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Cyclone Intensity Estimation Using Deep Learning

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Abstract: - Cyclone Intensity Estimation based on Deep Learning focuses on cyclone intensity estimation, enhancing early warning systems and empowering decision-makers to take proactive measures to safeguard vulnerable communities and infrastructure, which aims to minimize the devastating impacts of cyclones worldwide. The challenge in cyclone intensity prediction persists due to the complex and dynamic nature of these storms. Traditional methods fall short of capturing rapid changes. This research project leverages the power of deep learning to enhance the accuracy of cyclone intensity prediction by utilizing both satellite images and grayscale representations as input datasets. It involves preprocessing and feature extraction from satellite images captured during cyclonic events. Convolutional Neural Networks (CNN) are employed to automatically learn and extract relevant patterns from these complex datasets. In parallel, grayscale images derived from the original satellite images are utilized to capture essential structure information that contributes to cyclone intensity. The fusion of information from both modalities is achieved through a novel deep learning patterns that go beyond the capabilities of traditional intensity estimation methods, and architecture, fostering a comprehensive understanding of cyclonic patterns that go beyond the capabilities of traditional intensity estimation methods. A new approach seeks to automate cyclone estimation, streamlining timelines and increasing efficiency by merging deep learning with hurricane-focused satellite data. This approach might result in more precise forecasts, Reducing the amount of casualties and property damage in prone areas.

Keywords: Convolutional Neural Networks, Deep learning, backpropagation, Multilayer neural network.

I. INTRODUCTION

Cyclones are gigantic storms that originate in oceans, acquire energy, and intensify, posing a considerable threat to people due to their destructive resentment [1]. Accurately calculating cyclone strength is critical for determining the threats to people and property. The eye, or central section of a cyclone, is an important landmark for detecting and tracking its path. Researchers' ongoing efforts to automate intensity measurement using satellite photos aim to eliminate the need for human involvement [1][2]. The early stages of tropical cyclones are extremely dangerous, with accompanying hazards such as floods and tornadoes having disastrous results. Timely detection and prediction are critical, emphasizing the relevance of classical approaches for cyclone identification that use characteristics such as temperature and wind speed [1][3].

The primary goal is to create a robust and extensible model for predicting cyclone intensity, with goal of greatly improving accuracy over existing methods. The scope of the research includes combing deep learning algorithms with satellite and grayscale pictures to gain a full understanding of cyclonic patterns. As the frequency and intensity of tropical cyclone increase, better approaches for predicting cyclone intensity become critical for reducing the destructive repercussions of these natural disasters. The study aims to bridge the gaps in current methodologies, presenting a promising way to improve disaster preparedness and response measures for vulnerable communities around the world.

II. RELATED WORKS

To predict the strength of a Tropical Cyclone (TC), researchers used classic machine learning approaches combined with infrared satellite images [4]. Several models, such as multivariate linear regression [5], the K-nearest neighbour technique [6], multilayer perceptron modeling, the support vector machine (SVM), and relevance vector machine (the RVM), have proven effective in this effort [7][8]. The recovered features include the cyclone center, rain band characteristics, cloud top brightness temperature gradient, radial cloud top brightness

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temperature statistic, slope of the TC inner-core cloud peak, deviation angles, spiral rain band attachment, and inner core regularity [9]. The strength of TCs is currently estimated mostly using microwave data from geostationary and polar-orbiting satellite photography. However, in adverse environments, like persistent rain, microwave data may be interrupted. Geostationary satellites are more frequently used for TC intensity assessment due to their superior temporal resolution and steady image quality, even though polar- orbiting satellites can provide insights into near-surface TC structures. Dvorak, drawing on forecaster knowledge, invented techniques for assessing TC intensity using infrared satellite pictures. Even while several improved Dvorak methods have less subjective components, they frequently fall short when it comes to determining the strength of lesser TCs [4].

