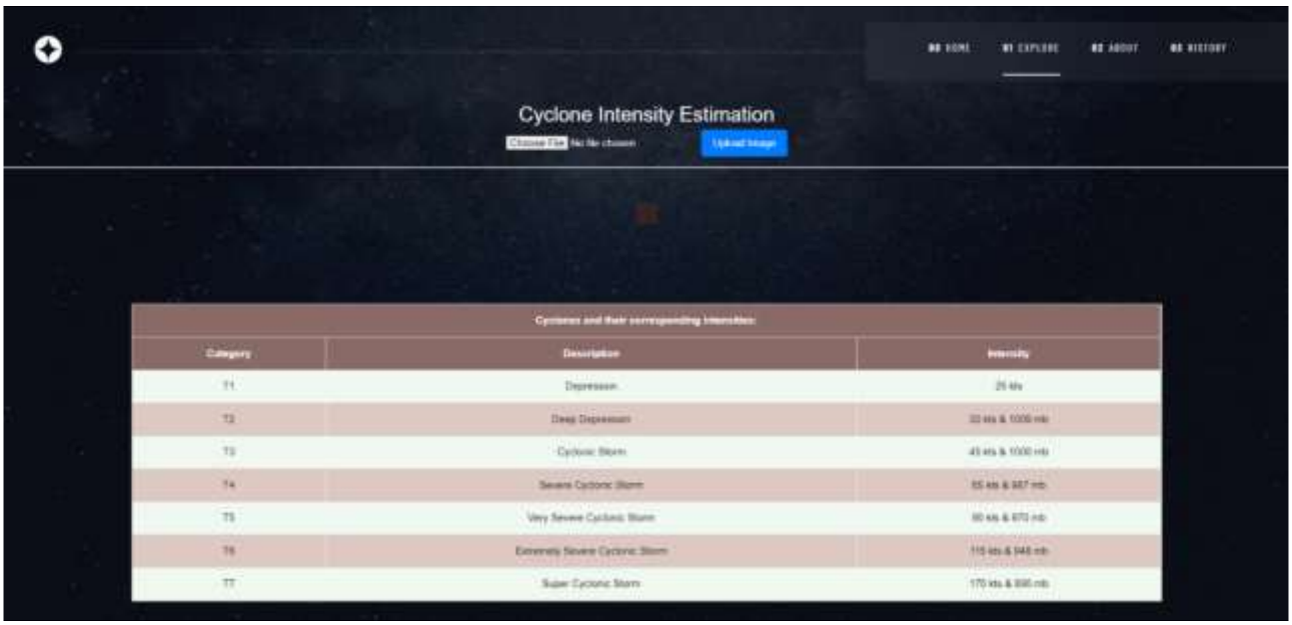



Fig 8.4– Explore page

In addition to image-based input for cyclone intensity estimation, our "Explore" tab also features a comprehensive table showcasing the categorization of cyclones based on their intensity. This table provides users with a clear understanding of the various categories of cyclones, ranging from tropical depressions to major hurricanes, along with corresponding wind speeds and potential impact levels. By presenting this information in a structured format, users can quickly assess the severity of cyclonic events and take appropriate precautions or response measures. This integration of cyclone categorization enhances the utility of our interface, enabling users to make informed decisions and prioritize actions based on the intensity of impending storms.

