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# DEEP-LEARNING BASED CYCLONE INTENSITY ESTIMATION


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**PROJECT GUIDE:-**

PROF. SEEMA PATIL

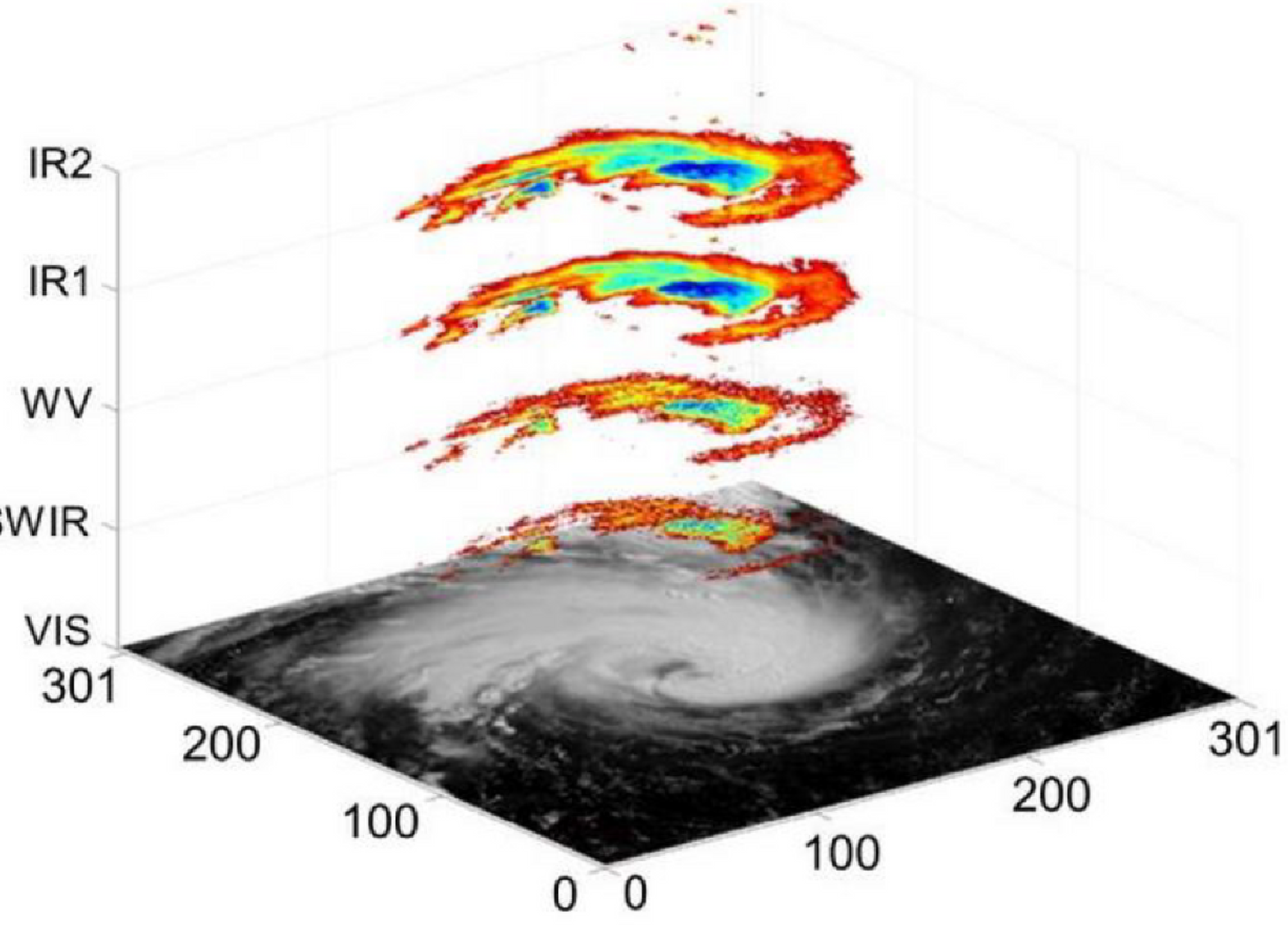

NUMBER OF TIME STUDENTS MET THE PROJECT GUIDE :

4

ARE THE SLIDES APPROVED BY PROJECT GUIDE YES/NO :

**YES**

# INTRODUCTION




- Cyclones are a natural disaster that can cause severe damage and loss of life. Early prediction of cyclone intensity can help in mitigating the impact of such disasters.

- In recent years, deep learning has emerged as a promising approach for image processing and analysis. In this study, a deep learning based approach for cyclone intensity estimation using imagery dataset is proposed. The model will be trained on a large dataset of historical cyclones and validated on a new cyclone data.

- The proposed approach has the potential to improve early warning systems for cyclones and reduce the risk of damage and loss of life caused by these natural disasters. The accurate and reliable prediction of cyclone intensity can help in taking timely and effective measures to evacuate people and protect property.