Chinmoy Kar et al (2019) proposed a novel image processing-based approach for assessing (TC) intensity using satellite photos, with an 84% success rate in recognizing TC images across the Bay of Bengal and the Arabian Gulf. Unlike classic methods such as the Dvorak technique, which rely on pattern recognition, this method employs geometric features and a multilayer perceptron model. It outperforms the Dvorak technique in terms of accuracy and enables automation over human feature extraction methods. However, constraints include regional applicability and the necessity for extensive training data. Despite this, the suggested method shows potential for improving TC intensity estimation, albeit with need improvements for wider use [2].

A. Nair et al (2021) describes approaches for detecting and tracking tropical cyclones (TCs) using satellite imagery. Pattern correlation coefficient, 3-D segmentation, gradient vector flow, and machine learning are all used to aid with TC detection through land use classification. It identifies current uncertainties in TC data archives and proposes automated strategies to address them. This detailed study highlights several approaches and emphasizes the significance of advanced methodologies for improving TC monitoring and forecasting accuracy [3].

C. -J. Zhang et al (2021) introduced TCICENet, a new machine learning model for TC severity classification and estimation. TCICENet uses infrared satellite images from the Pacific Ocean's northeast region to train a cascade deep CNN with two modules: TC intensity categorization and TC strength estimation. TCICENet provides improved accuracy (87.4%), automation, and efficiency compared to existing systems that rely on microwave data or geostationary images, both of which are error-prone. However, its application is limited to the northwest Pacific Ocean region. While outperforming the subjective Dvorak technique in accuracy, TCICENet streamlines procedures by eliminating manual feature extraction and lowering training data needs as Compared with different machine learning methods [4].

R. Sun et al (2016) described an objective multiple linear association (MLR) model for assessing TC intensity using satellite infrared radiation data. Unlike subjective procedures such as the Dvorak technique or computationally expensive physical models, this method directly correlates satellite-derived features to TC intensity. The model predicts maximum sustained wind speed, an important intensity indicator, by extracting numerous information from infrared images, such as brightness temperature profiles and statistical factors. When tested on Northwestern Pacific Ocean TC data, It achieves comparable accuracy, with an RMSE of 12.01 knots. Objectivity, a data-driven methodology, and computational efficiency are all promising advantages, but more validation and refinement are required for widespread deployment [5].

G. Fetanat et al (2013) introduced FASI, a novel objective method for assessing (TC) intensity using past disaster satellite data (HURSAT). Unlike subjective methods like the Dvorak technique, FASI uses a k-nearest neighbors (k-NN) algorithm to find similar historical TC pictures using azimuthal brightness temperature (BT) profiles. FASI's strong accuracy is demonstrated by an evaluation with 2016 North Atlantic TC observations, The mean of the absolute error (MAE) was 10.9 kt, while the root mean square error (RMSE) was 8.4 mb. FASI proposes a data-driven method to worldwide TC intensity estimates, leveraging available satellite data to promise improved accuracy and complementing previous techniques. Further research can improve and widen its applicability [6].

W. Tian et al (2022) introduced 3DAttentionTCNet, a model for estimating (TC) intensity with the help of multichannel satellite pictures. The model uses 3D convolution to automatically extract environmental Variables from infrared light (IR), moisture vapor (WV), and active microwave rain raterain rate (PMW) pictures. Furthermore, adding a convolutional block attention module (CBAM) increases the model's focus on underlying cloud topology and critical pathways. The results of the experiment demonstrate a 25% improvement in root-mean-square error (RMSE) over the (ADT) and an improvement of 9.2% over traditional deep learning methods. This unique approach has the potential to significantly enhance TC intensity measurement accuracy, hence improving forecasting and warning systems [10].

K. M. Wood et al (2014) explains the Deviation-Angle Variation Technique (DAV-T), a novel method for assessing the intensity of (TCs) in the northern Pacific Ocean using satellite imagery. DAV-T calculates the fluctuation in the angle among the brightness and temperature gradient. and the TC center, which relates axisymmetry to intensity. Testing on western and eastern North Pacific data produces root-mean-square intensity errors of 14.3 kt and 13.4 kt, respectively, which are comparable to other approaches. DAV-T provides impartiality, simplicity, and interoperability with a variety of satellite photos. However, disadvantages include a dependency on axisymmetry, vulnerability to cloud interference, and lesser precision when compared to microwave-based approaches. Overall, DAV-T shows promise for estimating TC intensity, although it must be considered in terms of restrictions [11].