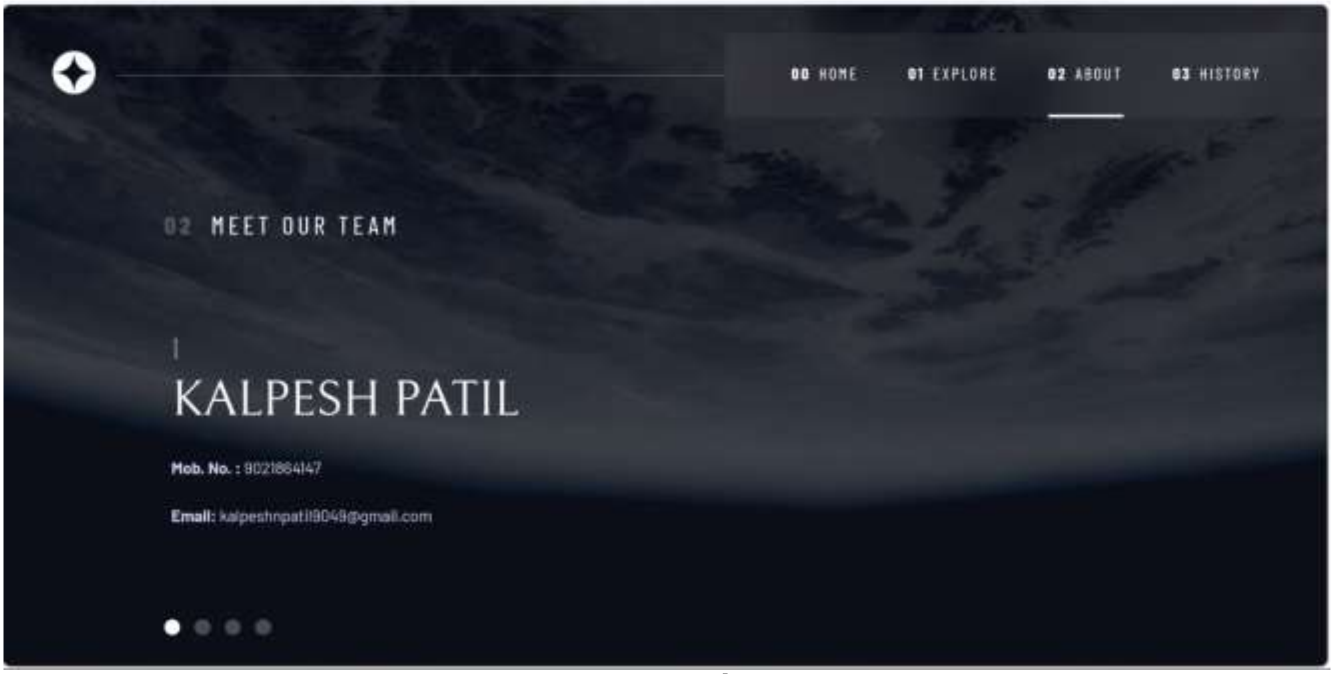



Fig 8.5 About

Within our cyclone intensity estimation interface, the "About" section stands as a testament to the dedication and expertise of our contributors. Here, users can explore detailed information about the individuals and organizations behind the development of this crucial tool. From meteorologists to data scientists, each contributor has brought their unique skills and insights to the table, ensuring the accuracy and reliability of our intensity estimation algorithms. Additionally, users can learn about the collaborative efforts between research institutions, government agencies, and technology companies that have fuelled the creation of this interface. Through transparent disclosure of our contributors' backgrounds and affiliations, we aim to instil confidence in the reliability and credibility of our cyclone intensity estimation platform.