# LITERATURE SURVEY

| Sr.no | Publication Title | Publication Year | Key Findings of the paper | Gaps in Publication Work |
|---|---|---|---|---|
| 1 | Deepti: Deep Learning-based Tropical Cyclone Intensity Estimation System<br>Manil Maskey, Rahul Ramachandran, Muthukumaran Ramasubramanian, Iksha Gurung, Brian Freitag, Aaron Kaulfus, Drew Bollinger, Dan Cecil, JJ Miller<br>IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing | 2020 | The authors of this paper introduced a wind speed estimation system for tropical cyclones that relies on end-to-end deep learning and can operate in real-time. The system involved creating a new convolutional neural network model that can objectively estimate wind speed using only satellite images. The model underwent rigorous evaluation and was smoothly integrated into production by comparing its features to Dvorak T-number images. Additionally, the paper describes a new approach for detecting new storms and initiating the workflow to provide real-time wind speed estimates through a situational awareness portal. | Passive microwave data to estimate wind speed for tropical cyclones at lower intensity can be used. In addition, a detailed analysis of a particular storm to understand model performance with storm structural changes during rapid intensification can be done. |

# LITERATURE SURVEY

| Sr.no | Publication Title | Publication Year | Key Findings of the paper | Gaps in Publication Work |
|---|---|---|---|---|
| 2 | Estimating Tropical Cyclone Intensity from Infrared Image Data Miguel F. Piñeros, Elizabeth A. Ritchie and J. Scott Tyo Journal Paper | 2011 | The study presented the outcomes of an objective method for estimating the intensity of tropical cyclones in the North Atlantic Ocean basin using near-real-time satellite infrared imagery. The method quantified the degree of organization or axis symmetry of the infrared cloud pattern of a tropical cyclone as a proxy for its maximum wind speed.The researchers used a total of 78 tropical cyclones occurring during the 2004-09 seasons to both train and test the intensity estimation technique. The study conducted two separate tests to evaluate the accuracy of the method in estimating the intensity of tropical cyclones. | The physical processes behind the robustness of the DAV–intensity relationship can be studied using the high-resolution simulation output to understand better, and thus improve, the DAV–intensity relationship for intensity estimation. |

# LITERATURE SURVEY

| Sr.no | Publication Title | Publication Year | Key Findings of the paper | Gaps in Publication Work |
|---|---|---|---|---|
| 3 | Tropical Cyclone Intensity Estimation Using a Deep Convolutional Neural Network<br>Ritesh Pradhan , Ramazan S. Aygun,Manil Maskey, Rahul Ramachandran, Senior, and Daniel J. Cecil<br>Journal Paper | 2018 | The paper introduced a dependable and strong method for estimating tropical cyclone intensity using a deep convolutional neural network. The network consisted of several convolutional and fully connected layers, incorporating regularization techniques to effectively extract complex features from hurricane images. Through the use of satellite images alone, their model achieved superior accuracy and lower root-mean-square error compared to 'state-of-the-art' techniques. | Tweaking the parameters like regularization and learning rate for further optimization might improve the accuracy. |

# LITERATURE SURVEY

| Sr.no | Publication Title | Publication Year | Key Findings of the paper | Gaps in Publication Work |
|---|---|---|---|---|
| 4 | Tropical Cyclone Intensity Estimation Using Multi-Dimensional Convolutional Neural Networks from Geostationary Satellite Data<br>Lee, Juhyun & Im, Jungho & Cha, Dong-Hyun & Park, Haemi & Sim, Seongmun<br>Journal Paper | 2019 | In this study, a convolutional neural network (CNN) was utilized to estimate tropical cyclone (TC) intensity by analyzing satellite images. Both two-dimensional (2D) and three-dimensional (3D) CNNs were employed to investigate the relationship between multi-spectral geostationary satellite images and TC intensity. The optimized model yielded a root mean squared error (RMSE) of 8.32 kts, outperforming the existing model by approximately 35%. Furthermore, a heat map was used to visualize the characteristics of multi-spectral satellite-based TC images according to intensity. | Hyper-parameter-optimization of the 3D-CNN model using cost-effective approaches (e.g., auto-parameterization tools such as AutoKeras and Keras-tuner) can be conducted. |