C. Wang et al. (2022) use (CNNs) to estimate (TC) strength across the Northwest Pacific Ocean using Advanced Himawari Imager data. Between 2015 and 2018, 97 TC cases were utilized to train multiple CNN models with numerous inputs and parameters required. The findings emphasize the importance of infrared (IR) channel selection, with a four-channel combination producing the best results: 84.8% accuracy, 5.24 m/s RMSE, and -2.15 m/s mean bias. Incorporating attention layers enhanced accuracy, while a focal_loss function handled unbalanced TC category samples, increasing accuracy to 88.9% The RMSE was 4.62 meters per second, with an average bias of -0.76 m/s. This technique promises to measure the TC strength reliably and efficiently utilizing geostationary satellite information., despite noise and data dispersion problems [12].

S. Jin et al (2017) described an automated technique for detecting the core of partially veiled tropical cyclones in SAR pictures. It uses salient region recognition and pattern matching to identify rain bands based on their high contrast and spiral orientation, followed by particle swarm optimization for center localization. Evaluation of SAR pictures yields up to 90% accuracy. This approach outperforms previous algorithms that don't use pattern matching. However, because to its automated nature, it requires user-defined regions of interest and may be inaccurate for incompletely captured cyclones. Nonetheless, it offers a promising method for properly finding cyclone centers in SAR images, with efficiency and robustness to changes and noise [13].

X. Yu et al (2021) describes TCNN, a model for estimating (TC) intensity using multispectral pictures from China's FY-4 satellite. TCNN overcomes the constraints of existing methods by combining a tensor-based method for low-rank extraction of features with CNNs for abstract depiction of features. It uses a multi-task structure for intensity segmentation and wind velocity regression, which improves accuracy. Comparative evaluations demonstrate that TCNN is more accurate and efficient. The article also addresses traditional Dvorak techniques, machine learning methods, and tensor network approaches to TC intensity estimation, highlighting TCNN's advantages in dealing with high-dimensional data and leveraging low-rank characteristics. [14].

R. Chen et al (2020) fully investigates the integration of machine learning (ML) approaches into tropical cyclone (TC) forecasting, addressing a variety of issues. It describes ML's ability to refine TC forecasts, including tasks such as genesis, track, intensity, and wind speed estimation. The research focuses on specific ML methods like demonstrating successful implementations in TC forecasting. However, it acknowledges ongoing issues like as data scarcity, the complex dynamics of TCs, and the need for interpretable models. Despite these challenges, machine learning (ML) is positioned to improve TC forecast accuracy and efficiency. The study provides a complete review and is a helpful resource for researchers and practitioners interested in investigating the role of machine learning in TC forecasting [15].

M. Xue et al (2022) proposed paper introduces TC_PRENET, a multitask CNN model tailored for global TC The amount of precipitation projection utilizing HURSAT-B1 data. Comprising three modules, TC_PRENET begins with feature extraction from fused infrared and water vapor imagery, followed by Air quality assessment and precipitate prediction. Trained and assessed using HURSAT-B1 data and the IMERG precipitation-induced product., TC_PRENET exhibits robust performance, achieving a probability of detection of 0.68 and an accuracy of 0.81 for TC precipitation estimation. Notably, TC_PRENET surpasses benchmark models like multi linear regression (MLR) and random forest model (RF), showcasing its efficacy and potential for operational applications such as flood forecasting and disaster warning [16].

Jinkai Tan et al (2020) proposes an innovative method of determining the location and severity of (TCs) using microwave-sounding equipment. Employing the scene-dependent single-dimensional variation (SD1DVAR) method, it recovers atmospheric profiles from Advanced Technology Microwave Sounder (ATMS) data, allowing intensity and location estimation using the hydrostatic balance equation. Compared to NOAA's operational method and a combined Fengyun-3D MWTS/MWHS approach, the proposed method is more accurate, lowering intensity estimation errors by up to 37.2%. Notably, it has improved computational performance, making it ideal for real-time applications. This technique shows potential for TC analysis, with plans to expand testing with more TC data [17].

