VISVESVARAYA TECHNOLOGICAL UNIVERSITY

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A Project Synopsis

On

" FLOOD DETECTION USING SATELLITE IMAGES AND MACHINE LEARNING"

Submitted for partial fulfillment of the requirement for the award of the Bachelor degree in Computer Science and Engineering during the year 2025-2026.

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2025-2026

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CERTIFICATE

This is to Certify that the project entitled "**FLOOD DETECTION USING SATELLITE IMAGES AND MACHINE LEARNING**" is a bonafied work carried out by **MADEGOWDA N** bearing USN **4CA22CS041** in partial fulfilment for the degree of 7th Semester, Bachelor of Engineering in Computer Science and Engineering of the Visvesvaraya Technological University, Belgaum during the year 2025- 2026. It is certified that all corrections or suggestions indicated for Internal Assessment have been incorporated on the report deposited in departmental library. This technical seminar report has been approved as it satisfies the academic requirements in respect of the technical seminar prescribed for the Bachelor of Engineering Degree.

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ACKNOWLEDGMENT

I'm grateful to the management of the **CAUVERY INSTITUTE OF TECHNOLOGY**, for providing us with the opportunity to carry out the project.

I have great pleasure in expressing deep sense of gratitude, to our principal **Dr. SRIKANTAPPA A S** for creating an excellent and technically sound environment in our Institution.

I'm extremely grateful to **Prof. RAKSHITHA B H, Asst. Professor & HOD,** Department of Computer Science and Engineering for her valuable suggestions and for helping me in completing my Project.

I would like to express my profound senseof gratitude to our guide **Prof. RAJANI K C, Asst Prof** Department of Computer Science and Engineering for the Valuable Suggestions and for helping me in completing our Project.

I'm extremely grateful to my project co-ordinator Prof**. RADHIKA K P, Asst. Prof,** Department of Computer Science and Engineering for her valuable suggestions and for helping me in completing my Project.

I thank all the teaching and non-teaching staff of Computer Science and Engineering department who has helped me on various occasions during the course of this work.

MADEGOWDA N

ABSTRACT

Tropical cyclones can bring minacious conditions such as flooding rain, high winds, inundation of low-lying coastal communities, and devastating storm surges For the purpose of managing and preventing disasters, it is essential to be able to precisely determine the type and severity of cyclones. The tropical cyclone (TC) examining strategy has been consistently improved since the initial approach put forth by Dvorak in the 1970s, both for forecasting and operational analysis of tropical storm intensity. This project proposes a method for the classification and intensity estimation of tropical cyclones using image processing and convolutional neural networks (CNNs). The proposed method uses satellite images of tropical cyclones to extract features such as cloud patterns and shapes. This study uses image processing-based methodology to categorize and gauge the strength of tropical cyclones (TCs) using a convolutional neural network (CNN). The model which has been proposed consists of two models: a TC intensity classification model and a TC intensity estimation model. The outcome of this study can provide a few scientific backing for initiatives aimed at averting catastrophic tropical cyclone events.

CHAPTER 1

INTRODUCTION

Tropical cyclones are dangerous because they can bring strong winds, flooding rain, and destructive storm surges that can submerge low-lying coastal regions. Failure to forecast these cyclones could lead to more occurrences and create a warmer climate scenario. Therefore, it is crucial to improve cyclone prediction and estimate their impact.

Aircraft detection was first employed as a reliable method of keeping track of the location, intensity, and stage of development of TCs in the 1940s. The very first technique, known as the systematic approach, was developed by Dvorak and is still used as a basis in many operational centers. However, Dvorak's approach involves frequent human interactions and complicated decision rules for various physical and environmental conditions, which can limit its efficiency. The deviation-angle variance technique (DAVT) is another approach that has shown less accuracy and efficiency.

In contrast to the techniques, this project makes use of a CNN model in order to estimate the intensity of tropical cyclones (TCICENet) by making use of images from an infrared geostationary satellite. The TCICENet model takes on infrared satellite images as its input. This model comprised two modules, TC intensity classification(TCIC) module and the TC intensity estimation(TCIE) module, which performs a regression task for three TC categories.

Integration of IoT-Based Real-Time Flood Alert Subsystem

In addition to cyclone intensity estimation using image processing and deep learning techniques, the project has been enhanced with an IoT-based real-time flood alert subsystem. This subsystem uses a compact hardware model built using ESP8266 Wi-Fi module, a water-level sensor, a buzzer, and an LED indicator. The objective of integrating the IoT unit is to provide an early warning mechanism when sudden water level rise or localized flooding is detected.

The ESP8266 continuously monitors the sensor data and communicates with the cloud using MQTT protocol. When a predefined flood threshold is crossed, the system immediately sends an alert command to the hardware to activate the buzzer and LED, ensuring local on-ground

warning. Additionally, a parallel alert notification is pushed to a mobile application developed using Flutter, allowing remote users or authorities to receive alerts instantly.

This integration ensures that along with large-scale cyclone prediction, localized flood events can also be detected and reported in real time, thereby improving overall disaster response capability.

1.1 Motivation

Tropical cyclones, also known as hurricanes or typhoons, can cause significant damage and loss of life when they make landfall, making accurate classification and intensity estimation critical for disaster preparedness and response. Currently, tropical cyclones are classified and their intensities estimated based on satellite imagery, which requires human analysis and interpretation. This process can be time-consuming and prone to error, particularly in areas with limited access to trained meteorologists. By developing an automated system that can accurately classify and estimate the intensity of tropical cyclones, we can improve our ability to respond to these natural disasters and potentially save lives.

1.2 Aim of our Project

The aim of the project is to develop a system that can automatically classify and estimate the intensity of tropical cyclones using image processing techniques and convolutional neural networks (CNNs). The specific objectives of the project may include:

- Collecting and preprocessing satellite imagery data of tropical cyclones
- Designing and training a CNN model to classify tropical cyclones into different categories (such as tropical depression, tropical storm, hurricane, etc.)
- Designing and training a CNN model to estimate the intensity of tropical cyclones
- Evaluating the performance of the developed models on a test dataset and comparing it with existing methods
- Developing a user-friendly interface for the system to allow easy access for meteorologists and disaster response personnel

1.3 Need for the proposed system

The need for the proposed system arises from the fact that accurate classification and intensity estimation of tropical cyclones is crucial for disaster management and response. The current methods of classification and intensity estimation rely heavily on human interpretation of satellite imagery, which can be time-consuming and prone to errors.

CHAPTER 2

LITERATURE SURVEY

[1] "Tropical Cyclone Risk Assessment on Information Diffusion Theory" -Wangdi Du et al(2019) - presented a tropical cyclone risk estimation on the basis of information diffusion theory. The theory of probability statistics, which was previously used to assess disaster risk, was proven to be ineffective and mostly focused on statistical risk. The data analysis is fairly simple, and the risk assessment methodology which is based on information diffusion theory used in this work requires less data than previous methodologies. By making use of the best track data on CMA tropical storms, Data sets were obtained from the CMA tropical cyclone information centre.

[2] "SMAP Tropical Cyclone Size and Intensity Validation" -A. Fore et al(2018) - proposed SMAP mission's objective to find soil moisture on land. With a 9 km resolution and an 8-day return duration, the SMAP mission's hybrid active and passive L-band microwave instrument measures soil moisture across land. In this work, the Automated Tropical Cyclone Forecasting (ATCF) system B-deck files are compared with the SMAP cyclone sizes in order to update the SFMR analysis. First, the study validates the size of the cyclone and then validates the intensity. The magnitude of tropical cyclones is estimated using SMAP data using an algorithm that exclusively uses best-track sites. Once the cyclone's size has been confirmed, in order to improvise the hurricane track predictions and forecast the storms, the SFMR airborne instrument is used. The dropsondes are being used to confirm the speeds of the wind up to category 5 wind speed (70 m/s).

