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Convolution Neural Network Based Algorithm for Estimating the Intensity of Tropical Cyclone from Infrared Satellite Images

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Abstract: The Comprehensive Intention Of The Present Study Is To Develop A Convolution Neural Network (Cnn) Based Prediction Model To Estimate The Intensity Of Tropical Cyclone From The Infrared Satellite Imagery. The Proposed Methodology Is A Two Phase Unsupervised Machine Learning Algorithm. The First Phase Is A Data Acquisition Part That Extracts Data From The Hursat - B1 And Hurdat2 Satellites And Merges Them. The Second Phase Involves Converting The Image Matrix Into Convolved Matrix Which Is Then Passed Through A Rectified Linear Unit Layer To Extract The Important Information From The Images. Finally The Information Are Passed Through A Fully Connected Layer Comprising Of Number Of Neurons That Are Connected To The Previous Layer. In The Proposed Model, Rms prop Optimizer Is Used to Get the Optimized Configuration. At Last, The Proposed Model Is Validated With Pictures Of 10 Different Tropical Cyclones And The Mean Absolute Error And Root Mean Square Error Computed Is 8.42 Knots And 11.14 Knots Respectively Which Is Well Within The Acceptable Range.

Keywords: Unsupervised Machine Learning, Convolution Neural Network (Cnn), Satellite Imagery, Tropical Cyclones, Intensity Prediction

1. Introduction

In the past decade, significant advancement is made in the satellite imagingtechnologies. With the help of satellite images, it is now possible to estimate the intensity of cyclones, path of the cyclones and risk assessment of the cyclone disaster. The satellite images are obtained in the form of visible images during daytime and enhanced infra-red (eir) images for the entire day.

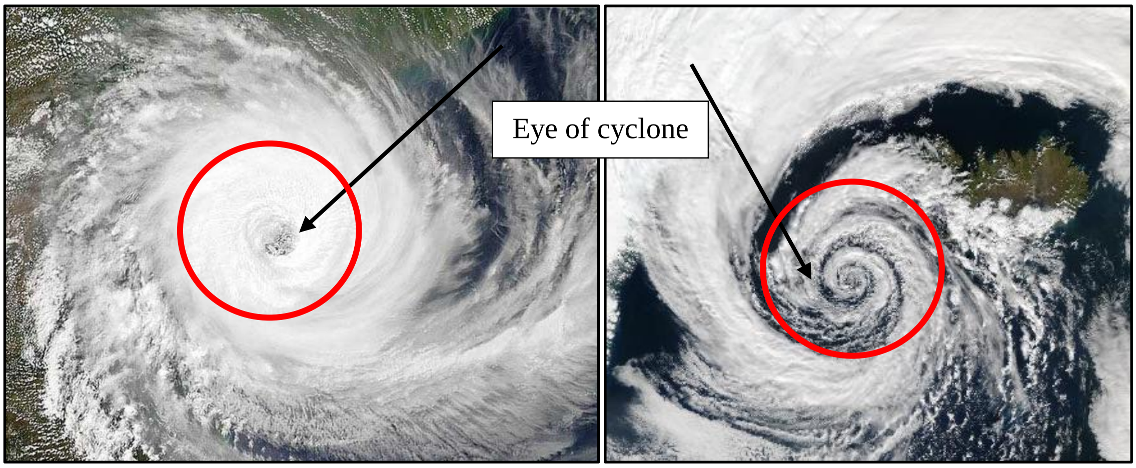
Cyclone is a meteorological phenomenon characterized by large scale rotating and converging air mass around a center of low atmospheric pressure. Figure 1 shows picture of two cyclones in the southern and northern hemisphere respectively. Mostly, cyclone rotates in clockwise in southern hemisphere counterclockwise in northern hemisphere. Moreover, typical cyclone is characterized by a central eye surrounded by spiraling cloud bands of varying intensity. Cyclones are often classified based on the wind speed. The classification of cyclones as per the world meteorological organization [1] is shown in table 1.

Table 1: Cyclone Classification

Sl. No.	Category	Wind Speed		Damage Capacity
		$\left({km}/{hr}\right)$	$(knots)$	
1	Tropical Depression	≤ 62	≤ 33	None
2	Tropical Storm	63– 118	34– 63	None To Very Little
3	Category 1	119– 153	64– 82	Minimal
4	Category 2	154– 177	83– 95	Moderate

5	Category 3	178– 208	6– 112	Extensive
6	Category 4	209– 251	113– 136	Extreme
7	Category 5	≥ 252	≥ 137	Catastrophic

The category of a cyclone is also classified based on the changing cloud intensity patterns which are measured using the dvorak technique of t-numbers [2]. This technique analyzes the satellite image pattern and the top cloud temperatures [3]. However, one of the major drawback of this technique is that it is greatly dependent on expert human judgment, and so, efforts are in progress to automate the technique.



(i) (Ii)

Figure 1: Pictures Of Cyclones In (I) Southern And (Ii)

Northern hemisphere over the years, researchers has successfully implemented machine learning algorithms to classify and estimate the intensity of the cyclones. However, one of the major disadvantages of supervise learning algorithms is to provide with a target value. This drawback is overcome with the development made in the field of unsupervised learning algorithm. Convolution neural network (cnn) is one of the many unsupervised machine learning algorithms that is capable of extracting useful information from satellite imagery and classify the intensity of the tropical cyclones [4]. Convolutional neural networks (cnns) have been used for many different computer vision tasks ranging from image classification [5 – 7] to object detection [8] and even visual saliency detection [9].