Snehlata Shakya et al, (2020) demonstrates an innovative learning method for cyclone detection on satellite pictures, which uses a (CNN) to categorize images as storm or not storm. Trained on a large dataset of labeled satellite photos, the system improves accuracy by using optical flow to predict cloud motion between frames. Using a detailed case study on cyclone data, various mathematical frameworks and error estimation methodologies are investigated to maximize data conversion for CNN use. Furthermore, various strategies for interpolating optical flow between consecutive images are evaluated. The results suggest that the system outperforms alternative approaches for cyclone detection, demonstrating its usefulness and creativity in cyclone detection using deep learning [18].

W. Tian et al (2020) presents a hybrid convolutional neural network (CNN) model that aims to address the constraints of existing techniques. The model, consisting a classification, three regression, and one backpropagation networks, shows great accuracy with an RMSE of 8.91 knots, exceeding conventional approaches. Advantages include increased accuracy, shorter training times using independent regression networks, and better interpretability. This hybrid model outperforms conventional CNN-based approaches, promising more accurate TC intensity forecasts and warnings. The model's design and results help to a better knowledge of TC dynamics and predictions, which improves operational meteorological applications [19].

Chen Zhao et al (2019) presents a unique semi supervised system for (TC) strength estimate, which addresses the difficulty of inadequate labeled data. The system consists of Feature extraction with primary component analysis (PCA) and (CNNs), CNNO and CNNI, which are iteratively fine-tuned using a hybrid similarity measurement to pick reliable unlabeled samples. A dataset of 5243 TC pictures from the FY-4 meteorological satellite was evaluated, and it outperformed SVMs, BPNNs, k-NNs, MLR, and a cutting-edge CNN-based technique. The framework's accuracy and efficiency show promise in improving TC intensity estimates, with the hybrid similarity measurement playing a critical part in its success [20].

Z. Chen et al (2018) presents an approach for assessing intensity of the cyclone using multispectral images (MSI) taken from the FY-4 satellite. The framework, which makes use of three important components such as band determination, band-wise categorization, and also fusion allows for reliable TC intensity calculation. Using basic approaches the framework achieves excellent accuracy by majority voting fusion. The results imply that the FY(4) MSI data is suitable for automatic cyclone intensity calculation, emphasizing possible operational implications. Overall, the research proposes a flexible and effective technique. [21].

R. S. Aygun et al (2018) developed a (CNN) model for estimating (TC) intensity using satellite imagery. Unlike subjective techniques like the Dvorak technique and DAVT, their CNN architecture learns crucial properties immediately from images, eliminating the need for human extraction or pre-processing. Trained on TC images from the northern Atlantic and Pacific regions., the model outperforms earlier techniques on a test set, achieving 89.2% accuracy. Experiments have demonstrated its generalizability, resistance to noise, and capacity to interpret features such as storm eyes and spiral arms. Overall, the study demonstrates the potential of deep CNNs for accurate and adaptable TC intensity assessment, as well as insights into enhanced monitoring and forecasting methodologies [22].

III. PROPOSED METHODOLOGY

Convolutional Neural Networks (CNNs) are employed in the proposed methodology to classify tropical storm intensity from pre-processed infrared images. The CNN architecture employed in this study includes many layers of convolution, layers of pooling, and completely linked layers. The output layer employs the SoftMax activation function, whereas the layers that are hidden use the rectified liner unit (ReLu) activation mechanism.

The model has been optimized via the categorical cross- entropy loss function during training. During the backpropagation phase, the model's weights are updated using the Adam optimizer.