# LITERATURE SURVEY

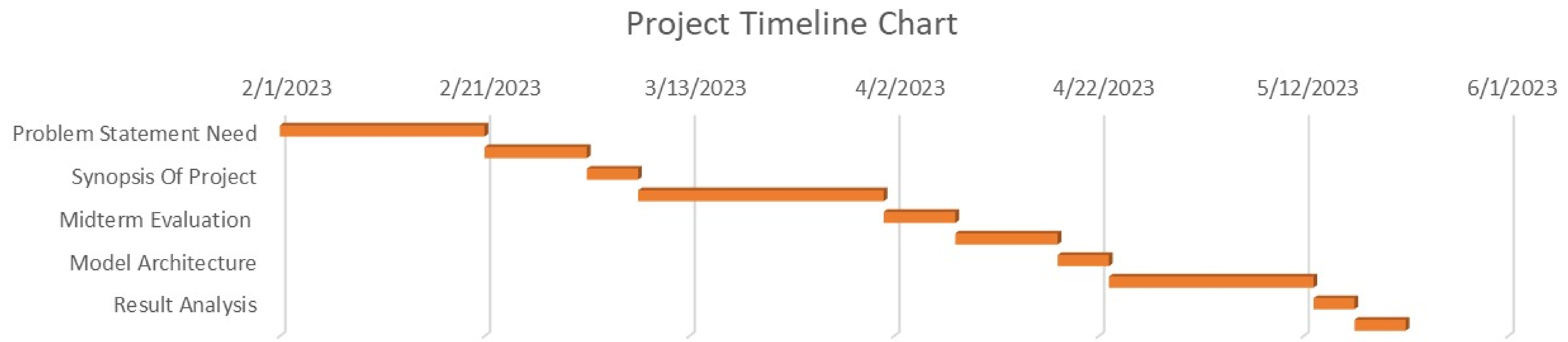
| Sr.no | Publication Title | Publication Year | Key Findings of the paper | Gaps in Publication Work |
|---|---|---|---|---|
| 5 | Tropical Cyclone Intensity Classification and Estimation Using Infrared Satellite Images With Deep Learning Chang-Jiang Zhang , Xiao-Jie Wang, Lei-Ming Ma , and Xiao-Qin Lu Journal Paper | 2019 | The study proposed a model that consisted of two CNN network modules: a TC intensity classification (TCIC) module and a TC intensity estimation (TCIE) module. First, the TCIC module was utilized to categorize TC intensity into three groups using infrared satellite images. Next, three TCIE models based on the CNN regression network were presented, which combined different types of infrared satellite images with the TC best track data. . A total of 1001 TCs from 1981 to 2019 were used to verify the proposed TCICENet model. The model achieved the best performance with an image size of 170x170 pixels. | The training dataset can be expanded in order to enhance the generalization ability and robustness of the TC intensity estimation model. |

# RESEARCH GAPS

The following research gaps were found while doing the literature survey:

- Limited use of image dataset in cyclone prediction.
- Limited research on the use of deep learning for cyclone prediction - potentially improve the RMSE and MAE.
- Image augmentation can be used to increases training data and has the potential to improve model performance.