In the 2017, literature [1] involves the application of cnn in estimating the tropical cyclone intensity (tci). In the research article [10] used cnns to estimate cyclone intensity using passive microwave imagery (37, 89 ghz bands) as input to the model. The developed model uses satellite imagery from 1987 to 2012 along with the wind speed as maintained in the hurricane database (hurdat2) and joint typhoon warning center. The performance of the model is evaluated by computing the root mean square error (rmse) value between the predicted and target value. In the research article [11] developed a 3-dimensional cnn model to predict the cyclone intensity of western northern pacific region the input to their proposed model is satellite imagery from communication, ocean and meteorological satellite - meteorological imager and joint typhoon warning center advisories are used to obtain wind speed labels. Giffard-roisin et al. [12] uses track data and 3d reanalysis data as input to cnn, along with other features such as location information and maximal sustained wind speed to develop storm track models. They formulate the tracking problem as estimating the displacement between current location and future location of cyclone. Other variations of cnns have also been successfully used in tracking and forecasting climate events such as hurricanes [13 – 15]. The model presented in this paper is purely a diagnostic model for estimating tci.

2. The problem

In this paper, we propose cnn model for estimating tci from infrared satellite images. The infrared satellite images are adopted as the input of the tci model. The model consists of two modules: the cyclone intensity grade classification (tcic) module and the cyclone intensity estimation (tcie) module. The cnn model classify the tropical cyclone intensity into seven categories namely depression, storm, category 1, category 2, category 3, category 4 and category 5.

3. Methodology

Convolutional neural network has had ground breaking results over the past decade in a variety of fields related to pattern recognition; from image processing to voice recognition. The most beneficial aspect of cnns is reducing the number of parameters in ann. This achievement has prompted both researchers and developers to approach larger models in order to solve complex tasks, which was not possible with classic anns. The most important assumption about problems that are solved by cnn should not have features which are spatially dependent. In other words, for example, in a face detection application, we do not need to pay attention to where the faces are located in the images. The only concern is to detect them regardless of their position in the given images. Another important aspect of cnn, is to obtain abstract features when input propagates toward the deeper layers. For example, in image classification, the edge might be detected in the first layers, and then the simpler shapes in the second layers, and then the higher level features. The steps carried out for predicting the intensity of cyclones using cnn is shown as a flow diagram in figure 2.

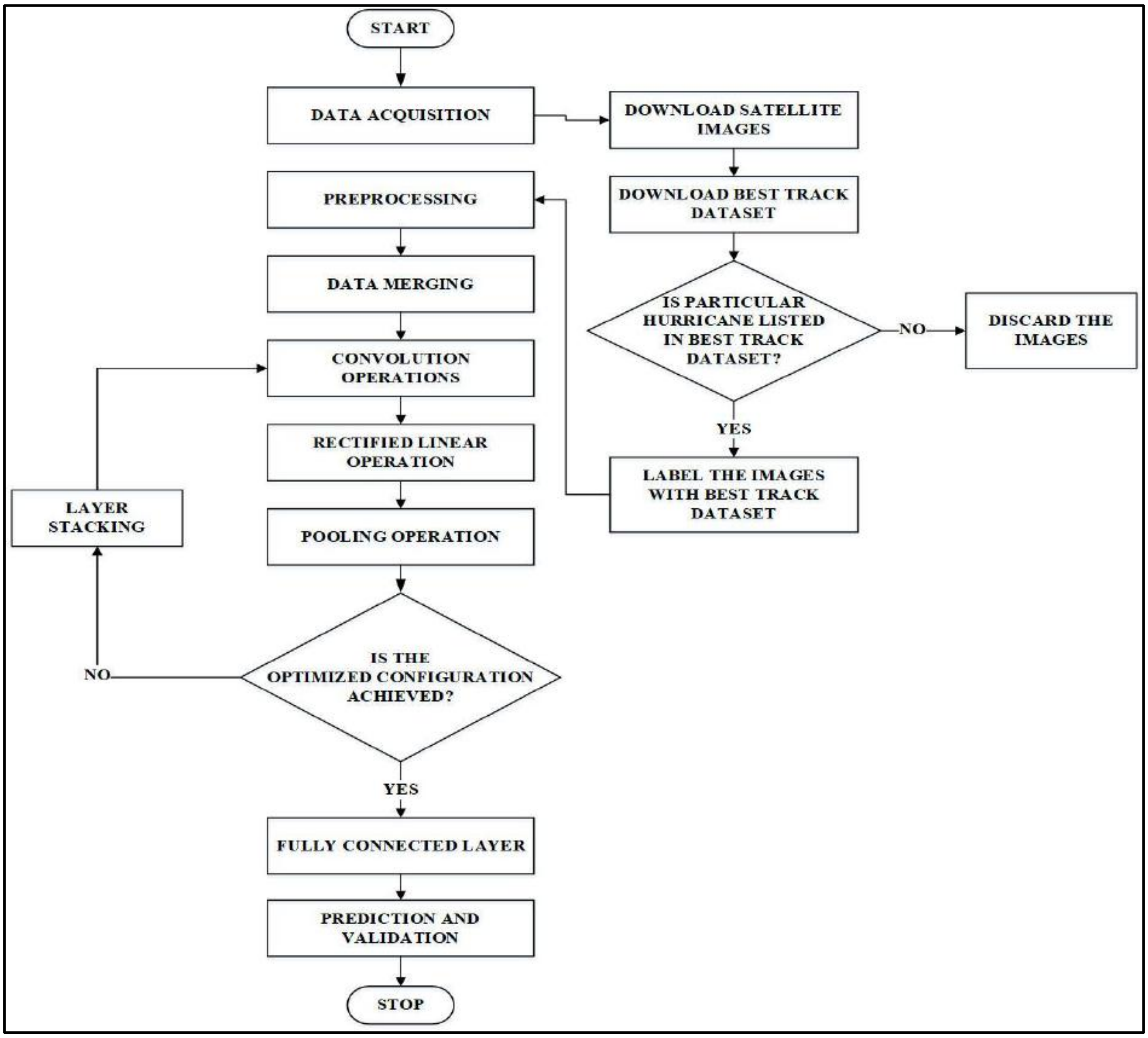
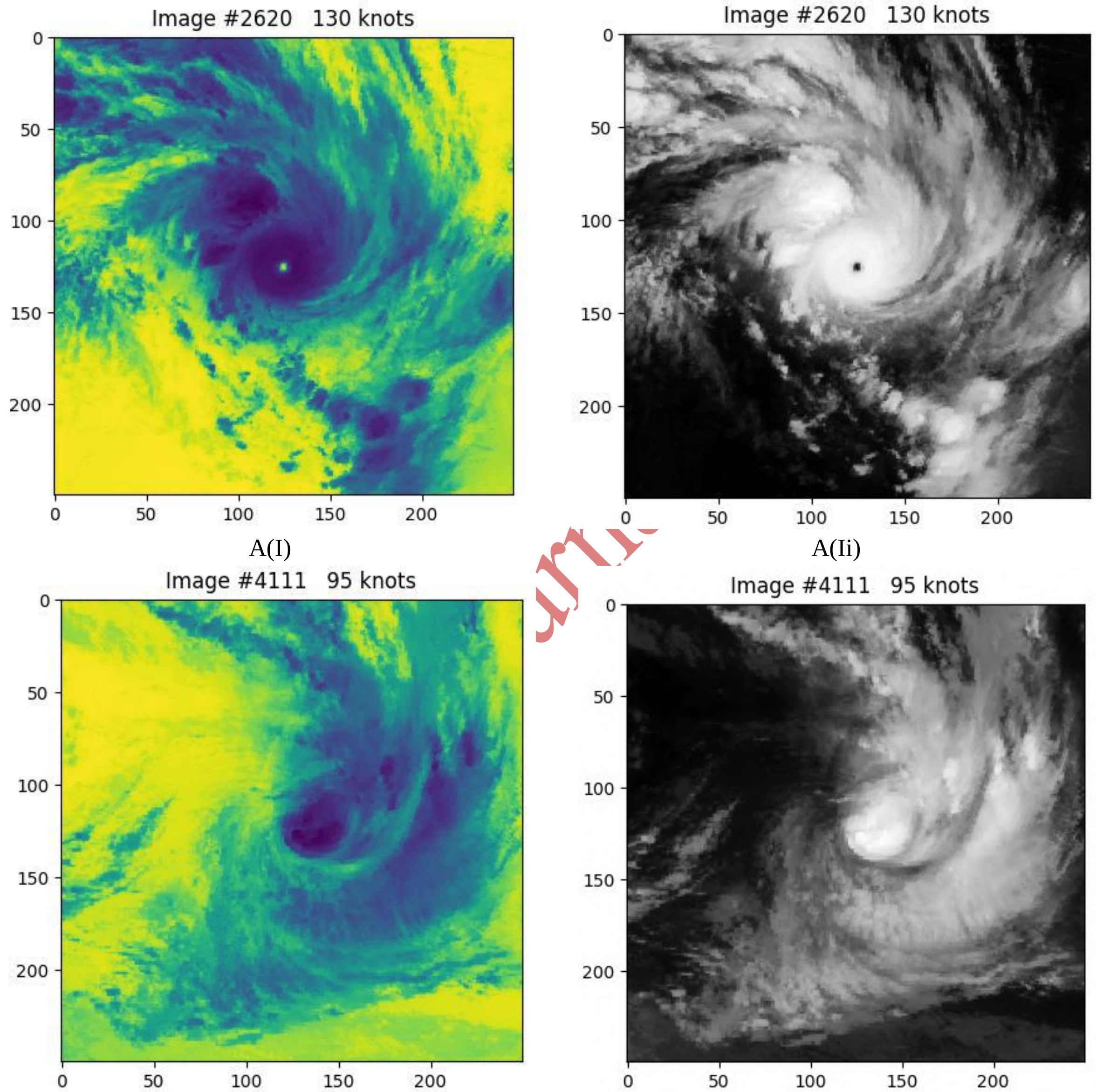