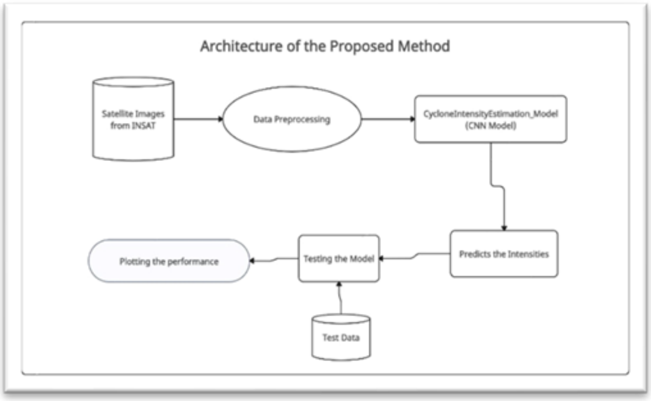

Fig 1: Architecture for the proposed methodology

3.1 Dataset Description

The dataset used in this study was derived from infrared (IR) photographs captured by the INSAT-3D . The dataset consists of labeled images obtained between 2012 and 2021 of TCs in the Indian Ocean geographic area. The maximum wind speed in each image is used as the ground truth label and to categorize the photographs. The severity is classified into five categories: cyclonic winds (48-63 knots), intense cyclonic storm (64-89 knots), depression (≤33 knots), profound depression (34-47 knots), and very severe cyclonic storms (≥90 knots). This dataset can be loaded using a python library called numpy.

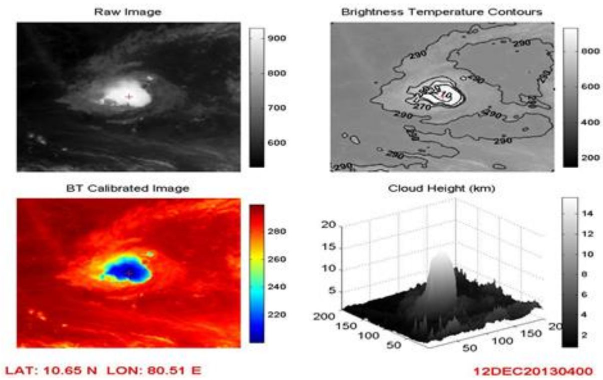

Fig 2: Sample Hurricane Images

3.2 Convolutional Neural Network

Our decision to use deep CNN for tropical cyclone intensity forecasting was prompted by the numerous high-accuracy image recognition applications that CNN has produced in previous years. The most popular application of convolutional neural networks (CNNs) is to handle two- dimensional visual input, such as photos and videos A convolutional neural network (CNN) is a type of multilayer neural network or deep learning architecture that is inspired by living organisms' visual systems.

The CNN model seeks to produce an additional feature that encapsulates the initial collection of features while reducing the total number of features in the dataset. Three layers make up the CNN model: fully-connected, pooling, an convolutional layers. After processing the data, each layer transmits the completed task to the subsequent layer. A deep CNN's initial layers pick up basic traits, and its subsequent layers pick up more intricate ones. CNN is made of fully connected layers. Convolution is a mathematical procedure that combines two sets of information in the matrix form. The process of obtaining the values for a resultant matrix involves overlying a 3x3 matrix onto 5x5 matrix. By multiplying the values in each corresponding cell and summing them, we derive the entries of the resultant matrix. The operation is repeated by sliding these windows until the matrix is complete.

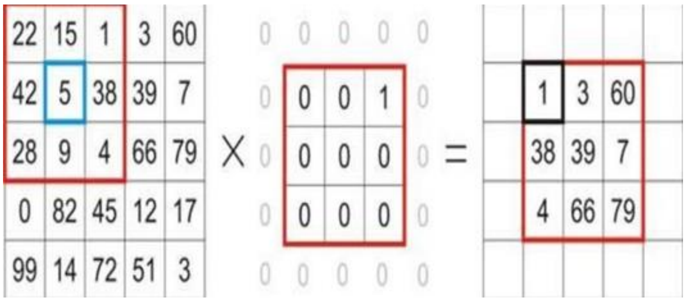

Fig 3: Convolutional Matrix Representation

When an image of size (n*n) is convolved with another of size (f*f), the output is (n-f+1)*(n-f+1).

The CNN model presented adheres to a fundamental principle of employing a shallow neural network architecture. This particular model intricately incorporates distinct 2D convolutional layers (Conv2D), each intricately coupled with a batch normalization layer strategically introduced to mitigate the challenges associated with internal covariate shift. Notably, the Batch normalization layer serves a dual purpose, not only as a means of addressing internal covariate shift but also functioning as a potential regularizer. In many instances, the inclusion of a Dropout layer may be obviated due to the regularization effects conferred by the Batch normalization layer.