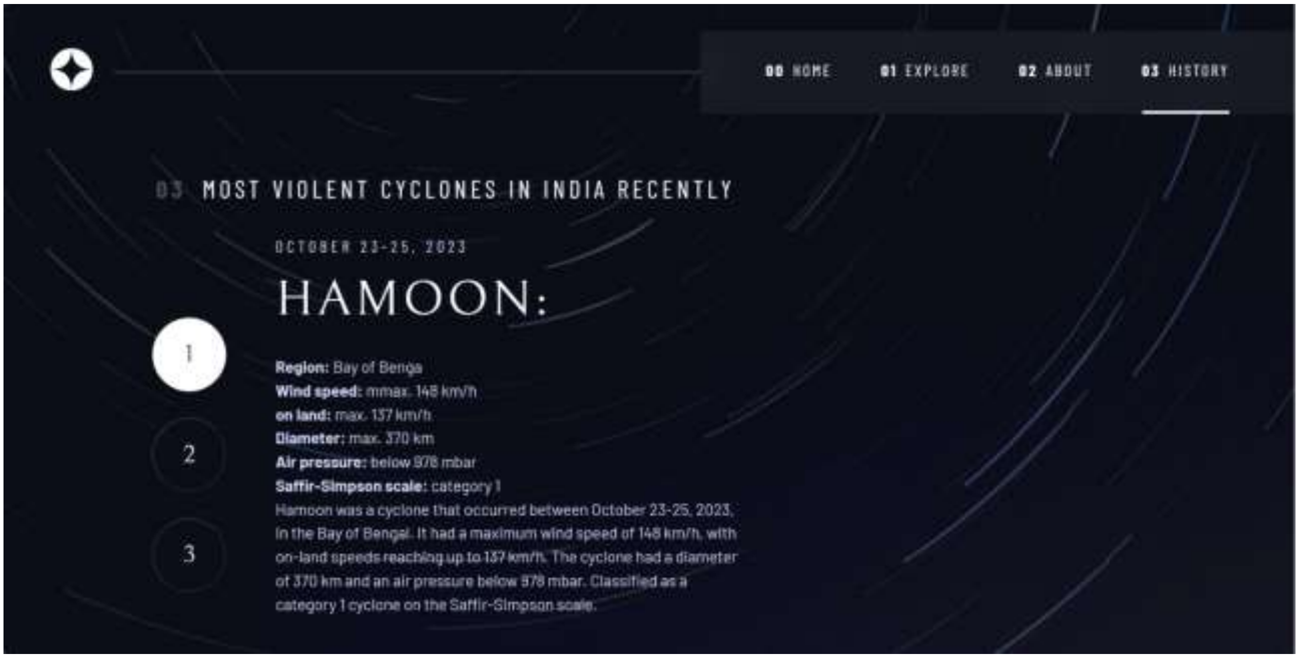



Fig 8.6 History of Recently Cyclone

Our interface for cyclone intensity estimation features a dedicated tab showcasing the "History of Previous Cyclones," offering users a comprehensive repository of past cyclonic events. This invaluable resource allows users to explore a wealth of historical data, including cyclone tracks, intensity profiles, and associated impact metrics. By studying the trajectory and behaviour of previous cyclones, users can glean insights into patterns, trends, and regional vulnerabilities, empowering them to make informed decisions in disaster preparedness and response efforts. With intuitive navigation and interactive visualization tools, this tab serves as a vital component in enhancing understanding and resilience against future cyclonic events

# 9. CONCLUSION

In conclusion, the project on cyclone intensity estimation employing deep learning techniques represents a significant advancement in improving the precision and dependability of meteorological predictions. The incorporation of deep learning algorithms has shown promise in capturing intricate patterns and relationships within meteorological data, leading to more nuanced and accurate intensity estimates for cyclones. The utilization of deep learning models, particularly neural networks, has proven effective in handling the complex dynamics inherent in cyclones. This project harnesses the capabilities of deep learning to interpret complex atmospheric conditions, resulting in more robust predictions of cyclone intensity. The model's capacity to autonomously extract features from extensive datasets enhances its adaptability to diverse cyclonic patterns and reinforces its predictive performance. Moreover, the project underscores the importance of continuous refinement and validation. Ongoing efforts are dedicated to improving the deep learning model, incorporating new data, and validating predictions against observed outcomes. This iterative approach ensures the project's adaptability to evolving meteorological conditions, enhancing its relevance over time. The outcomes of the project bear significance for disaster preparedness and response, providing an advanced tool for meteorological agencies and disaster management authorities. Accurate cyclone intensity estimates enable timely and targeted interventions, minimizing the impact of these natural disasters on communities and infrastructure. While the project shows promising results, it's essential to acknowledge the dynamic nature of meteorological phenomena. Future work should focus on expanding the dataset, enhancing model interpretability, and collaborating with meteorological agencies to integrate the deep learning model into operational practices. Through these efforts, the project not only contributes to the scientific understanding of cyclone dynamics but also aids in the practical implementation of advanced technologies to mitigate the impact of cyclones on vulnerable regions.

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## CERTIFICATE OF PAPER PUBLISHED IN JOURNAL

**Appendix A: Certificates**

Certificate of Publication

YMER

Open Access | Peer reviewed | Scopus Active 2024 | Care UGC Group- II Journal | ISSN - 0044-0477

Title

Cyclone Intensity Estimation Using Deep Learning

Author

Mangesh Balpande

From

SVKM's IOT, Dhule-424001, Maharashtra, India

Has been published in

YMER: VOLUME 23, ISSUE 05, MAY - 2024

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Title

Cyclone Intensity Estimation Using Deep Learning

Author

Kalpesh Patil

From

SVKM's IOT, Dhule-424001, Maharashtra, India

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YMER: VOLUME 23, ISSUE 05, MAY - 2024

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Title

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Author

Aditya Mali

From

SVKM's IOT, Dhule-424001, Maharashtra, India

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**YMER: VOLUME 23, ISSUE 05, MAY - 2024**

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Title

Cyclone Intensity Estimation Using Deep Learning

Author

Abhinash Joshi

From

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Author

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From

SVKM's IOT, Dhule-424001, Maharashtra, India

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YMER: VOLUME 23, ISSUE 05, MAY - 2024

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**Appendix B: Proof of Research Paper Submission (YMER ISSN NO-0044-0477)**

Editor Y... Yesterday

to me

# Acceptance Letter

YMER (ISSN NO-0044-0477)

Dear author,

It's my pleasure to inform you that after the peer review, your paper entitled

**"Cyclone Intensity Estimation Using Deep Learning"**

Manuscript ID: **YMER230549**

has been ACCEPTED with content unaltered to publish with YMER Digital, ISSN 0044-0477 in Volume 23 Issue 05(May 2024).

Though the reviewers of the journal already confirmed the quality of your paper's current version, you can still add content to it, such as solidifying the literature review, adding more content in the conclusion, giving more information on your analytical process and giving acknowledgement.

Again, thank you for working with YMER Digital. I believe that our collaboration will help to accelerate the global knowledge creation and sharing one-step further. Please do not hesitate to contact me if you have any further questions.