[3] "CNN-Based Tropical Cyclone From Satellite Infraded Images -Chong Wang et al(2020) - proposed Satellite-based technologies that use a neural network to predict the direction of a typhoon in a matter of seconds. Convolutional, pooling, and fully linked layers are all included in the CNN model, which gives it objectivity and speed. The fully connected layers learn picture features after they have been entirely lowered by the pooling layers and extracted by the convolutional layers. The Himawari-8 geostationary satellite's Advanced Himawari Imager (AHI) on Channels 13 and 15 was used in the study. Every ten minutes, AHI is able to deliver infrared and visible images thanks to its 16 spectral channels.

[4] "Estimation of Location and Intensity of Tropical Cyclones based on Microwave sounding Instruements" -Hao Hu and Fuzhong Weng(2020) - having accurate data on the depth and region of tropical cyclones (TCs) is crucial for climate prognostication and warning. This study aims to forecast the position and depth of two storms that occurred in 2018. It does this by using the hydrostatic stability equation and the thermal data recovered from microwave sounding equipment. Four tests were done to see how well the algorithm worked with different instruments. The results demonstrated that the SD1DVAR retrieval technique significantly reduced the area and depth estimation error by approximately 52.79% and 36.91% in comparison to that of MIRS products while using the same instruments. Additionally, including 118 GHz channels led to a reduction in depth errors by approximately 37.2%. Moreover, this SD1DVAR-based method performed consistently between ATMS and CMWS [16].

[5] "Tropical Cyclone Intensity Estimation using Microwave fusion network" -Yu Xie et al(2022) - have proposed a MVFF network to estimate the TC intensity. The MVFF network is trained and calibrated using the TC warm core temperature anomalies obtained from the S-NPP ATMS. The MVFF employs a multi-view structure that can make full use of the complementary information of different views, and also uses FEF Chong Wang et al.,[3] proposed Satellite-based technologies that use a neural network to predict the direction of a typhoon in a matter of seconds. The CNN model was trained using roughly 2250 infrared pictures from 97 typhoon cases between 2015 and 2018. Convolutional, pooling, and fully linked layers are all included in the CNN model, which gives it objectivity and speed. The fully connected layers learn picture features after they have been entirely lowered by the pooling layers and extracted by the convolutional layers. The Himawari-8 geostationary satellite's Advanced Himawari Imager (AHI) on Channels 13 and 15 was used in the study. Every ten minutes, AHI is able to deliver infrared and visible images thanks to its 16 spectral channels.

[6] "Cyclone Identify using two- branch Convolutional Neural Network from Global forecasting System Analysis" -Fan Meng et al(2021) - have designed a two-branch convolutional neural network model to explore the role of deep learning in cyclone recognition. A total of 10 types of cyclone phenomena are involved. The water vapor map and the lowest sea level pressure are used as model inputs. The results reveal that the model can accurately identify various types of cyclones, and can also learn the characteristics of different cyclones and classify them. However, it is undeniable that our model is not very accurate in classifying different cyclones, and it is easy to be confused with adjacent categories. The confusion

between the types of cyclones is firstly related to the similar characteristics of adjacent types of cyclones, and it is also difficult for human experts to distinguish accurately. Secondly, this is related to the imbalance of the number of samples of different categories in the data set used.

[7] "Hurricane intensity prediction based on time series data mining" -Shuhan Yang et al(2019) - have made use of the Bagging-IBK & LMT models in the hurricane intensity forecast model. The present strength forecasts, which are based on statistical techniques and storm track patterns, are inadequate. Therefore, data mining methods can be utilized to forecast changes in hurricane intensity, and several researchers have employed dynamic statistical models and prediction models with neural networks. Although tropical cyclone prediction models apply data mining methods to hurricane intensity, they cannot meet actual application requirements. Yang used the RI technique (Rapid Intensification) to analyse this problem and evaluate whether hurricanes were fast intensifying. To get beyond the limitations of a single classifier, the Bagging approach was utilised to combine numerous weak classifiers.

[8] "Deep learning approach for Tropical Cyclones Classification" -Ana Raquel Carmo et al(2021) - have proposed a system based on topological patterns. The experimental findings show that the proposed method not only successfully identifies TCs but also has the capacity to precisely pinpoint their centres and compete with current manual and automated intensity estimation methods. Convolutional neural networks are the typical DL network model used with picture data. In this work, two alternative CNNs trained well on the datasets of ImageNet, ResNet50 and MobileNetV2, are put to the test. Gradient-based class activation maps have been used to display the internal depictions that the CNN's have learned and for the better understanding of their characteristics (Grad-CAM).

[9] "A Semi Supervised Deep Learning Framework for Tropical Cyclone Intensity Estimation"-Guangchen Chen et al(2019) - proposed a new semisupervised deep learning framework for accurate tropical cyclone classification, which only requires a small number of labeled samples. The proposed method updates training set by selecting the samples with reliably predicted labels based on a specially designed hybrid similarity measurement. It trains two CNN's in a semisupervised and iterative manner. Experiments show that the proposed method is significantly better than several popular classification methods.

CHAPTER 3

SYSYTEM REQUIREMENTS AND SPECIFICATION

3.1 Software Requirement and Specification

Software Requirements Specification (SRS) provides an overview of the entire SRS with purpose, scope, definitions, acronyms, abbreviations, references and overview of the SRS. A software requirements specification (SRS) is a comprehensive description of the intended purpose and environment for software under development. The SRS fully describes what the software will do and how it will be expected to perform the various gestures and determining its accuracy. The SRS is a requirements specification for a software system, is a description of the behavior of a system to be developed and may include a set of use cases that describe interactions the users will have with the software. In addition it also contains non- functional requirements.

3.2 Functional Requirements

A functional requirement defines a function of a software system or its components. A function is described as a set of inputs, the behavior, and outputs. Functional requirements may be calculations, technical details, data manipulation and processing and other specific functionality that define what a system is supposed to accomplish. Behavioral requirements describing all the cases where the system uses the functional requirements are captured in use cases. Functional requirements are supported by non-functional requirements (also known as quality requirements), which impose constraints on the design or implementation (such as performance requirements, security, or reliability).

3.3 Non-Functional Requirements

In systems engineering and requirements engineering, a non-functional requirement is a requirement that specifies criteria that can be used to judge the operation of a system, rather than specific behaviors. They are contrasted with functional requirements that define specific behavior or functions. Non-functional requirements define how a system is supposed to be. Non-functional requirements are in the form of "system shall be <requirement>", an overall property of the system as a whole or of a particular aspect and not a specific function.

- **Security**

  The system should have security measures in place to ensure the confidentiality, integrity, and availability of sensitive data, such as user data and system logs.

- **Concurrency and Capacity**

  System should be able to handle multiple computations executing simultaneously, and potentially interacting with each other.

- **Performance**

  Performance is generally perceived as a time expectation. This is one of the most important considerations especially when the project is in the architecture phase.

- **Reliability**

  It is necessary to ensure and notify about the system transactions and processing as simple as keep a system log will increase the time and effort to get it done from the very beginning. Data should be transferred in a reliable way and using trustful protocols.

- **Maintainability**

  Well-done system is meant to be up and running for long time. Therefore, it will regularly need preventive and corrective maintenance. Maintenance might signify scalability to grow and improve the system features and functionalities. Data should be transferred in a reliable way and using trustful protocols.