Delving into the specifics of the Conv2D layers, both layers are characterized by a Rectified Linear Unit (ReLU) activation function, and they are equipped with filters, each possessing a kernel size of 3×3. To maintain consistent input dimensions, padding is judiciously applied. These Conv2D layers are seamlessly connected through the intermediary of a max pooling layer featuring a 2×2 size and a stride of 2×2. This cohesive architectural design ensures the effective extraction of pertinent features while incorporating mechanisms for regularization and addressing internal covariate shift within the CNN framework.

3.3 Building Blocks of CNN

Padding:

Padding is the process of combining untrue pixels to the image's pixel matrix borders. This is done since every time the original picture dimension is reduced following the convolutional process, our original image is significantly reduced; nevertheless, we do not want the image to be reduced every time.

The another issue by performing convolution is from the fact that as the kernel traverses the real images, it makes fewer contacts with the image edges and more with the central regions. Additionally, there is overlapping in the middle. Consequently, the corner elements and border of any image are underutilized in the output. To address this concern, the padding concept is used.

If the n*n image matrix is convolved with the f*f matrix with padding p, the resultant image size will be

$$[(n + 2p - f + 1) * (n + 2p - f + 1)], \text{ where } p=1.$$

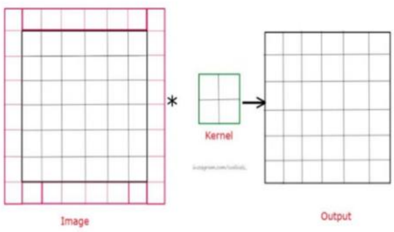

Fig 4: Padding

By introducing random values from the full 0 to 255 colour spectrums into the input matrix, superfluous information becomes embedded within the image. To mitigate this undesired effect, a strategic choice is made to include solely 0 values, denoting black, or 255 values, representing white, thereby ensuring that the kernel selectively extracts relevant features without incorporating unnecessary details.

Stride:

In convolutional layers, there is often a need to generate an output smaller than the input. This can be accomplished through the use of a pooling layer or by implementing striding. Striding involves skipping certain areas as the kernel slides over the input, such as skipping every 2 or 3 pixels. Striding entails bypassing specific locations as the kernel moves over the input, such as every 2 or 3 pixels. This method reduces geographical resolution, increasing the computational efficiency of the network. For fill p, filter size f*f and input image matrix of size n*n and step ‘s’ our output image dimension will be

$$[\{(n+2p-f+1)/s\}+1] * [\ \{(n+2p-f+1)/s\}+1]$$

Pooling:

A pooling layer takes the output from a convolutional layer and condenses it. The filter used in a pooling layer is consistently smaller than the corresponding feature map, typically taking the form of a 2x2 square (patch) that condenses the information into a single value. Different approaches of pooling can be used. The most frequent are:

• **Maximum Pooling:** Determines the maximum value for each patch of the feature map.

• **Average Pooling:** Determines the average value for each patch on the feature map.

The pooling layer in CNN enhances stability; formerly, even little changes in pixels resulted in misclassification; now, modest changes are captured in a combined feature map with an element in the same area.

IV. SYSTEM DESIGN

When dealing with tropical cyclones, CNN’s prove valuable for both classifying and estimating strength based on features extracted from Infrared imagery images. This involves subjecting IR pictures to convolutional processes with in the CNN’s convolutional layer. This approach incorporates a series of filters that scan the image for patterns and distinguish traits. The output of the convolution layer is then sent to the following layer, which is usually a max pooling layer that combines the outputs of a group of neurons from the previous layer into a single layer. To measure the strength of tropical cyclones, a CNN model can be constructed for classifying infrared (IR) images into different categories according to the storm intensity. Another CNN model can then predict the intensity of a specific cyclone by analysing its IR image. In each case, the last layer of the CNN is completely linked, establishing connections between every neuron in the current layer and the subsequent on.

This architecture enables the CNN to understand deep patterns and correlations in the data. To reduce the risk of overfitting, regularization methods like L2 regularization with a 0.01 factor can be used to the completely linked layers at a 0.5 rate, further aids in preventing overfitting. Through meticulous network design and the application of regularization and callback strategies, one can construct a highly accurate and resilient model for forecasting tropical cyclones.