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Appendix D: Research Paper

# Cyclone Intensity Estimation Using Deep Learning

[1]Mangesh Balpande, [2]Kalpesh Patil, [3]Aditya Mali,
[4]Abhinash Joshi, [5]Rohan Mahajan

*[1-5]SVKM's IOT, Dhule-424001, Maharashtra, India*

## Abstract
This study addresses the critical task of accurately estimating tropical cyclone intensity, vital for predicting severe weather events. The approach treats this as a classification problem, using intensity categories as classes. Unlike traditional supervised methods that demand abundant labeled data, real-world situations often provide only a handful of labeled samples. To overcome this, a novel semi-supervised deep learning framework is proposed. This framework, based on convolutional neural networks (CNNs), is tailored for FY-4 multispectral images. This model stands out by achieving precise classification and intensity estimation using a small initial set of labeled samples. It employs iterative training with a custom hybrid similarity measurement, enhancing classification performance throughout iterations. Experimental results highlight consistent performance improvement across iterations and demonstrate the superiority of the proposed method compared to existing approaches, even when working with small training sets. Overall, the study presents an efficient solution for cyclone intensity estimation, combining CNNs, semi-supervised learning, and iterative refinement.

**Keywords:** Convolutional Neural Network (CNN).

## 1. INTRODUCTION
High-intensity tropical cyclones can wreak havoc on coastal regions, underscoring the urgency of accurately analyzing remote sensing cyclone images and predicting their intensity in advance. Approaching cyclone intensity estimation as a classification challenge, machine learning techniques offer solutions. Various methods, including Multiple Logistic Regression (MLR), Support Vector Machine (SVM), and Back-Propagation Neural Network (BPNN), have been successfully applied to multispectral cyclone images, demonstrating favorable outcomes [1].Among these methods, the Convolutional Neural Network (CNN) stands out as a potent classifier, having undergone extensive exploration in recent years. A range of CNN variations, such as LeNet, GoogLeNet, and ResNet, have been proposed, achieving noteworthy advancements across diverse visual tasks. Notably, CNNs have been effectively employed for estimating cyclone intensity from infrared (IR) images [6].

However, both CNNs and many existing supervised techniques share a common challenge: their reliance on sizable training datasets. Unfortunately, the availability of accurately labeled samples remains limited, especially for cyclone intensity estimation using multispectral images from China's No. 4 meteorological satellite (FY-4), launched in December 2016. The intricate features within these multispectral images make it difficult for unsupervised methods to attain satisfactory classification accuracy since such methods are solely data-driven.The distinctiveness of the problem necessitates a nuanced approach. Neither purely supervised nor unsupervised methods are optimal for cyclone intensity estimation. Yet, amidst the scarcity of labeled data, the vast collection of unlabeled images holds immense potential due to their rich information. This establishes an opportunity for semisupervised classification to address these challenges. In this approach, both labelled and unlabeled data synergize to tackle the complexities of cyclone intensity estimation.[3]

## 2. LITERATURE REVIEW

[7] The CNN-TC employs adaptable CNN architecture to accurately gauge tropical cyclone intensity. It crafts specific CNN models for predicting cyclone formation based on diverse satellite factors. This innovative approach enhances prediction precision and adapts to varying conditions, revolutionizing cyclone forecasting. Reference [1] employs the Multilayer Perceptron (MLP) algorithm to predict cyclone intensity, using image-based geometric traits of tropical cyclones (TC). The Dvorak technique extracts significant features from satellite TC images. These features train the MLP model, enabling it to effectively estimate TC intensity based on learned patterns from the data. [4] This approach involves developing and deploying models for manufacturing after evaluating them against CAM-recognized functions and Dvorak T-wide variety images. The models are trained on local servers to minimize training costs. Once trained, they're integrated into the manufacturing system. The user interface for interacting with these models is built using React and Redux, known for their dynamic interface design and efficient state management. An analytical assessment and skill evaluation study is conducted over a thirty-minute timeframe, focusing on various levels of design and efficient state management. An analytical assessment and skill evaluation study is conducted over a thirty-minute timeframe, focusing on various levels ofcyclone attributes such as intensity and structure. This evaluation involves measuring the model's performance and its ability to make accurate predictions within this specific timeframe. Different aspects of cyclone behavior are taken into consideration during this analysis.[9] The model introduced in the context focuses on Very High-Resolution (VHR) remote sensing images. Its primary contribution lies in enhancing the precision of object detection and instance segmentation. Notably, this model incorporates a technique to compute the two-order integral, significantly elevating its accuracy levels .The Dvorak technique for calculating cyclone intensity has been used for a long time, but it relies on human judgment, which can be inconsistent and make it hard to use on big datasets. Convolutional Neural Networks (CNNs) combined with INSAT 3D images offer a solution to automate the process of cyclone intensity assessment. By leveraging these technologies, the system becomes proficient in autonomously recognizing patterns within the images that correspond to cyclone strength. This eliminates the necessity for human interpretation, ensuring a uniform approach across diverse datasets.