Figure 2: Flowchart for cnn

3.1 Extracting the Dataset

In the present study, two datasets were used for predicting the intensity of the cyclone. The first datasets are satellite imagery obtained from hursat - b1.the satellite imagery are downloaded from noaa's national centers for environmental information (ncei) archive and nasa’s website for the year 2016 to 2020. The net cdf library is used to read the downloaded dataset. The advantages of using this dataset is that the center of each hurricane was in the middle of each image. On the other hand, the second dataset are the best track data from the hurdat2 database provided by the national hurricane center. 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 are shown in figure 2.



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B(I) B(Ii)

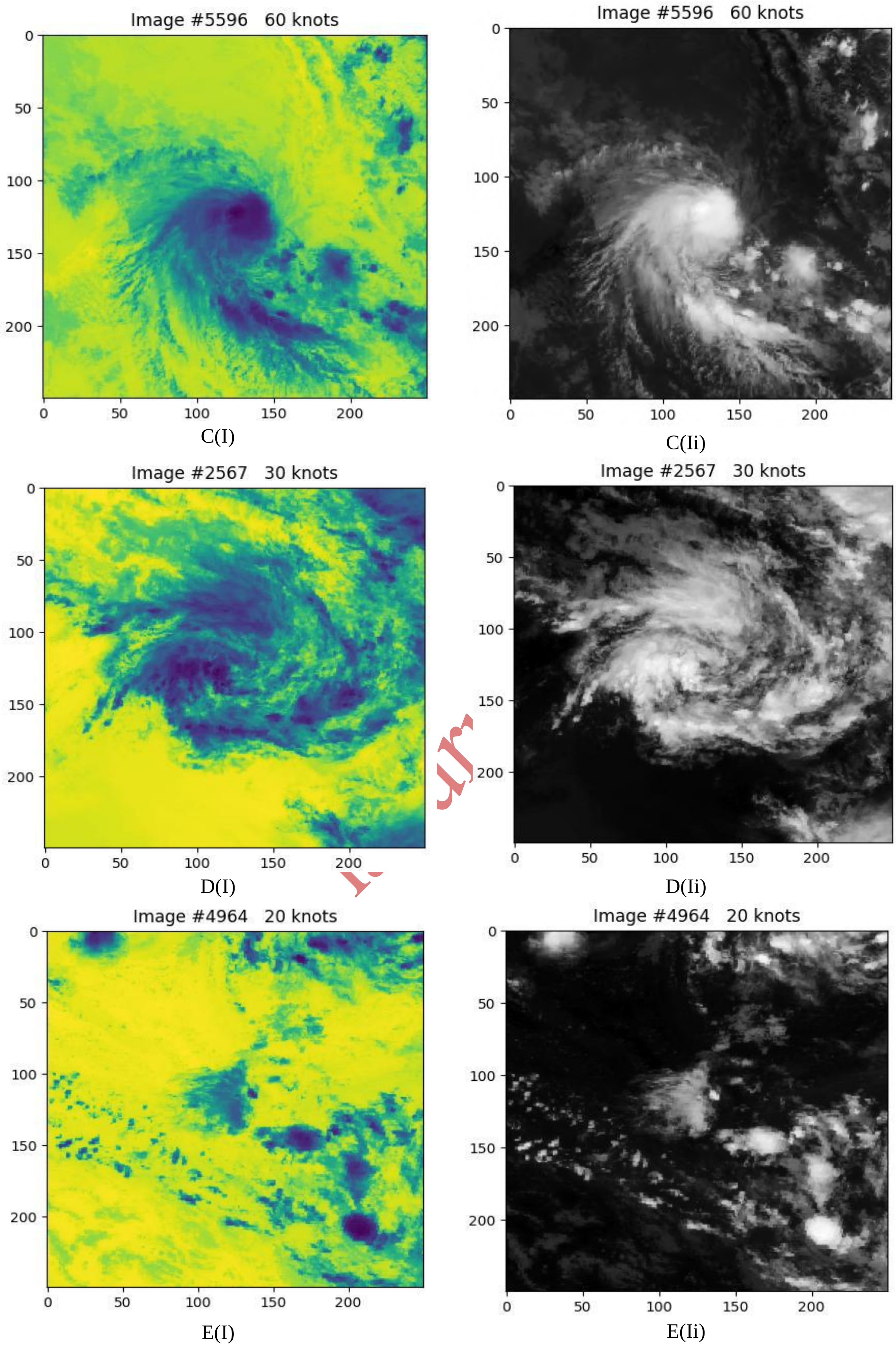


Figure 3: Visualization Of Hurricane Number A. 2620, B. 4111, C. 5596, D. 2567 And E. 4964along With Their Binary Images

From figure 3 it is observed that higher the maximum wind speed the size of the hurricane increases. In this study the size of the tropical cyclone is mapped with the tci.

3.2. Preprocessing 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 net cdf library and converted to array by numpy library. The images are cropped to a 50-by-50-pixel square at the center. Specimen of a cropped image is shown in figure 4.

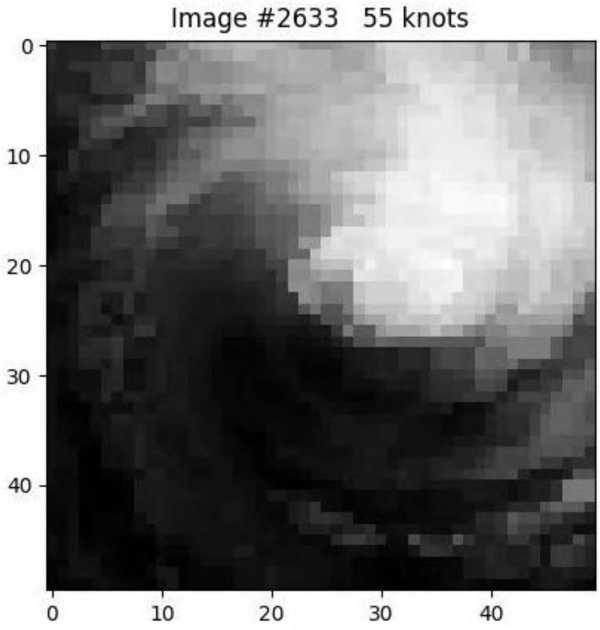


Figure 4: Visualization Of A Crop Image

3.3. Merging Of The Two Datasets

This Step Is Carried Out In Order To Merge The Dataset Of Hursat And Hurdat2 Satellite Images With Their Wind Speed. This Effectively Labels The Satellite Image With Its Wind Speed. Each Satellite Image File Provides With The Name Of The Hurricane, As Well As The Time And Date Of The Satellite Image. However, It Does Not Provide With The Wind Speed Of The Hurricane At That Time. Therefore The Best Track Dataset Is Used To Search For The Hurricane's Name With Date, Time, Latitude, Longitude, Maximum Wind Speed And Pressure.

3.4. Convolution Layer

During The Convolutional Part, The Network Extracts The Essential Features Of The Image And Excludes Irrelevant Noise. It Preserves The Relationship Between Pixels By Learning Image Features Using Small Squares Of Input Data. The Layer Contains N Filters Which Are Small In Size. These Filters Are Convoluted With The Input Image Matrix By Sliding The Filter Slide Through The Width And Height Of The Image. Firstly, The Feature Matrix Is Multiplied Pixel By Pixel With The Selected Square From The Image. Then The Values Are Added And Finally Divided By The Total Number Of Pixels. The Obtained Value Is Inserted In A New Matrix. This Process Helps To Reduce The Image Without Loss Of Any Feature. Representation Of The Filter Matrix Is Shown In Figure 4