# PROJECT TIMELINE

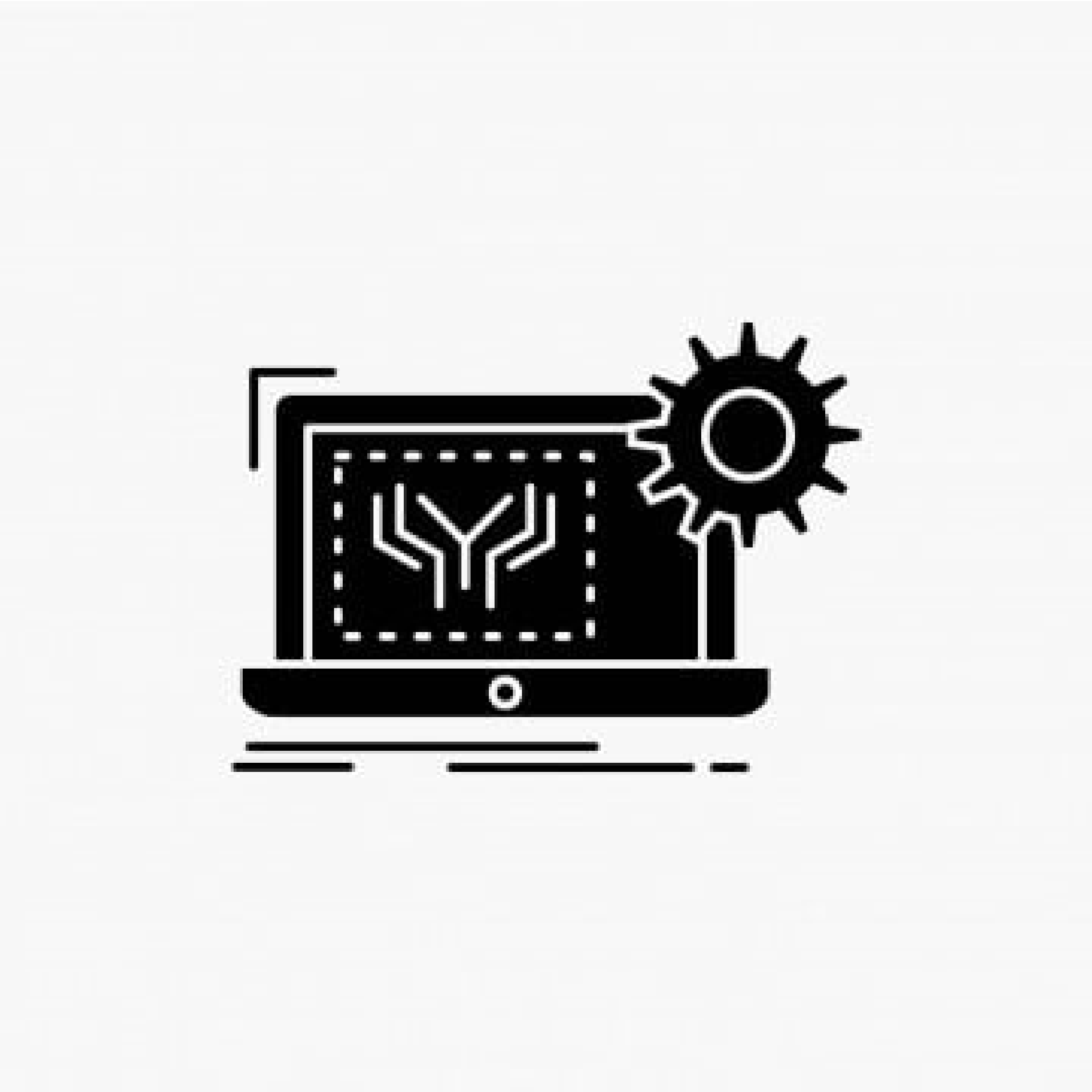



| | End Term Evaluation | Result Analysis | Development | Model Architecture | Data Cleaning | Midterm Evaluation | Dataset Collection | Synopsis Of Project | Literature Survey and Gaps | Problem Statement Need |
|---|---|---|---|---|---|---|---|---|---|---|
| Start_Date | 5/17/2023 | 5/13/2023 | 4/23/2023 | 4/18/2023 | 4/8/2023 | 4/1/2023 | 3/8/2023 | 3/3/2023 | 2/21/2023 | 2/1/2023 |
| Days_to_complete | 5 | 4 | 20 | 5 | 10 | 7 | 24 | 5 | 10 | 20 |

# Objectives

- To develop a deep learning model that can accurately estimate the intensity of cyclones using satellite imagery datasets.
- To explore various deep learning algorithms and identify the most suitable one for the task of cyclone intensity estimation.
- To collect and preprocess a large dataset of satellite images of cyclones with corresponding intensity labels for training and testing the model.
- To train and optimize the deep learning model using the prepared dataset, and validate the model's performance on a separate test dataset.
- To analyze the accuracy and reliability of the developed model, and suggest potential improvements for future research in this area.
- To present the findings of the project in a clear and concise manner, including visualizations and statistics to support the results.

# REQUIREMENTS

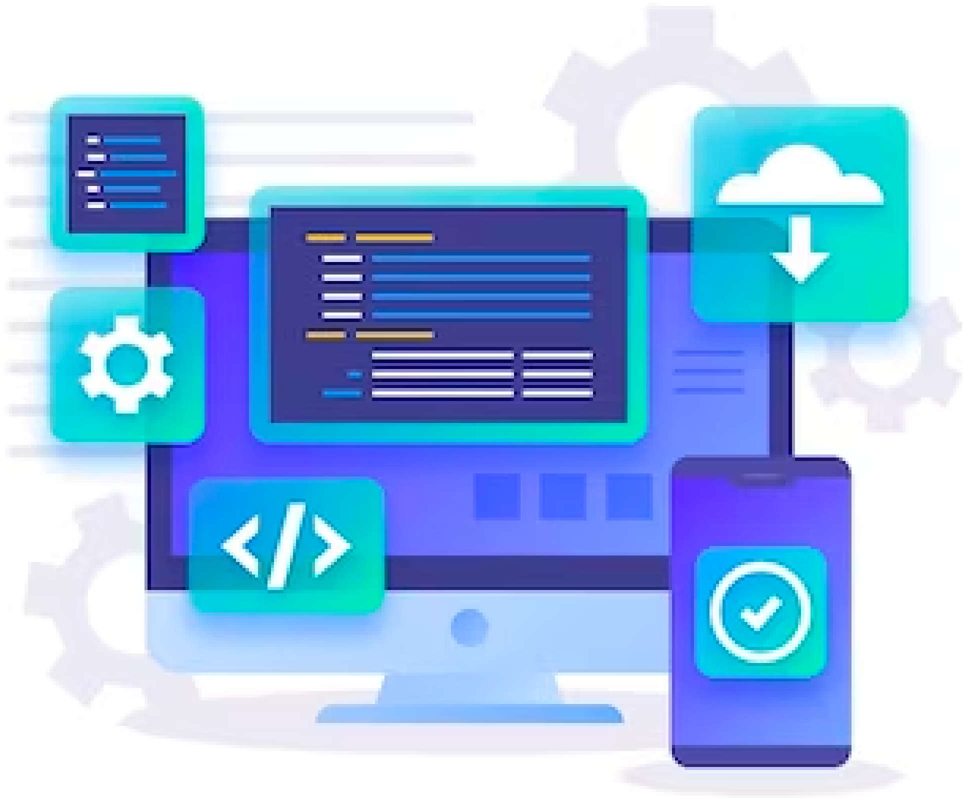


## HARDWARE:

- A mid-range or high-end GPU is commonly advised for deep learning model training.
- 8 GB or more of RAM is needed, although larger datasets and more complicated models might demand for more.
- Given the size of some deep learning datasets, it is advised to have a 5 GB of storage minimum.

# REQUIREMENTS

## SOFTWARE:



- For the model to be created and trained, a deep learning framework is required. The well-known frameworks are TensorFlow, PyTorch, and Keras.