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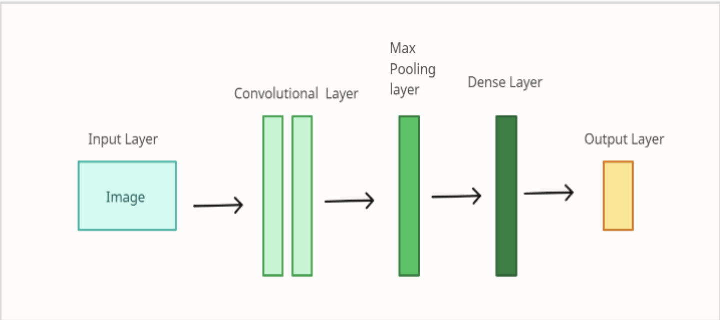



**Fig 1.** Methodology of Cyclone CNN model.

## A COLLECTION AND CLASSES OF DATASETS

The INSAT 3D Infrared & Raw Cyclone Imagery dataset serves as a comprehensive collection of imagery covering the Indian Ocean region, spanning from 2012 to 2021. These images have been harnessed for training our model, INSAT3D, which is equipped with a CNN (Convolutional Neural Network) architecture. The dataset encompasses high-resolution infrared images captured by the IR Imager instrument onboard the INSAT 3D meteorological satellite.

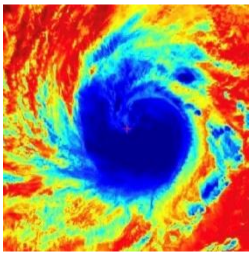
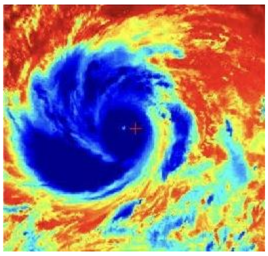



**Fig. 2** Dataset of INSAT 3D IR Imagery

An accomplishment of ISRO (Indian Space Research Organisation).One of the pivotal aspects of this dataset is the pairing of each image with its corresponding timestamp and geographical coordinates. This integration allows for the creation of intensity graphs that reveal the fluctuations in temperature and cloud cover over time. Before being fed into the CNN, all images are standardized to a uniform size through resizing.In order to facilitate effective model training, the dataset is segregated into two subsets: the training set and the validation set. This separation enables the model to learn and generalize from a diverse range of imagery, enhancing its ability to accurately predict and analyze meteorological patterns.The INSAT 3D satellite itself is outfitted with an IR Imager instrument, capable of capturing intricate details of Earth's surface and atmosphere through infrared imagery This rich dataset offers valuable insights into the distribution of temperatures and cloud cover, thereby proving invaluable for an array of applications, including weather forecasting, climate monitoring, agricultural management, oceanography, and disaster response.The significance of this dataset lies in its consistent updates and open accessibility via ISRO's Meteorological Data Archive website. The platform provides an array of tools, such as maps, charts, and graphs, that empower meteorologists, researchers, and policymakers to scrutinize and interpret the data. This real-time resource has become a cornerstone for monitoring current weather conditions and predicting severe weather phenomena within the Indian subcontinent and its neighboring areas.Consequently, the INSAT 3D IR imagery dataset stands as an indispensable asset for those engaged in weather analysis and forecasting, research endeavors, and decision-making processes related to meteorological occurrences.

**B.IMPLEMENTATION OF THE MODEL**

In the implementation of the model firstly it takes an image and after processing the input it is passed through the deep learning CNN architecture.

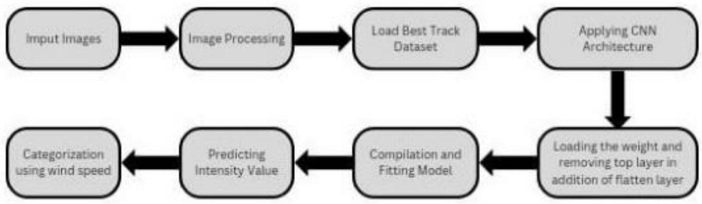



**Fig. 3**. Architecture For Intensity estimation and its classification.

In the case of intensity estimation, imagery data of satellite is often used, which consists of a series of images of the cyclone taken over time. Therefore, the problem can be viewed as an image classification task, where each image represents a different stage of the cyclone's development, and the goal is to accurately classify the cyclone based on these features and assign it to the appropriate intensity category, which can then be used for various purposes, such as predicting its potential impact on an area and informing emergency response efforts. CNNs are well-suited to this type of task because they are designed to extract features from images in ordered manner, using a series of convolutional layers that learn increasingly complex representations of the image data. This allows the CNN to capture the spatial relationships and patterns in the image data that are relevant to the task at hand.Therefore, CNNs are a suitable choice for tropical cyclone intensity estimation, as they can effectively handle the image data and learn the relevant features and patterns needed to classify the cyclone into different intensity categories based on the image data.The CNN architecture works as mentioned in the flowchart. Convolutional neural network (CNN) is used in image processing that is designed to process pixel data. After the images are passed, the images will be processed, and the datasets are loaded with a batch size of 16. A mean absolute error loss function is commonly used to calculate the difference between predicted and actual values. The activation function ReLU is often applied to the hidden layer, while a linear function is used for the final layer activation function. These techniques can help improve the accuracy of machine learning models. Rectified Linear Units (ReLU) function is given as

$$f(x) = \max(0,x) \tag{1}$$

x is input to the layer.