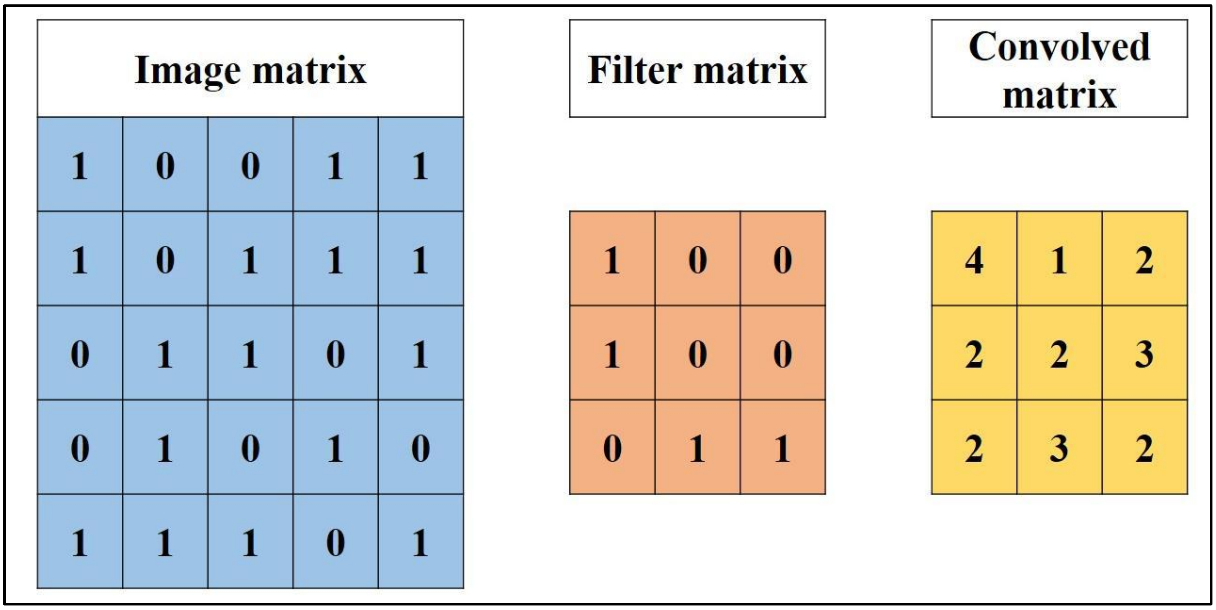


Figure 5: Representation Of The Filter Matrix

3.5. Rectified Linear Unit Layer

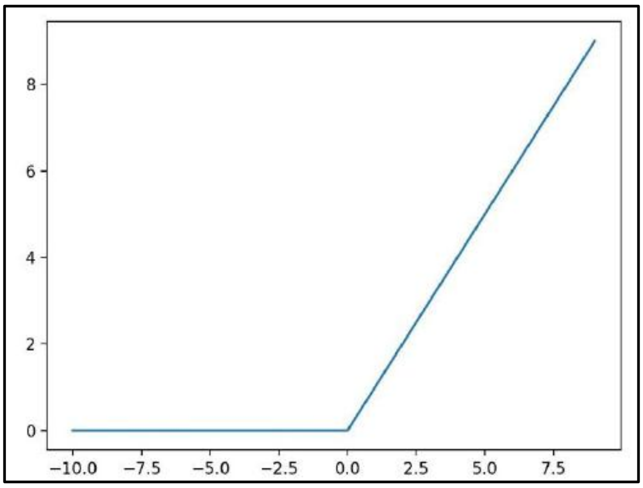


Figure 6: Graphical Representation Of Relu

In Rectified Linear Unit Layer (Relu), 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. Graphical Representation Of Relu Is Shown In Figure 6.

3.6. Pooling Layer

The Pooling Layer Compresses The Dimension Of The Input Image. A Filter Is Selected It Is Applied To The Dimension Matrix Obtained From The Convolution Layer. The Maxpooling Operation Selects The Maximum Element From The Region Of The Feature Map Covered By The Filter.

3.7. Layer Stacking

In Layer Stacking Operation, The Convolution Layer, Relu Layer And The Pooling Is Stacked And Repeated Until The Output Obtained Is A Minimized Matrix Of The Input Image.