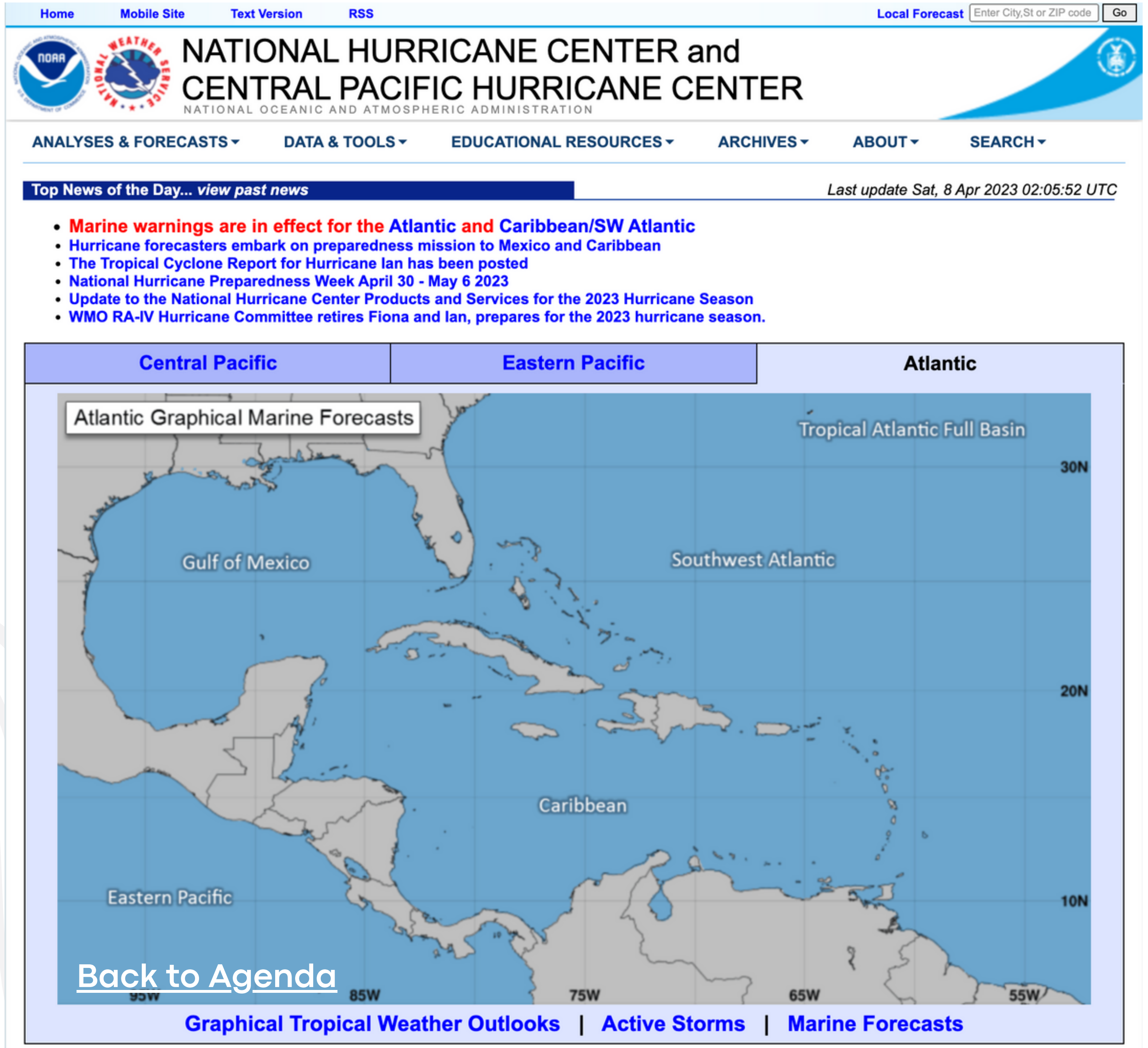
- Python is commonly used to program deep learning models, therefore familiarity with the language is necessary.

- Images can be pre-processed and made ready for training using libraries like OpenCV or Pillow.

- The writing and testing of the code require a development environment. Integrated development environments (IDEs) like Google Colab or Microsoft Studio Code are frequently used, as well as Jupyter Notebook.

- Data management and visualization are made easier by the usage of libraries like NumPy, Pandas, and Matplotlib.

# DATA GATHERING




[Back to Agenda]

- Images of cyclones from the HURSAT data project run by the National Centers for Environmental Information. This database contains satellite images of cyclones in NetCDF file format.
- The database aligns the center of each cyclone with the center of its corresponding image.
- Data from the HURDAT2 database provided by the National Hurricane Center. It contains records of all known cyclones in the Atlantic and Pacific basins, as well as their wind speeds at 6-hour intervals.