Loss function used here is Mean Squared Error:

$$MSE = 1/n \sum_{i=1}^{n} (yi - \hat{y}i) \tag{2}$$

Where, MSE: Mean Squared Error n: Number of data points yi: observed values ŷi: predicted values

Other formulas used for the comparison of CNN architectures are

*Mean Absolute Error:*

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}| \tag{3}$$

MAE: Mean Absolute Error n: Number of data points yi: observed values ŷi: predicted values

|i=1 to n|: absolute value of the difference between actual and predicted values

*Root Mean Squared Error:*

$$RMSE = \sqrt{MSE} = \sqrt{1/n \sum_{i=1}^{n} (yi - \hat{y}i)} \tag{4}$$

RMSE: Root Mean Squared Error n: Number of data points yi: observed values ŷi: predicted values

*R2 score:*

$$R^2 = 1 - \frac{\sum (y_i - \hat{y})^2}{\sum (y_i - \bar{y})^2} \tag{5}$$

RMSE: Root Mean Squared Error n: Number of data points yi: observed values ŷi: predicted values Σ: sum of values

|i=1 to n|: absolute value of the difference between actual and predicted values.

*1. InceptionV3*:

Inception-v3 is a type of convolutional neural network that consists of 48 layers. The ImageNet consists of a trained variant network that was created in advance and trained on thousands of images. Several animals, a keyboard, a mouse, and a pencil are among the 1000 different item categories that the pretrained network can classify photographs into. As a result, the network now includes comprehensive feature representations for a range of photos. The input image for the network is 299 by 299 pixels in size [19].

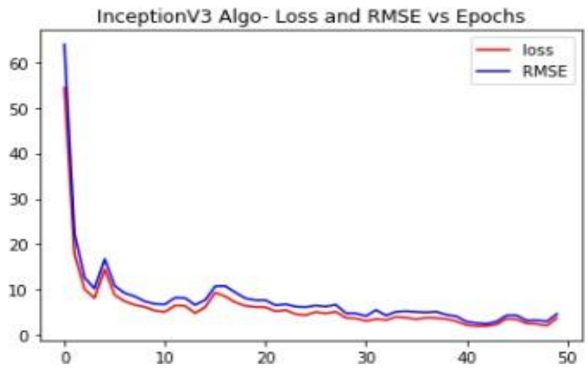



**Fig. 4** Graph of Loss and RMSE vs epochs in InceptionV3

2. *VGG16:*

As a 16-layer transfer learning architecture with only CNN as its foundation, VGG16 is relatively comparable to earlier architectures, however the configuration is a little different. For this architecture, the input image with a standard dimension of 224 x 224 x 3, where 3 stands for the RGB channel has been used [20]. As a 16-layer transfer learning architecture with only CNN as its foundation, VGG16 is relatively comparable to earlier architectures, however the configuration is a little different. For this architecture, the input image with a standard dimension of 224 x 224 x 3, where 3 stands for the RGB channel has been used [20].

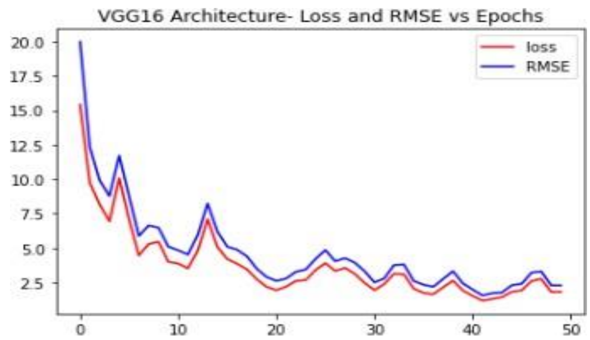



**Fig. 5** Graph of Loss and RMSE vs epochs in

3 *Ensemble Learning:*

Ensemble learning is a popular technique used in computational intelligence to address various problems by creating and integrating multiple models, such as classifiers or experts. The main goal of ensemble learning is to enhance classification, prediction, function approximation, etc