- **Usability**

  End user satisfaction and acceptance is one of the key pillars that support a project success. Considering the user experience requirements from the project conception is a win bet, and it will especially save a lot of time at the project release, as the user will not ask for changes or even worst misunderstandings.

3.3.1 Software Requirements

- **Jupyter Notebook:** Jupyter Notebook is an open-source software program this is an interactive computational environment, wherein you could integrate code execution, wealthy text, mathematics, plots, and wealthy media, it's far used for modifying and walking the application, additionally it turned into first-rate appropriate for us to broaden our challenge
- **VSCode:** Visual Studio Code is a code editor that may be used with a whole lot of programming languages, it's far a code editor made with the aid of using Microsoft for

Windows, Linux, and macOS. Features encompass guide for debugging, syntax highlighting, sensible code completion, snippets, code refactoring, and embedded Git

- **Anaconda:** Anaconda is an open-source distribution of Python and R programming languages for scientific computing, data science, and machine learning. It provides an integrated environment for data analysis and includes over 1,500 data science packages out-of-the-box. It is a powerful tool for data scientists and machine learning practitioners, providing a complete and integrated environment for developing, testing, and deploying machine learning models
- **Streamlit:** It is a Python framework that enables developers to build web applications for machine learning and data science. Streamlit allows developers to create interactive web applications with minimal effort by providing easy-to-use widgets for user input and output display. It also enables integration with popular machine learning and data science libraries like TensorFlow, PyTorch, and Pandas, among others.

3.3.2 Hardware Requirements

- CPU: A multi-core CPU with at least 4 cores, such as an Intel Core i5 or i7
- GPU: A graphics processing unit (GPU) can significantly accelerate the training process for deep learning models. A mid-range GPU with at least 4GB of VRAM, such as an Nvidia GTX 1660, may be sufficient.
- RAM: Atleast 4GB of RAM is recommended
- HDD: A minimum of 10GB is recommended.

CHAPTER 4

SYSTEM ANALYSIS

4.1Existing System

Since 1940, a lot of experiments and systems that have been proposed to estimate the intensity of a tropical cyclone. Existing TC intensity estimation models rarely consider the intensity grade classification before intensity estimation, although some researchers have recently divided the TC intensity grades into many categories using CNNs. Due to the high misclassification probability when directly dividing TC intensity grades into too many categories, the accuracy of the intensity estimation is bound to be affected. Some of the existing system includes:

- Microwave data from polar-orbiting and geostationary satellite imagery are currently used for TC intensity estimation. Geostationary satellites have a higher temporal resolution and stable image quality, but cannot obtain near-surface structure of TC
- The Dvorak technique and its improved versions are commonly used for TC intensity estimation using infrared satellite images, but they rely on the experience of the forecaster and may not be suitable for estimating the intensity of weak TCs.
- Traditional machine learning techniques such as multivariate linear regression, K-nearest neighbors algorithm, multilayer perceptron, SVM, and RVM have been used to estimate TC intensity, but they mainly focus on the manual extraction of statistical or structural features that are largely dependent on human subjectivity and experience.
- Convolutional neural networks (CNNs) of deep learning have been used to extract deep features directly from infrared satellite images without the need for manual feature extraction. Recent studies have used CNN-based models for TC intensity estimation as a regression task, but these single models may not fully cover TC changes, especially when the TC samples of different intensities are not balanced.

4.2 Proposed System

The proposed system, called TCICENet, is a CNN model designed for estimating the intensity of tropical cyclones (TCs) from infrared geostationary satellite images. It consists of two modules: the TC intensity classification (TCIC) module and the TC intensity estimation (TCIE) module. The TCIC module performs the classification of TC intensity grade, which is a challenging task because TCs are not rigid bodies, and their structure changes greatly in

different development stages with continuous rotation and translation. The TCIE module estimates the TC intensity from three TC categories as a regression task.

IoT-Based Flood Detection Subsystem

The enhanced system now includes an IoT module responsible for detecting sudden water level rise. The subsystem consists of the following components:

1. **ESP8266 NodeMCU** – acts as the central controller and MQTT client.
2. **Buzzer** – provides audible alert during flood condition.
3. **LED Indicator** – provides visual alert for quick identification.
4. **MQTT Cloud Broker** – facilitates communication between ESP8266, backend system, and mobile app.
5. **Flutter Mobile Application** – receives push notifications when flood level crosses the threshold.

Working Principle

- ESP8266 publishes sensor data to an MQTT topic at regular intervals.
- When threshold is crossed, deep learning subsystem or local logic sends MQTT command:
  "FLOOD=1"
- ESP8266 receives the command and immediately turns ON buzzer and LED.
- A notification is also sent to the Flutter app to alert the user.

This IoT unit acts as a real-time extension to cyclone intensity estimation.

CHAPTER 5

SYSTEM DESIGN

Systems design is the process of defining the architecture, components, modules, interfaces, and data for a system to satisfy specified requirements. Systems design could be seen as the application of systems theory to product development.

5.1 High Level Design

High-level design (HLD) explains the architecture that would be used for developing a software product. The architecture diagram provides an overview of an entire system, identifying the main components that would be developed for the product and their interfaces. The HLD uses possibly nontechnical to mildly technical terms that should be understandable to the administrators of the system.

5.2 System Architecture

A system architecture or systems architecture is the conceptual model that defines the structure, behavior, and more views of a system. An architecture description is a formal description and representation of a system, organized in a way that supports reasoning about the structures and behaviors of the system.