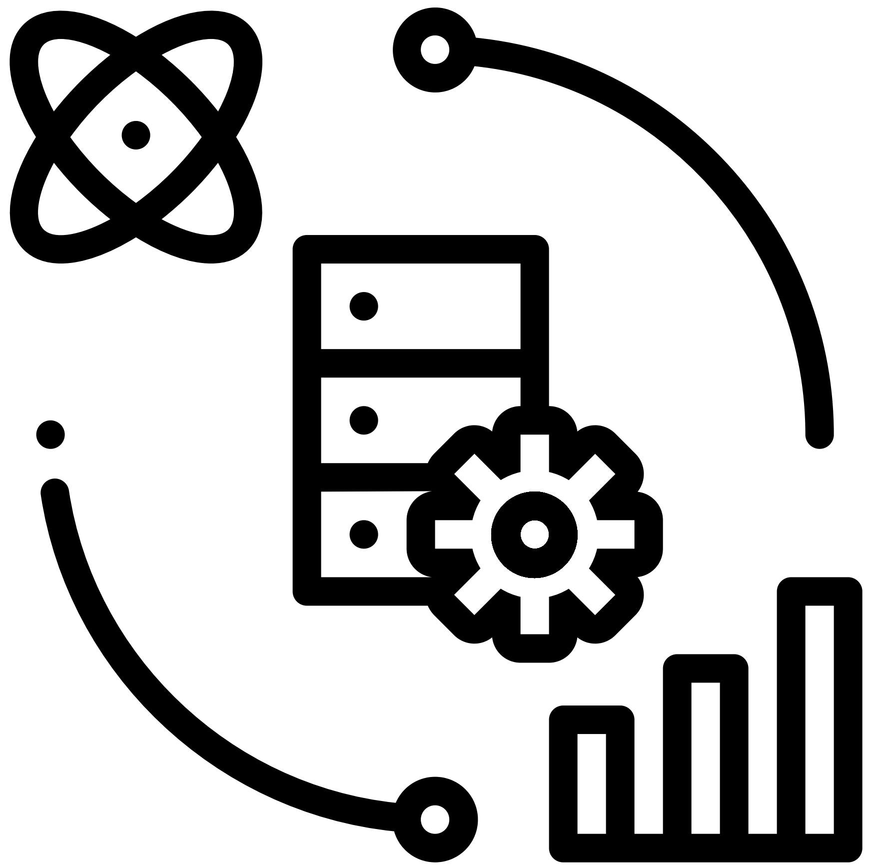
# DATA GATHERING

- The National Hurricane Center's HURDAT2 database provides numerical data on cyclones, including time, latitude, longitude, and wind speed, in the form of best track data.

- Data scraping is employed to extract cyclone imaging data from the HURSAT project, specifically targeting cyclones in the Atlantic and Pacific basins with wind speed and position records in the National Hurricane Center's Best Track dataset.

- The wind speeds are categorized as follows:
- ≤33: T. Depression
- 34-64: T. Storm
- 65-83: Category 1
- 84-95: Category 2
- 96-113: Category 3
- 114-134: Category 4

# DATA PREPROCESSING



- Reading and processing the cyclone dataset: Critical for ensuring data suitability for analysis.
- Data loading: Information on cyclones is loaded from image and label databases.
- Dataset subdivision: Dividing the dataset into subsets facilitates model evaluation, with k-fold cross-validation being employed.
- Image augmentation option: Provided to enhance the dataset by generating new images and labels for each subset using augmentation techniques. It increases training data and has the potential to improve model performance.
- Set formation: Subsets are joined to create sets for model iterations.

# Model Training

## 01

- Three convolutional layers
- Fully connected neural network
- Grayscale image input with a resolution of 50x50 pixels

## 02

- First layer: 32 filters of size 3x3 with ReLU activation
- Max-pooling layer with a pool size of 2x2
- Second layer: 64 filters of size 3x3 with ReLU activation
- Another max-pooling layer with the same pool size
- Final layer: 64 filters of size 3x3 with ReLU activation

## 03

- Dropout layer with a dropout rate of 0.5 to prevent overfitting
- Two dense layers with ReLU activation
- Output layer with a single neuron for continuous value prediction

## 04

- RMSprop optimizer used for model optimization
- Mean squared error loss function

## 05

- Mean absolute error
- Root mean squared error

## 06

- Benefits of the CNN model constructed using Keras toolkit:
- Well-suited for predicting continuous values in grayscale photos

# RESULTS

- The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values for several folds are compared in the table below. The column in Table 1 lists the precise fold or subset of the data set that was utilized in the study's validation. The purpose of reporting both MAE and RMSE is to provide different perspectives on the performance of the prediction model.