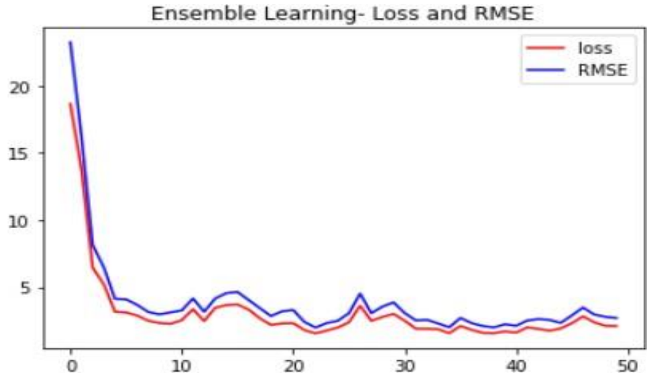



**Fig. 6** Graph of Loss and RMSE in Ensemble Model

## C.TRAINING AND TESTING MODELS

After the model is framed the training plays the major role. It is trained with the help of Keras and TensorFlow. We have run it on 50 epochs and saved the model. The system can effectively predict the wind speed for cyclone satellite IR imagery dataset. By minimizing the loss function (MSE), the model was trained. We have a single neuron in the last layer that is used to forecast a continuous value without any activation function being specified. The training was performed using the Adaptive Moment Estimation (Adam).

## D.INTENSITY ESTIMATION / WIND SPEED

The wind speed is calculated in knots (KN). A knot is a measure of speed that is directly related to the world's coordinate systems for latitude and longitude. Because they are simpler to travel with than MPH and KPH, knots are frequently employed in the aviation and maritime industries. The intensity values are assigned to the images before the training of the dataset. Which is also known as supervised learning algorithms. On the basis of the eye or the center of the cyclone it checks how much the patch is spread in the image.In the case of estimating speed of wind from satellite images, the CNN can learn to identify spatial patterns that are indicative of wind speed. For example, the CNN might learn to identify the shapes and sizes of cloud formations, which can be used to infer wind speed. The CNN might also learn to identify the direction and speed of cloud movement, which can provide additional information about wind speed. During training, the CNN is presented with a dataset of labeled images, where each image is paired with a corresponding wind speed measurement. The CNN learns to adjust the weights ofits filters in order to minimize the difference between its predicted wind speed and the ground truth wind speed. By iteratively adjusting the filter weights and evaluating the model on a validation dataset, the CNN gradually learns to identify spatial patterns in the images that are strongly correlated with wind speed.Once trained, the CNN can be applied to new satellite images to estimate wind speed in real-time. The CNN is able to quickly and accurately analyze the spatial patterns in the image, producing a reliable estimate of wind speed.

## E. CLASSIFICATION BASSED ON INTENSITY VALUES

**Table 1.** Classification based windspeed

| Index | Category of Cyclone | Wind Speed |
|---|---|---|
| 0 | Depression | 0-33KT |
| 1 | Storm | 33-64KT |
| 2 | Category 1 | 64-83KT |
| 3 | Category 2 | 83-95KT |
| 4 | Category 3 | 95-113KT |
| 5 | Category 4 | 113-134KT |
| 6 | Category 5 | <134KT |

With the help of intensity or wind speed values the cyclonescan be classified into 8 categories. Here we have assigned the index value as 0 when the image detects no cyclone or extremely low intensity cyclone which is less than 17 KN.

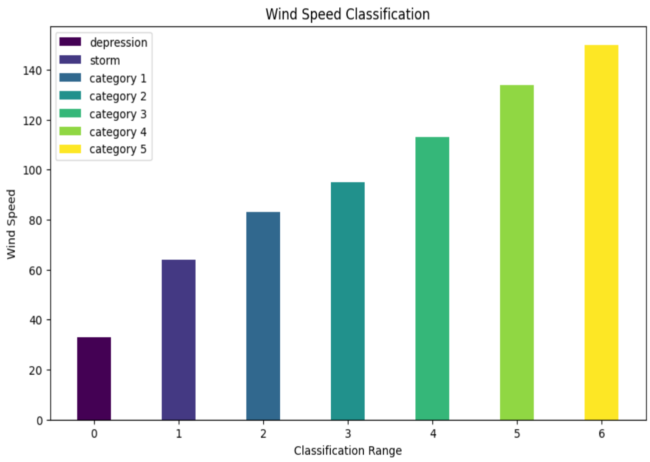



**Fig.7** Cyclone Categories

## F. SYSTEM WORKING

The first layer, a convolutional layer with an image size of 512 × 512, receives the preprocessed fish-eye IR pictures as input data. This layer's primary function is to identify various patterns and characteristics in the input pictures. Therefore, a filter is created also known as a kernel in order to discover these patterns/features. We identified the basic visual attributes in this method, which are helpful for CNN's initial layers. Multiple pictures will be convolved when different kernels or filters are applied to the same image. By utilizing numerous kernels, we may recognize different patterns in a picture, such as curves, lines, edges, and so on. After initializing the kernels with random values, the parameters will be updated with the ideal values during the training phase. The values will be changed with optimal values throughout the training phase, allowing the pattern to be detected.