3.8. Fully Connected Layer

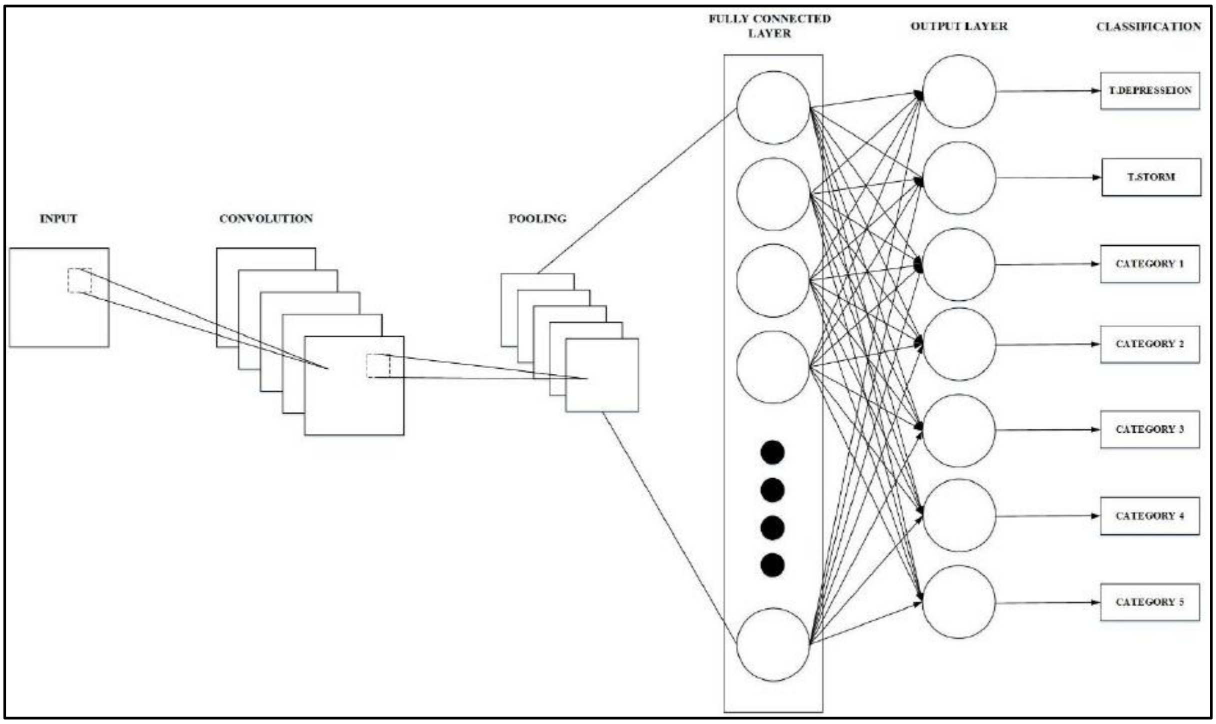


Figure 7: Diagrammatical Representation Of The Cnn Used In This Study

This Is The Last Layer Of A Cnn. The Fully Connected (Fc) Layer Consists Of Some Neurons That Are Fully Connected With The Neurons From The Previous Layers. The Fc Layer Predicts The Output Or The Label Of The Input Class. In Case Of Multi-Class Problems, Different Activation Functions Used Classify The Label Of The Inputs. In This Study, Softmax Activation Function Is Used To Classify The Label.Hence, It Has An Output Dimension Of [1x1xm] Where M Is The Number Of Classes Or Labels Used For Classification. Figure 7 Shows The Diagrammatical Representation Of The Cnn Used For Predicting The Intensity Of The Cyclone.

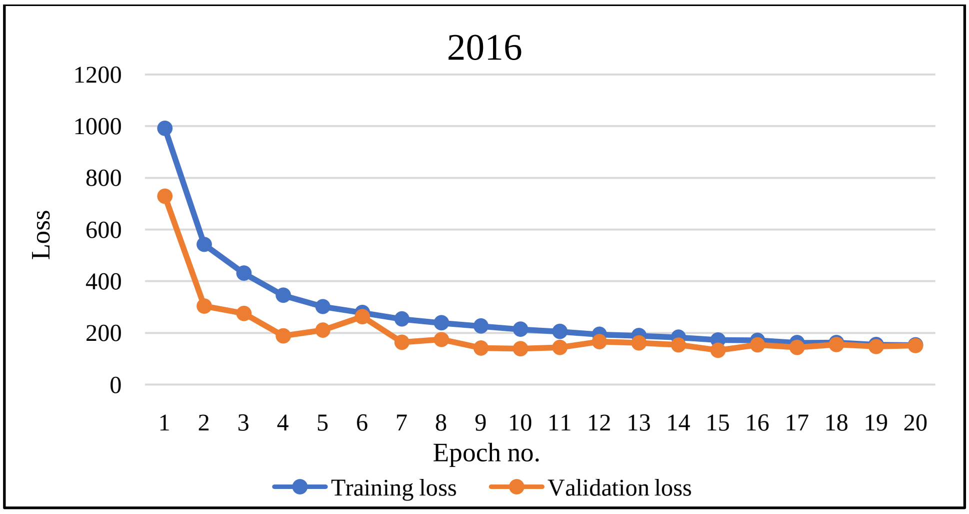
4. Result And Discussions

The Cnn Program Is Coded In Python 3.8 And Ran On A 64-Bit Windows 10 System With 8gb Ram And I5, 1.6ghz Processor. The List Of The Different Libraries Imported For Running The Code Are Given In Table 2.

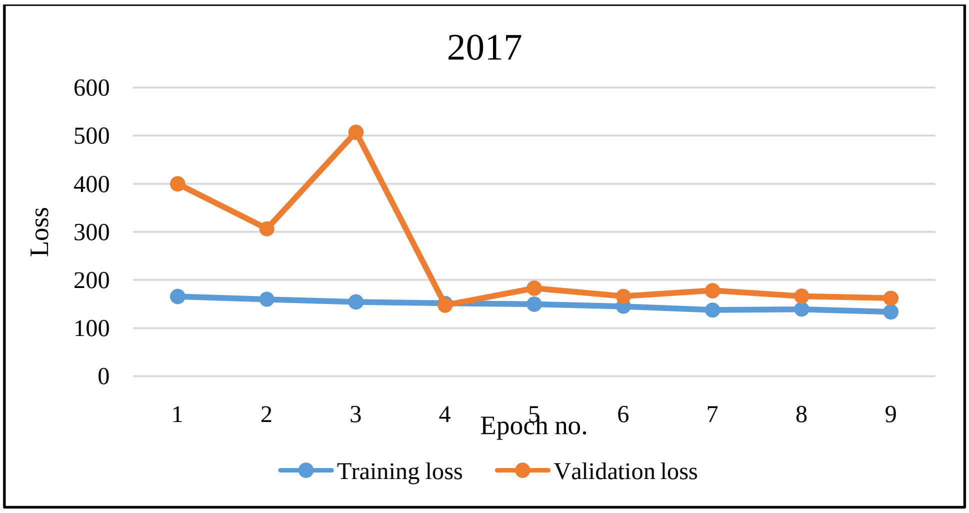
Table 2: Different Libraries Imported

Sl. No.	Library Imported	Usefulness
1	Requests	It Is An Apache2 Licensed Http Library.
2	Tarfile	Used To Read Tar Archives
3	Beautiful Soup	Used To Read Xml And Html Files.
4	Os	Used For Creating And Removing Directory And Fetching It Contents
5	Pandas	Used For Data Analysis
6	Numpy	Used For Array Operations
7	Netcdf4	Used For Reading The Satellite Imagery
8	Tensorflow	Used For Deep Learning
9	Keras	Used As A Backend For Tensorflow
10	Seaborn	Used For Making Statistical Graphics