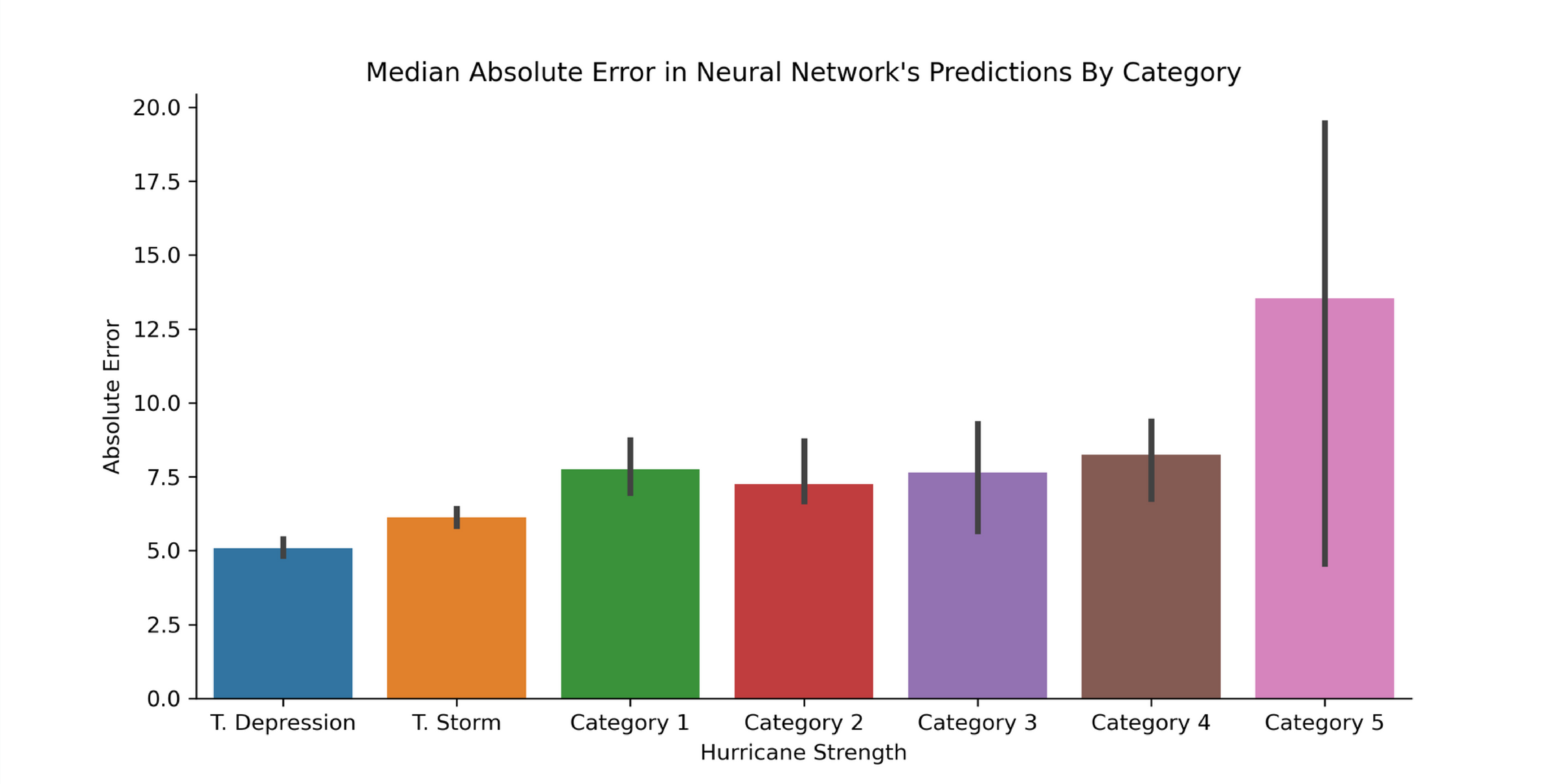
- The MAE over all folds for our cyclone intensity prediction model was 7.67 knots. In our situation, an MAE of 7.67 knots shows that, on average, the predictions of our model were 7.67 knots off from the actual cyclone strength estimates.

- The RMSE for our study was found to be 10.09 knots. A score of 10.09 knots indicates that, on average, our model's predictions were off by about 10.09 knots. The RMSE provides an indication of the typical forecast error.

# RESULTS

| Validation Fold | Mean Absolute Error | Root Mean Squared Error |
|---|---|---|
| Fold 1 | 8.669 knots | 11.089 knots |
| Fold 2 | 7.893 knots | 10.130 knots |
| Fold 3 | 7.809 knots | 10.042 knots |
| Fold 4 | 7.338 knots | 9.424 knots |
| Fold 5 | 7.170 knots | 9.242 knots |
| All folds | 7.67 knots | 10.09 knots |

# RESULTS IMAGES



# SYSTEM DIAGRAMS

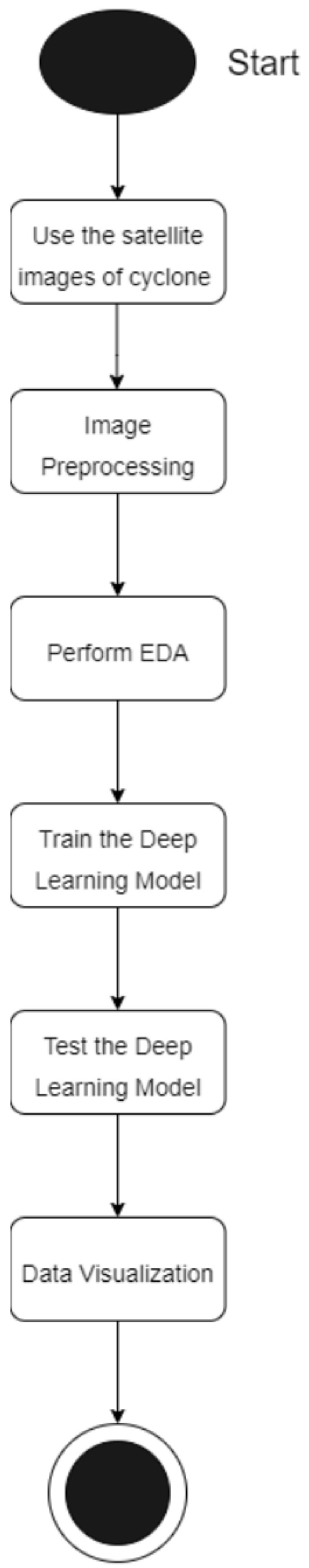
## 1.