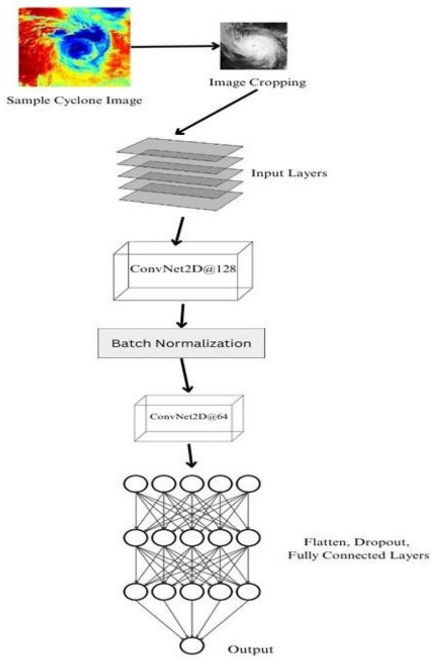

Fig 5: Decoding of CNN Architecture

V. RESULTS AND DISCUSSION

In this study, Convolutional Neural Networks (CNN) are used in conjunction with deep learning to understand satellite imagery of cyclones. Our goal is to identify "investment zones," or places where tropical cyclones could form, and then use that knowledge to begin wind speed computation processes in the National Hurricane Centre's outlook. We wish to give the larger scientific community with a readily understandable interpretation of the model results by comparing our predicted wind speeds to operational estimates and showing the data on a map.

Deep learning, particularly CNN, is a useful method for deriving significant insights from complex datasets, such satellite footage of cyclones. By using massive historical data sets to train the CNN model, we are able to find patterns and connections that may not be directly visible to the naked eye.

By employing those methods, we may generate much precise predictions on upcoming tropical cyclones, which may decrease the amount of property and human casualties in regions vulnerable to these kinds of natural catastrophes.

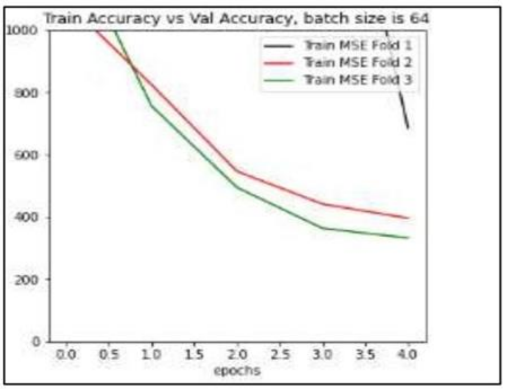

Fig. 6: Mean Square Error Plotting

	Intensity	Category
1	63	Tropical Storm
2	45	Tropical Storm
3	31	Tropical Depression
4	79	Typhoon
5	55	Tropical Storm

Fig 7: Category of Cyclones based on Intensity

VI. CONCLUSION

The project's objective is to provide a deep learning-based solution for both estimating and categorizing the intensity of tropical cyclones. The proposed approach involves leveraging geometric features within cyclone images and employing a combination of multilayer perceptron or CNN models for intensity estimation and classification.Through the integration of deep learning techniques and satellite data specifically focused on hurricanes, the envisioned framework aims to establish an automatic technique for cyclone estimation. This automation is anticipated to streamline the complexity associated with cyclone estimation timelines, ultimately enhancing the overall efficiency of the process. The technology may help lessen the confusion and anomalies brought on by tropical cyclones by increasing the precision and dependability of cyclone intensity estimation. Overall, the evaluation's findings have shown how well the designed approach works to precisely estimate and classify tropical cyclone intensity. Moreover, the intended system possesses the capacity to notably enhance the precision and dependability of cyclone intensity estimation, thereby contributing positively to mitigating the disarray and irregularities arising from tropical cyclones. This undertaking represents a noteworthy advancement in the domain of cyclone intensity assessment and categorization, underscoring the promise of deep learning research in furnishing much precise and resolutions for intricate challenges

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