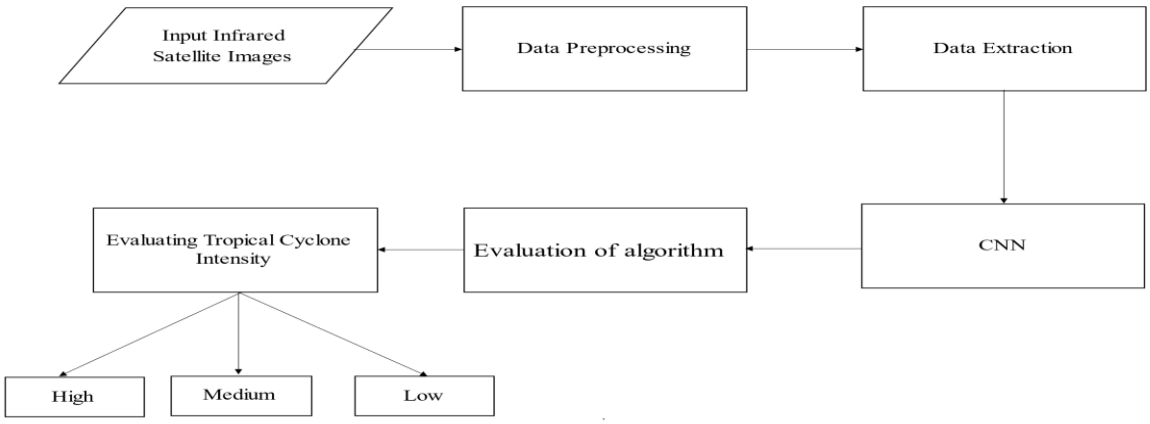


Fig 5.1: System Architecture using CNN

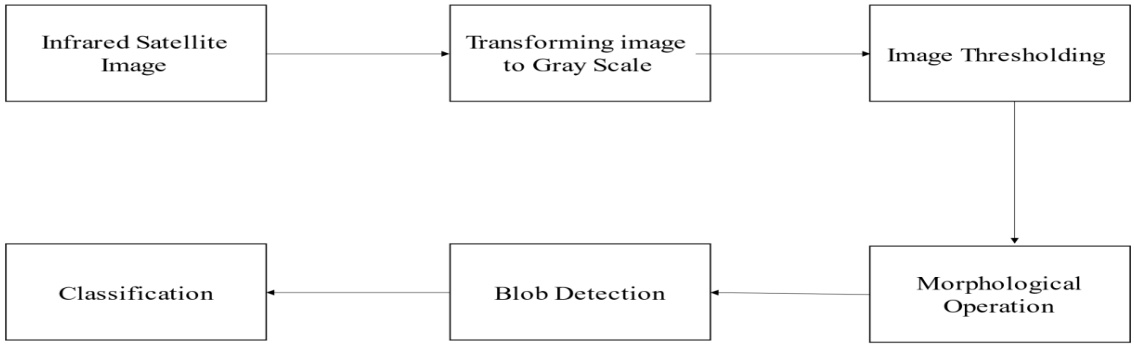


Fig 5.2: System Architecture using Image Processing

The architecture of the proposed system is shown in the Fig 5.1 and 5.2. The system architecture can be divided into two different architecture,

According to the deep learning architecture,

- Image acquisition: It is the very first step that requires capturing an image with the help of camera.
- Data Collection: Collect a large dataset of high-resolution infrared satellite images of tropical cyclones with corresponding intensity labels.
- Data Preprocessing: Preprocess the data to remove any noise, artifacts, or other inconsistencies in the images. This step may involve applying filters, normalization, and scaling to the data.
- Feature Extraction: Use a convolutional neural network (CNN) to extract features from the preprocessed images. CNNs are particularly good at learning spatial features in images, which makes them well-suited for this task
- Model Training: Train a deep learning model, such as a neural network, on the extracted features to predict the intensity of tropical cyclones from the infrared satellite images. This step may involve using various algorithms such as regression, classification, or ensemble methods.
- Model Evaluation: Evaluate the performance of the trained model using a different evaluation metrics.
- Evaluating Intensity: Estimating the intensity and categorizing it. According to the deep learning architecture,

- Image acquisition: It is the very first step that requires capturing an image with the help of camera.
- Transforming an image to grayscale: Grayscale images have only one color channel, instead of three (red, green, and blue) in a typical color image. This can simplify the image processing task and reduce the computational complexity, while still retaining the relevant information in the image.
- Image thresholding: It is a step in image processing that involves segmenting an image into foreground and background regions based on the intensity values of the pixels. The basic idea behind thresholding is to convert a grayscale or color image into a binary image, where each pixel is either black or white, depending on whether its intensity value is above or below a threshold value.
- Morphological operations: These are a class of image processing techniques that operate on the shape and structure of objects in an image. These operations are commonly used for tasks such as noise reduction, edge detection, segmentation, and feature extraction.
- Blob detection: Used to identify and locate regions of an image that have a similar intensity or color value. These regions are referred to as "blobs" or "connected components". Blob detection can be used for various image analysis tasks, such as object recognition, tracking, and segmentation.

5.3 Use Case Diagram

Figure 5.3 shows the graphic depiction of the interactions among the elements of a system. Use cases will specify the expected behavior, and the exact method of making it happen. Use cases once specified can be denoted both textually and visual representation.

In the "Image Processing" path, several image processing techniques are applied to the input image to extract relevant features for classification. These techniques include converting the image to grayscale, thresholding, morphological operations, and clearing border regions.

Requirements(external), requirement usages of a system under design or analysis to capture what the system is supposed to do. Requirements the specified subject poses on its environment – by defining how environment should interact with the subject so that it will be able to perform its services.

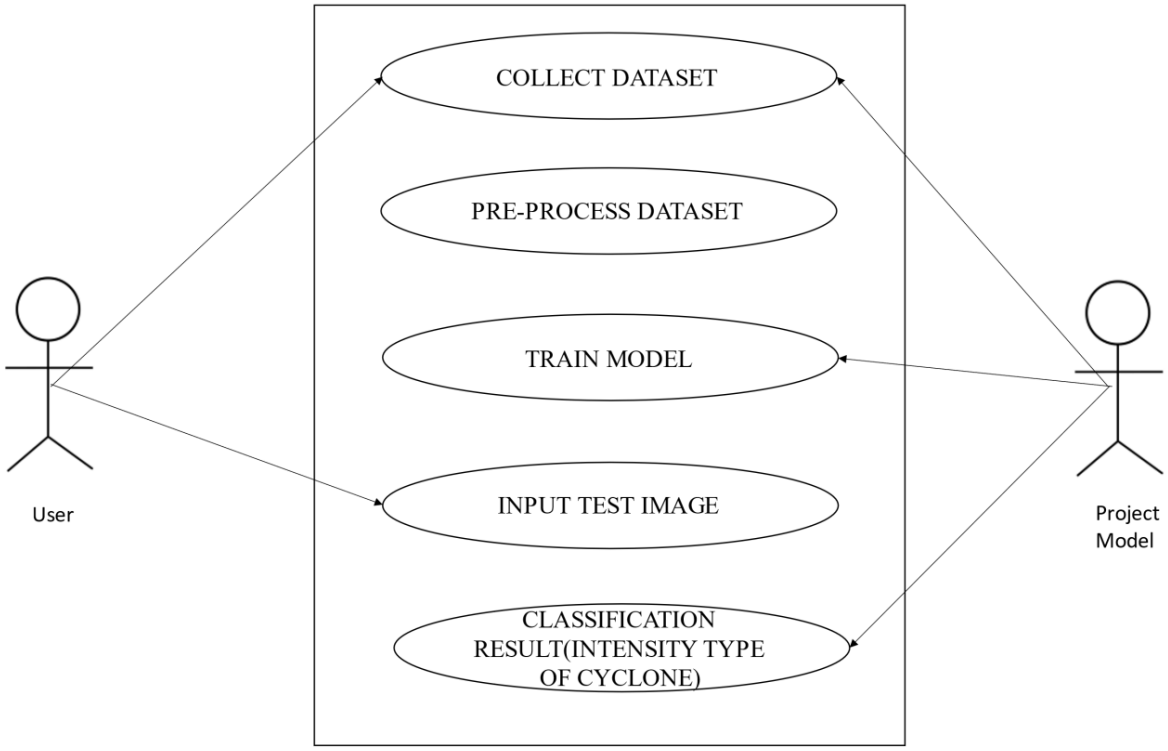


Fig 5.3: Use Case Diagram

Use case diagram are used to specify:

- Requirements(external), requirement usages of a system under design or analysis to capture what the system is supposed to do.
- The functionality offered by a subject – what the system can do
- Requirements the specified subject poses on its environment – by defining how environment should interact with the subject so that it will be able to perform its services.

5.4 Activity Diagram

Activity diagram is another important diagram in UML to describe dynamic aspects of the system. Activity diagram is basically a flowchart to represent the flow from one activity to another activity. The activity can be described as in the operation of the system. The control flow is drawn from one operation to another.

In the "Image Processing" path, several image processing techniques are applied to the input image to extract relevant features for classification. These techniques include converting the image to grayscale, thresholding, morphological operations, and clearing border regions. These

steps are represented by their respective nodes in the diagram.

After the image processing steps, the process continues with the "Connected Component Segmentation" node. This step segments the image into connected components, representing potential cyclone regions.