The convolutional layer's nodes get ReLu and linear activation functions that are applied to the neurons on top of them. Also included were dropout layers, which may be used to switch off neurons during training in order to avoid overfitting.
We added a layer named max-pooling layer, dense layer, flatten layer, and batch normalization after the convolutional layer and adding a dropout layer to it. By down sampling the images created by the ReLu function, this reduces the dimensionality of the active neurons As was noted in the preceding paragraph, down sampling is carried out via the operation of max-pooling, which also discovers the maximum values and streamlines the inputs. In other words, the model's parameter count is decreased. To avoid overfitting from the pooling layer, we then add the dropout layers once again after each convolutional layer. Then we add a completely linked layer; this layer creates a vector representation of the high-level filtered pictures from the preceding layers. The transfer learning algorithms were used where they are pretrained with millions of images, and on last layer the input images are validated. The model predicts the intensity and classifies the value (0-7) which is the categorization of Tropical cyclone categories in the output layer using a linear activation function.

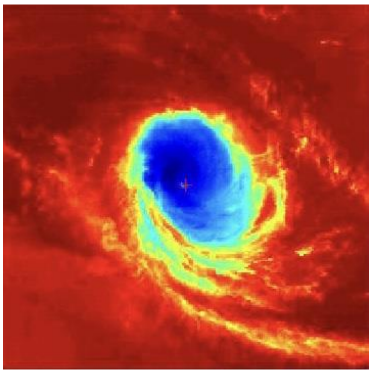
## 3...RESULTS AND DISCUSSIONS

The VGG16 Algorithm Model correctly analyzes and predicts the wind speed with the mean squared error of 1.8935 and the loss is 1.2124. The intensity and other characteristics, such as the regions affected, are predicted by the model. Additionally, it indicates which of the previously mentioned categories, from 0 to 7, the cyclone falls within. It becomes helpful for the public if there are any active cyclones whether it may be too harsh or too low on the basis of which they can take necessary action. After applying various algorithms using transfer learning and ensembling all them and comparing the values from above table the minimum loss of 1.1173 comes for VGG16 and after that Xception come out to be 1.3408 of loss. After integrating all the algorithms ensemble learning shows the loss 1.5124 and RMSE 1.8236 provided To distinguish between the header and body text in a document, users can utilize the options available in a dropdown menu.

From below figure, the various images are shown with their true output and predicted values by the model. The model is then further integrated with the android app where the cyclone intensity and its category is predicted.

**Table 2**:Classification based on wind speed

| Sr no. | Algorithm | Loss | RMSE | MAE | MSE | R2 Score |
|---|---|---|---|---|---|---|
| 1 | Inception V3 | 1.7421 | 2.1434 | 1.7802 | 5.0453 | 0.6345 |
| 2 | VGG16 | 1.2124 | 1.4320 | 1.2985 | 1.8935 | 0.8567 |
| 3 | Ensemble Learning | 1.6156 | 1.7846 | 1.2984 | 3.4985 | 0.8469 |



Output Intensity Value :79
Predicted intensity Value: 85 KN
**Fig.8** :Category 2

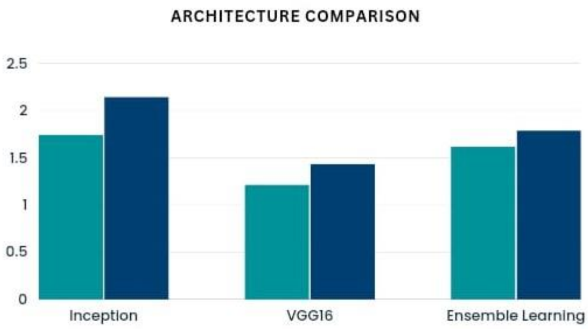



**Fig.9.**Comparison of Loss and RMSE in different CNN architectures

## 4. SCOPE OF PROJECT

This model can be trained on hurricanes and different types of natural disasters. On that basis, a larger integrated platform can be developed. An alert system can be made beforehand for the citizens if there is a chance of the cyclone or any other disasters

## 5. CONCLUSION

The suggested system aims to identify cyclone intensity by analyzing wind speeds and categorizing cyclone types within specific ranges. This is achieved through the application of CNN architectures, enhanced by ensemble learning techniques. The goal is to achieve heightened accuracy in results, updating on a half-hourly basis. This rapid and precise monitoring enables better awareness of potential hazards, prompting timely adjustments to mitigate risks and safeguard lives. Additionally, it aids in minimizing financial losses associated with cyclone-induced damages.

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