## USE CASE DIAGRAM

# SYSTEM DIAGRAMS

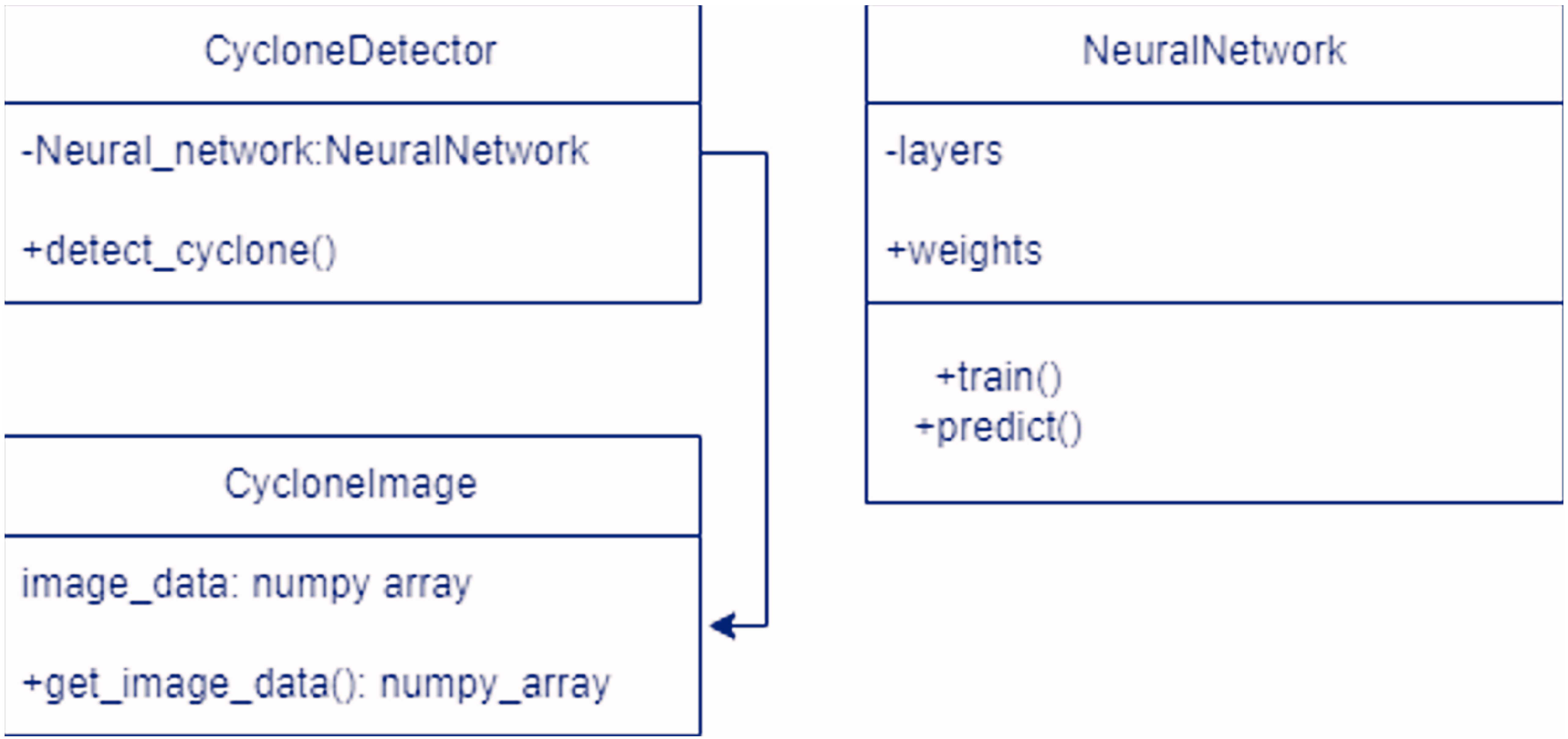
2.

## ACTIVITY DIAGRAM



# SYSTEM DIAGRAMS

## 3. CLASS DIAGRAM



# CONCLUSION

- Deep learning methods accurately estimate hurricane severity using satellite image sets.
- Convolutional Neural Networks (CNNs) play a crucial role in storm modeling applications.
- Early detection of intensifying hurricanes is enabled through effective data extraction from satellite imaging.
- Comprehensive measuring techniques (MAE, MSE, RMSE) verify the effectiveness of deep learning methods.
- Significance of deep learning methods in disaster management preparation is reinforced.

# FUTURE SCOPE

- Incorporate more sophisticated deep learning architectures (RNNs, attention mechanisms) to capture temporal relationships in sequential satellite images.
- Utilize additional data sources (oceanic, atmospheric) for more precise cyclone intensity estimation.
- Expand the study to include areas and basins beyond the Atlantic and Pacific for improved model generalizability.
- Combine real-time data streams to create an operational system for ongoing cyclone intensity monitoring and prediction.
- Enable prompt response and proactive mitigation techniques.

# PUBLICATION DETAILS

- We conducted a literature review of 20 papers, which included both conference and journal papers.
- The research paper has been finalized, encompassing the literature survey, methodology, conclusion, and future scope.
- Currently, we are actively seeking reputable journals or conferences for potential publication of our work.

# Thank You!