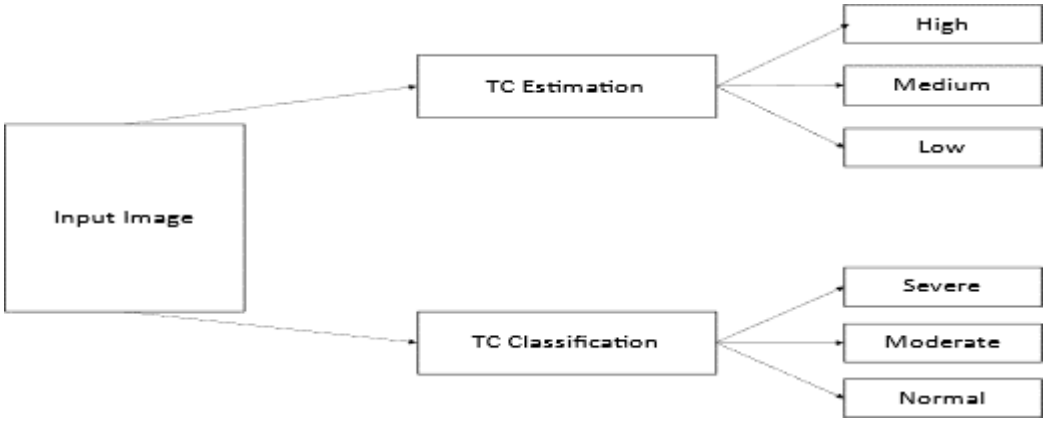


Fig 5.4: Activity Diagram

Next, the process branches into the "Size Classification" node, where the size of each connected component is determined. Based on predefined thresholds or criteria, the connected components are classified into different size categories.

Following the "Size Classification," the process moves to the "Intensity Classification" node. Here, the intensity of each cyclone region is classified as either "High Intensity" or "Low/Medium Intensity" based on predefined criteria.

If a cyclone region is classified as "High Intensity," the process follows the "High Intensity Classification" path, which may involve additional analysis or actions specific to high-intensity cyclones.

If a cyclone region is classified as "Low/Medium Intensity," the process follows the "Low/Medium Intensity Classification" path, which represents the handling for cyclones with lower intensity.

5.5 Data Flow Diagram

A data flow diagram (DFD) maps out the flow of information for any process or system. It uses defined symbols like rectangles, circles and arrows, plus short text labels, to show data inputs, outputs, storage points and the routes between each destination. Fig 5.5 is a data flow diagram and graphical representation of the flow of the data through an information system, modeling its process aspects. A DFD is often used as a preliminary step to create an overview of the system without going into great detail, which can later be elaborated.

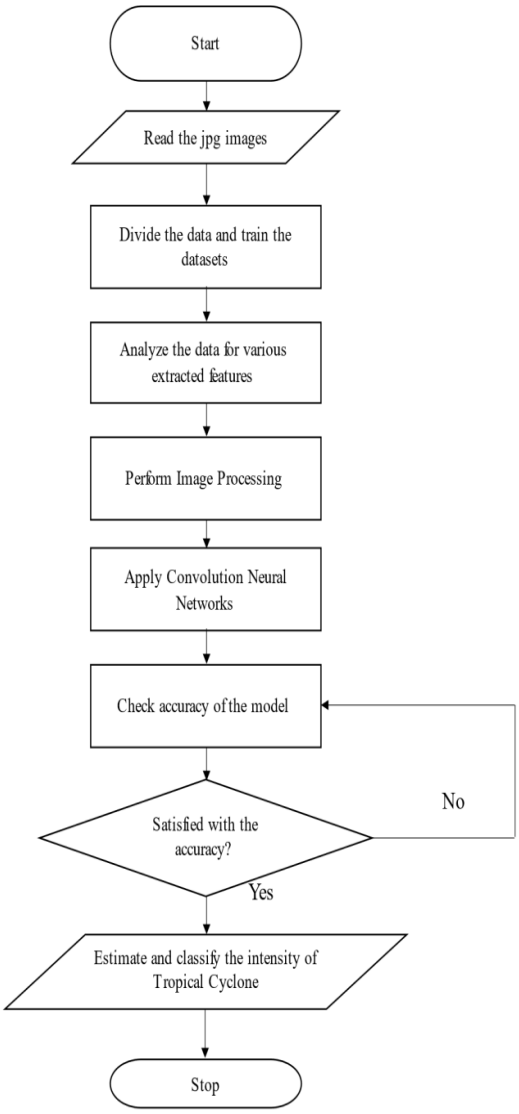


Fig 5.5: Data Flow Diagram

5.6 Low Level Design

Low-level design (LLD) is a component-level design process that follows a step-by- step refinement process. This process can be used for designing data structures, required software architecture, source code and ultimately, performance algorithms.

IoT Flood Alert System Architecture

This section describes the IoT subsystem added to the existing TCICENet system.

Components

- ESP8266 Wi-Fi module
- Buzzer

- LED
- MQTT broker (broker.emqx.io or similar)
- Flutter mobile alert app

Flow

1. Sensor measures water level.
2. Data sent to ESP8266.
3. ESP8266 publishes value to MQTT.
4. Backend or threshold logic checks if flood alert is required.
5. If alert is triggered, command sent back to ESP8266: "FLOOD_ALERT"
6. ESP8266 activates buzzer + LED.
7. Alert also sent to mobile application.

5.7 Pseudo Code

```
def detect_cyclone(img):
st_images = []
st_caption = []
input_image = np.array(img)
img_fastai = Image(pil2tensor(input_image, dtype=np.float32).div_(255))

# Convert the image to Grayscale
img = img.convert('L')
img = np.array(img)
orig=cv2.cvtColor(img,cv2.COLOR_GRAY2BGR)
st_caption.append('Grayscale Image')

# Image Thresholding
img = img > threshold
img = np.array(img) * 255
st_caption.append('Image Thresholding')

# Morphological operations
footprint = disk(2)
img = erosion(img, footprint) # Noise removal
```

```
footprint = square(4)
img = opening(img, footprint) # Opening operation on binary image

# Clear border region
img = clear_border(img)
img = img.astype(np.uint8) *255
img = np.array(img) * 255
st_images.append(img.copy())
st_caption.append('Clear Border regions')

# Blob Detection
num_labels, labels, stats, centroids = cv2.connectedComponentsWithStats(img)
min_area = 100 # Small object removal
filtered_labels = []
for label in range(1, num_labels):
if stats[label, cv2.CC_STAT_AREA] >= min_area:
cv2.circle(orig, (int(center[0]), int(center[1])), size, (135, 206, 235), thickness=3, lineType=8,
shift=0)
elif size >= 45 and size <= 75:
class_label = "moderate"
cv2.circle(orig, (int(center[0]), int(center[1])), size, (252, 245, 95), thickness=3, lineType=8,
shift=0)
elif size > 75:
class_label = "severe"
cv2.circle(orig, (int(center[0]), int(center[1])), size, (255, 87, 51), thickness=4, lineType=8,
shift=0)
st_images.append(orig.copy())
st_caption.append(‘Blob detection’)
return idx,max(sizes)
```

CHAPTER 6

IMPLEMENTATION

An implementation is a realization of a technical specification or algorithm as a program, software component, or other computer system through computer programming and deployment. Many implementations may exist for a given specification or standard. For example, web browsers contain implementations of World Wide Web Consortium-recommended specifications, and software development tools contain implementations of programming languages.

6.1 Tropical Cyclone Intensity Classification Module

In this module the classification of intensity is done using a convolutional neural network (CNN) that has been implemented using the fastai library. The CNN is trained on the image dataset to predict the intensity of new images.

The CNN is trained using transfer learning, where a pre-trained model is used as the base model and then trained on the new dataset. The pre-trained model used in this code is the VGG19_bn and ResNet101 models. These models have been trained on the ImageNet dataset and have been shown to work well on image classification tasks.