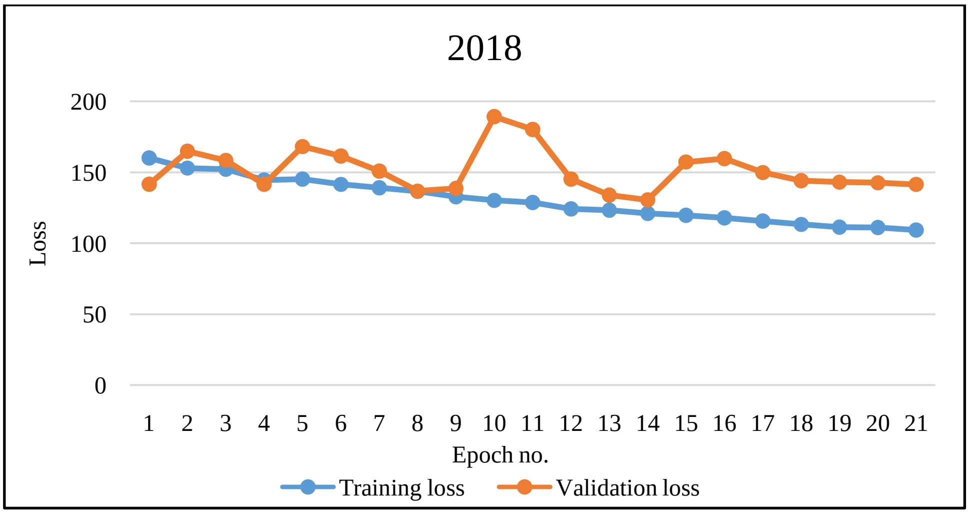
Rmsprop Optimizer Is Used To Get The Optimized Cnn Model Configuration. The Performance Of The Cnn Is Measured By Computing The Loss As Computed By Mean Square Error (Mse). The Loss Graphs For The Training And Validation Data Are Shown In Figure 8. In Case The Mse Value Computed For Training At Two Consecutive Epochs Is More Than The Previous Cases Then The Network Stops Further Training.



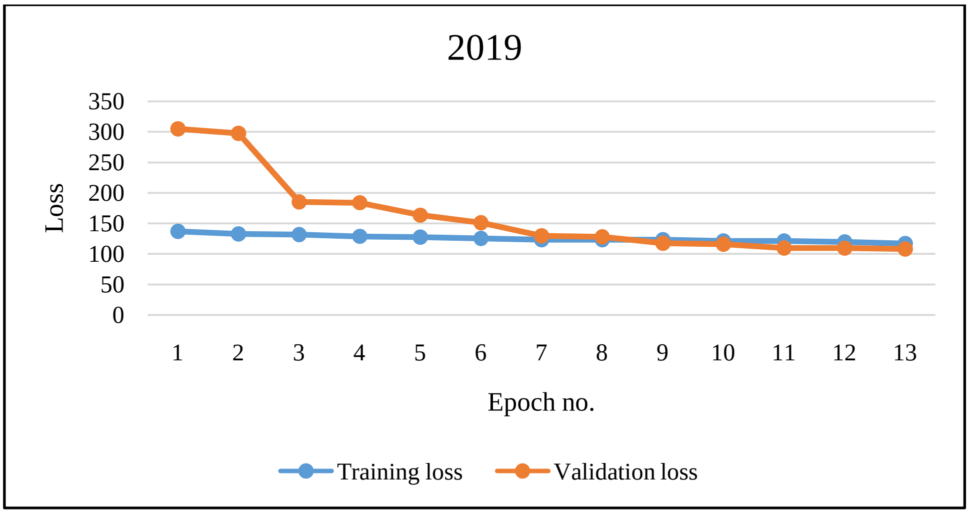
(A)



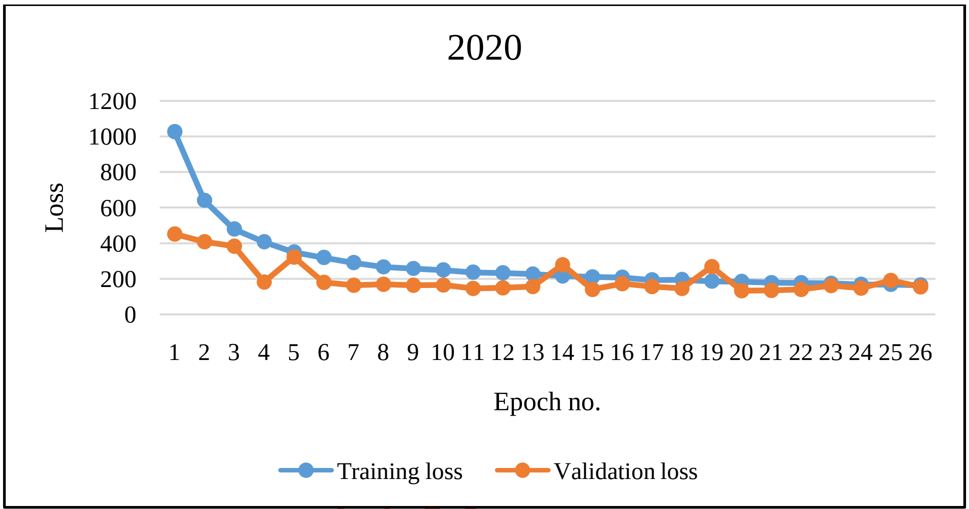
(B)



(C)



(D)



(E)

Figure 8: Training And Validation Loss Of The Dataset For The Year (A) 2016, (B) 2017, (C) 2018, (D) 2019 And (E) 2020

The Absolute Error Distribution And The Median Error Distribution Is Shown In Figure 9 And 10. From The Absolute Error Distribution It Is Observed That There Is High Probability Of Prediction Error For The Depression Category Of Cyclones. The Lesser The Number Of Samples Tested The Lesser Is Probability Of Prediction Error. From Figure 10, It Is Observed That The Cyclones Category With More Number Of Samples Are Less Likely To Have More Variations For Absolute Error Calculations.

In Order To Validate The Cnn Model, Satellite Imagery Of 10 Tropical Cyclones Are Given As Input And The Value Of The Predicted Intensity Is Compared With The Actual Output. The Mean Absolute Error And Root Mean Square Error Computed For The 10 Satellite Imageries Is 8.42knots And 11.14 Knots Respectively.