6.1.1 Libraries

- **Fastai:** Fastai is an open-source library built on top of PyTorch that provides high-level APIs for training and deploying deep learning models. It is designed to make the process of deep learning more accessible and easier for researchers, developers, and practitioners of all levels of expertise. Fastai offers a variety of pre-built models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers, which can be easily customized to suit the specific needs of a project. It also includes modules for natural language processing (NLP) and computer vision (CV) tasks.
- **Torch:** Torch is an open-source machine learning library that is widely used in the field of artificial intelligence and deep learning. Torch is designed to provide fast and flexible experimentation with neural networks, and it supports a wide range of algorithms and models for building and training deep learning models.

- **TorchVision:** TorchVision is a PyTorch package that consists of popular datasets, model architectures, and image/video transforms for computer vision tasks. TorchVision is designed to make it easy for researchers and practitioners to use PyTorch for image and video classification, segmentation, and detection tasks. TorchVision includes a number of standard computer vision datasets, such as CIFAR10, CIFAR100, and ImageNet, as well as tools for loading and preprocessing these datasets. TorchVision also includes a large number of pre-trained model architectures that can be used as the starting point for building more complex models.

6.1.2 Data

The infrared satellite images of Tropical Cyclones from 1981 to 2019, comprising four categories- Tropical Depression, Tropical Storm, Hurricane and Major Hurricane, were obtained from the National Institute of Informatics of Japan (http://agora.ex.nii.ac.jp/digital-typhoon/year/wnp/), and were then used to verify the performance of the proposed model. The infrared satellite images used in this project derive from the GMS1–5, GEO 9, MTSAT-1R, MTSAT-2, and Himawari 8 satellites in the northwest Pacific Ocean basin. A total of 3000 satellite images of Tropical Cyclones from 1981 to 2019 were selected to train and validate the proposed model. Out of which 80% were used for training and 20% for validation. Fig.6.1.2.1 shows sample infrafred satellite images.

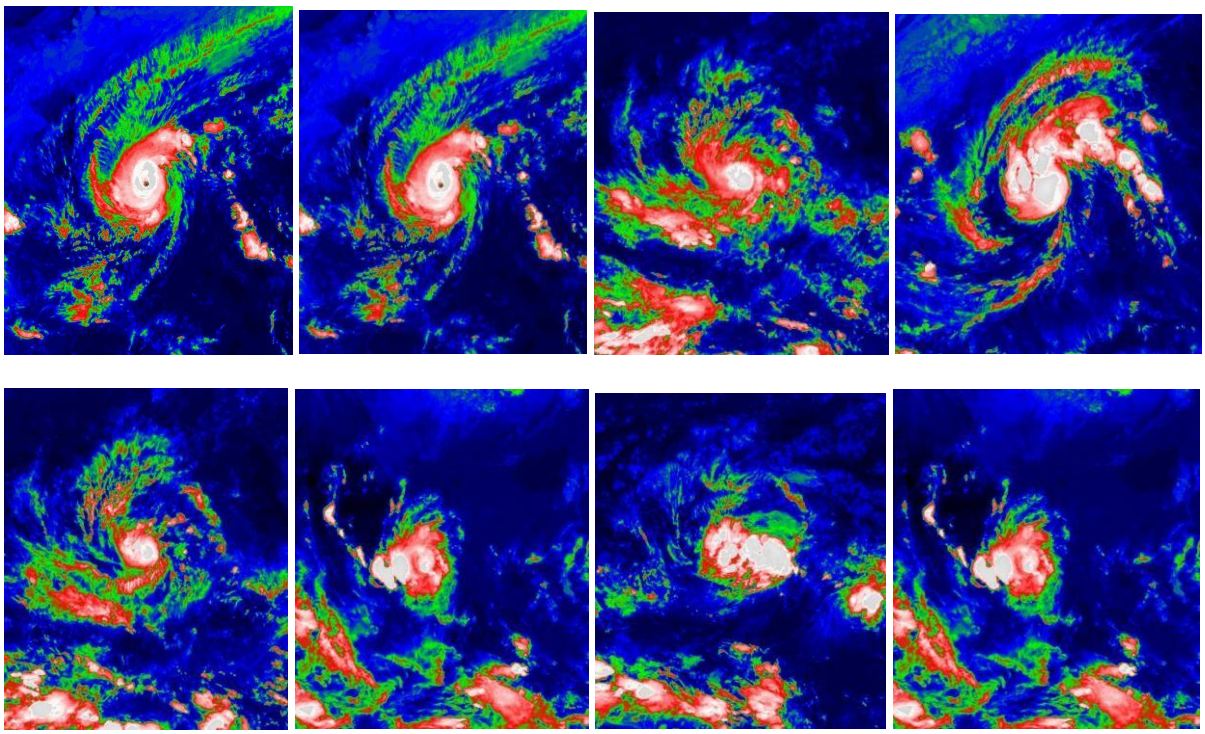


Fig 6.1: Sample Infrared Satellite Images.

6.1.3 Data Preprocessing

Data preprocessing plays a vital role in developing an accurate and efficient deep learning model for infrared satellite image analysis. To achieve this, there are various techniques used in data preprocessing for infrared satellite images. One such technique is image normalization, which rescales the pixel values of an image to a standard range, thereby reducing the effect of variations in illumination and contrast of the input images. Another technique is image resizing, which ensures that all the input images have the same size and aspect ratio, thereby simplifying the training process.

6.1.4 Convolutional Neural Network (CNN)

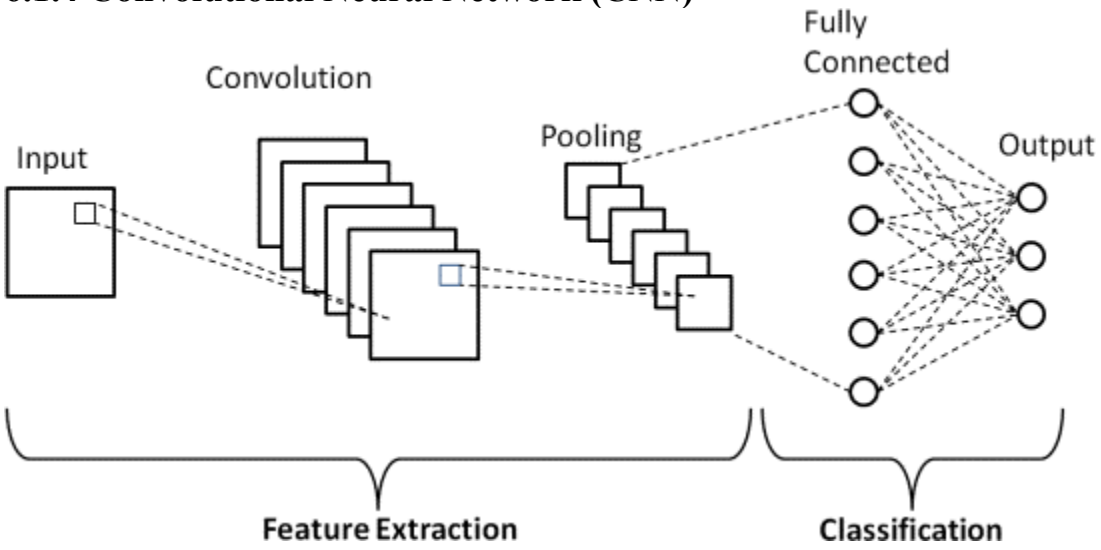


Fig 6.2: CNN architecture.