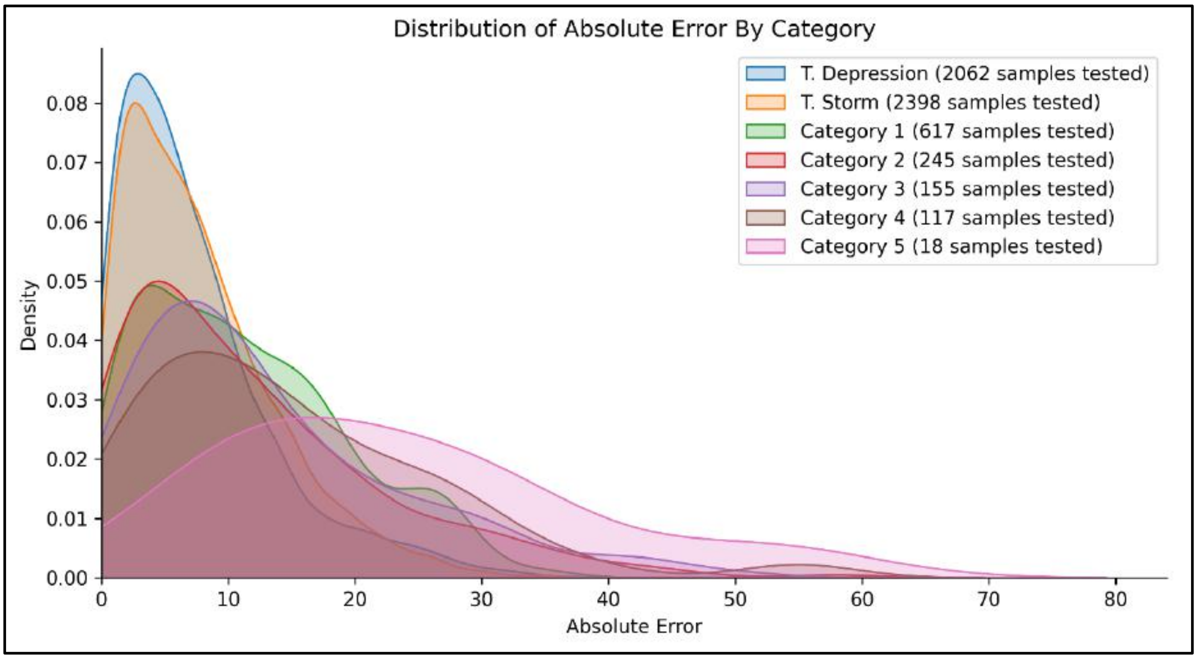


Figure 9: Absolute Error Distribution By Category

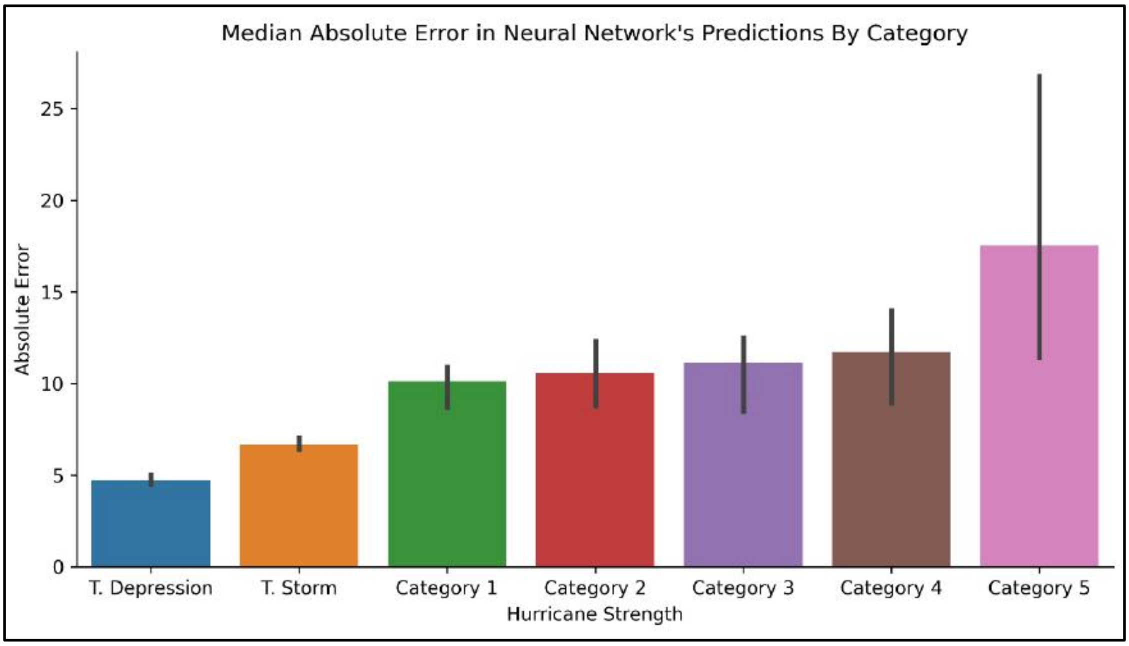


Figure 10: Median Absolute Error By Category

5. Conclusions

The comprehensive intention of the present study is to predict the intensity of the cyclones from the satellite imagery. Although many researchers have developed many techniques, yet there are a few scientist who are working on implementation of unsupervised machine learning algorithms to attain the desired objectives. In this paper, cnn is applied for the same. The dataset for the cnn model is obtained from satellite images of hursat - b1 and hurdat2. The satellite images does not provide with the wind speed and pressure. The size of a tropical cyclone matches varies with the wind speed. Therefore, best track dataset is downloaded which consists of the wind speed and pressure details of the cyclones till 2020. The satellites are labelled with the best track dataset and only those images are considered whose details are available in the best track dataset and remaining are discarded. The performance of the cnn model is measured by computing the mse value. With increase in training the mse value is decreased. In order to validate the cnn model, it is tested with pictures of 10 different tropical cyclones and the mean absolute error and root mean square error computed is 8.42 knots and 11.14 knots respectively which is well within the acceptable range. This paper provides better knowledge for further implementation of cnn to estimate the intensity of tropical cyclones even in the real-time.

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