A convolutional neural network (CNN) is a type of artificial neural network used primarily in image processing and computer vision. CNNs are composed of multiple layers, each layer performing a specific function to extract increasingly complex features from the input image. There are many CNN layers as shown in Fig 6.1.4. There are three types of layers that make up the CNN which are the convolutional layers, pooling layers, and fully-connected (FC) layers. In addition to these three layers, there are two more important parameters which are the dropout layer and the activation function.

1. **Input layer:** The input layer of a CNN receives the image data and passes it to the next layer.
2. **Convolutional layer:** This layer is the first layer that is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size MxM. By sliding

the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter (MxM).

3. **Pooling Layer:** In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim of this layer is to decrease the size of the convolved feature map to reduce the computational costs.
4. **Fully Connected Layer (FC):** The Fully Connected (FC) layer consists of the weights and biases along with the neurons and is used to connect the neurons between two different layers. These layers are usually placed before the output layer and form the last few layers of a CNN Architecture.In this, the input image from the previous layers are flattened and fed to the FC layer.
5. **Dropout:** Usually, when all the features are connected to the FC layer, it can cause overfitting in the training dataset. Overfitting occurs when a particular model works so well on the training data causing a negative impact in the model's performance when used on a new data.To overcome this problem, a dropout layer is utilised wherein a few neurons are dropped from the neural network during training process resulting in reduced size of the model.
6. **Activation Functions:** one of the most important parameters of the CNN model is the activation function. They are used to learn and approximate any kind of continuous and complex relationship between variables of the network. It adds non-linearity to the network. There are several commonly used activation functions such as the ReLU, Softmax, tanH and the Sigmoid functions.

CNN architectures can have different numbers of convolutional, pooling, and fully connected layers, depending on the complexity of the problem being solved. The number of neurons in each layer can also vary, depending on the size of the input image and the number of classes being classified. Overall, CNNs have proven to be highly effective in image processing and computer vision tasks and are widely used in a variety of applications. In our project we have made use of vgg19_bn and ResNet-101 architecture.

After training the model with VGG19_bn, the same model is trained on the dataset using the ResNet101 architecture. The CNN model is trained for 10 epochs with a learning rate of 3e-3 using the fit_one_cycle() method. The accuracy and error rate metrics are used to evaluate the performance of the model during training. It was observed that there was not much change in the accuracy when compared to VGG19_bn.

6.1.5 Deep Learning Algorithms for TC intensity Classification

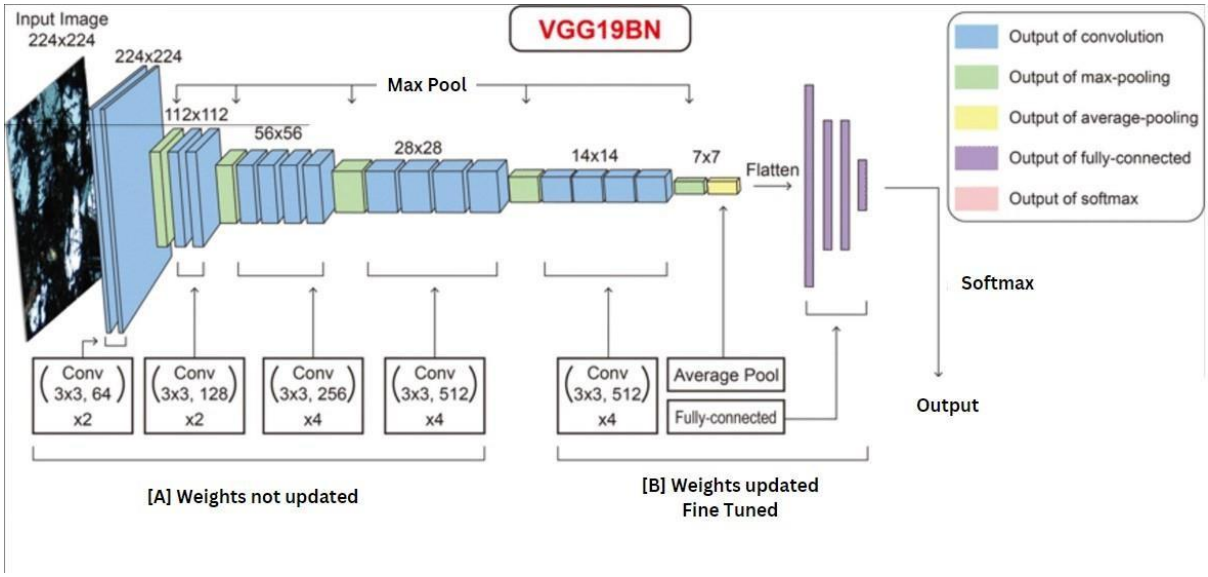


Fig 6.3: VGG19_bn architecture

- The tenth to thirteenth layers are convolutional layers with 512 filters each, followed by a max-pooling layer with a pool size of 2x2 and a stride of 2. These layers extract highly complex features from the input image.
- The fourteenth to seventeenth layers are convolutional layers with 512 filters each, followed by a max-pooling layer with a pool size of 2x2 and a stride of 2. These layers extract even more complex features from the input image.
- The eighteenth layer is a fully connected layer with 4096 neurons, which processes the output of the previous layer and outputs a feature vector of size 4096.
- The nineteenth layer is another fully connected layer with 4096 neurons, which further processes the output of the previous layer and outputs a feature vector of size 4096.
- The final layer is a softmax layer that produces the probability distribution over the different classes. This is equal to the number of classes in the dataset.

The VGG19_bn architecture is similar to the VGG16 architecture, but it includes batch normalization layers after each convolutional layer.

Residual Network (ResNet):

A residual neural network (ResNet) is an artificial neural network (ANN). It is also used for Control Neural Network. It is a gateless or open-gated variant of the HighwayNet, the first working very deep feedforward neural network with hundreds of layers, much deeper than previous neural networks.

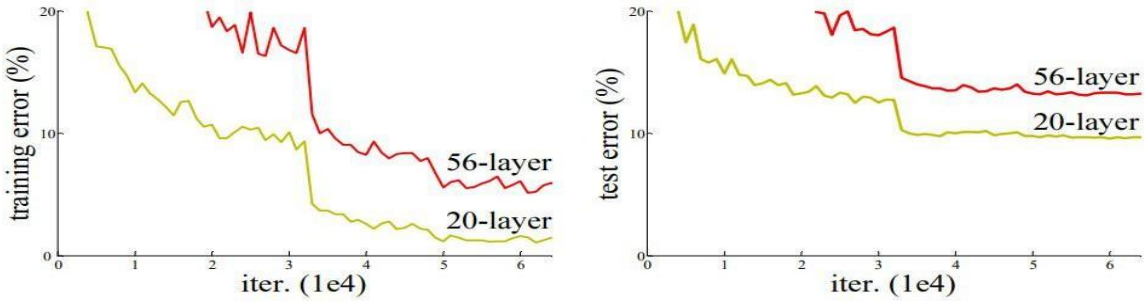


Fig 6.4: Comparison of 20-layer vs 56-layer architecture.

In the above plot, we can observe that a 56-layer CNN gives more error rate on both training and testing dataset than a 20-layer CNN architecture.

6.2 Image Processing

6.2.1 What is Image

An image is an array, or a matrix, of square pixels arranged in columns and rows(0-255).

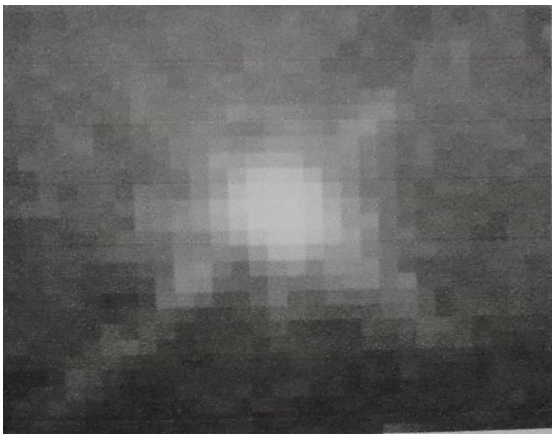


Fig 6.5: An image – an array or a matrix of pixels arranged in columns and rows.

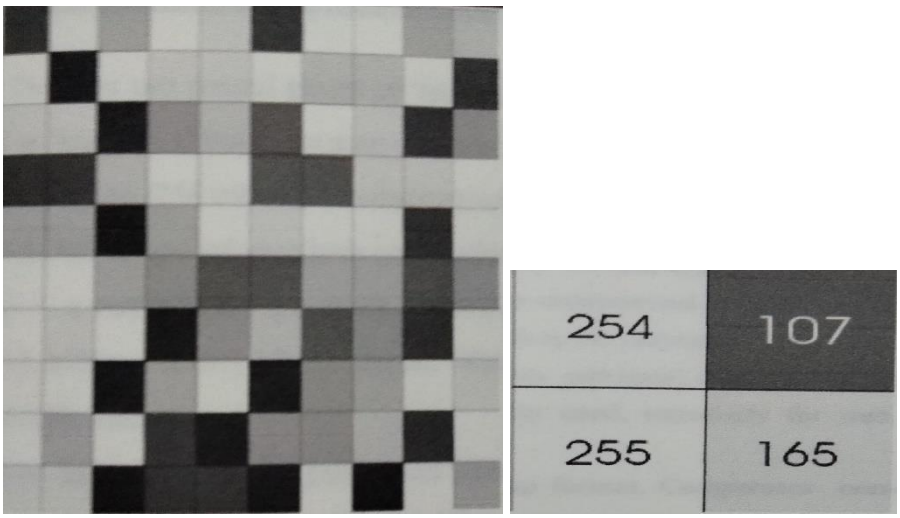


Fig 6.6: Each pixel has a value from 0 (black) to 255 (white)

The possible range of the pixel values depend on the colour depth of the image, here 8 bit = 256 Enes or greyscales. A normal greyscale image has 8 bit colour depth = 256 greyscales. A "true colour" image has 24 bit colour depth = 8 * 8 * 8 bits = 256 * 256 * 256 colors = ~16 million colors.

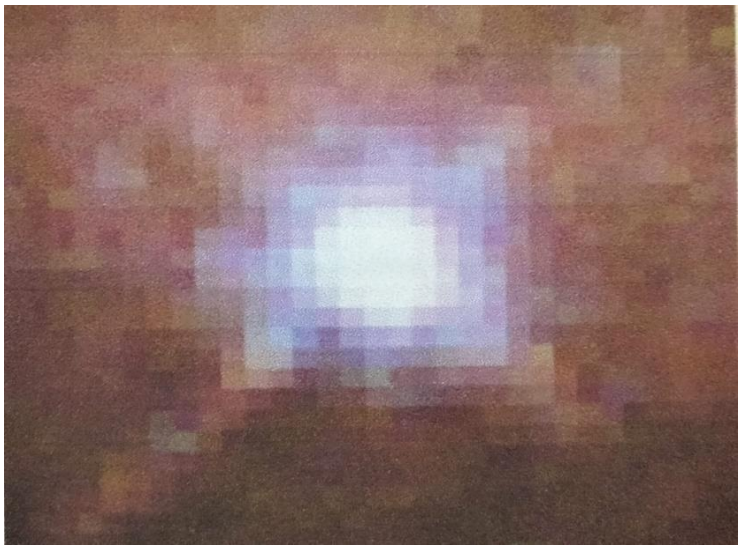


Fig 6.7: A true-color imager assembled from three grayscale images colored RGB

Three greyscale images can be combined to form an image with 281,474,976,710,656 greyscale images have more greyscales, for instance 16 bit = 65536 greyscales. There are two general groups of 'images': vector graphics (or line art) and bitmaps (pixel-based or 'images').

6.3 Images and Pictures

As we mentioned in the preface, human beings are predominantly visual creatures: we rely heavily on our vision to make sense of the world around us. We not only look at things to identify and classify them, but we can scan for differences, and obtain an overall rough feeling for a scene with a quick glance. Humans have evolved very precise visual skills: we can identify a face in an instant; we can differentiate colors; we can process a large amount of visual information very quickly.

1. Improve its pictorial information for human interpretation,
2. Render it more suitable for autonomous machine perception.

6.4 Images and Digital Images

Suppose we take an image, a photo, say. For the moment, let's make things easy and suppose the photo is black and white (that is, lots of shades of grey), so no colour. We may consider this image as being a two-dimensional function, where the function values give the brightness of the image at any given point.

6.5 Color Scale

The Two main color spaces are **RGB** and **CMYK**.

6.6.1 RGB

The RGB color model is an additive color model in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. RGB uses additive color mixing and is the basic color model used in television or any other medium that projects color with light. It is the basic color model used in computers and for web graphics, but it cannot be used for print production. This is shown in fig 6.5.3.2.

The secondary colors of RGB cyan, magenta, and yellow - are formed by mixing two of the primary colors (red, green or blue) and excluding the third color. Red and green combine to make yellow, green and blue to make cyan, and blue and red form magenta.

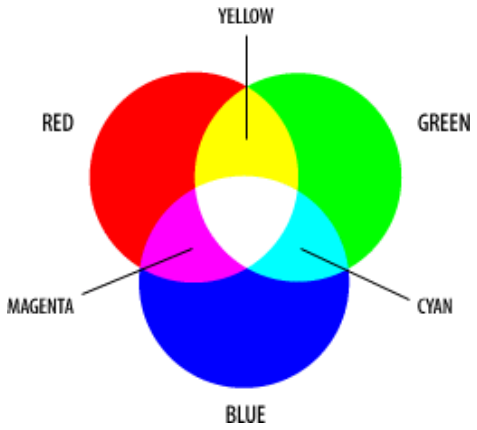


Fig 6.8: The additive model of RGB

To see how different RGB components combine together, here is a selected repertoire of colors and their respective relative intensities for each of the red, green, and blue components:

6.6 Aspects of Image Processing

It is convenient to subdivide different image processing algorithms into broad sunclasses. There are different algorithms for different tasks and problems, and often we would like to distinguish the nature of task at hand.

Image enhancement: This refers to processing an image so that the result is more suitable for particular application.

Example include:

- Sharpening or de-blurring an out of focus image
- Highlighting edges

- Improving image contrast, or brightening an image
- Removing noise

Image restoration: This may be considered as reversing the damage done to an image by a known cause, for example:

- Removing of blur caused by linear motion
- Removal of optical distortions
- Removing periodic interference

Image segmentation: This involves subdividing an image into constituent parts, or isolating certain aspects of an image:

- Circles, or particular shapes in an image
- In an aerial photograph, identifying cars, trees, buildings, or roads

These classes are not disjoint; a given algorithm may be used for both image enchancement or for image restoration. However, we should be able to decide what it is that we are trying to do with our image: simply make it look better (enhancement), or remove damage (restoration).

6.6.1 An Image Processing Task

We will look into some details at a particular real-world task, and see how the above classes may be used to describe the various stages in performing this task. The job is to obtain, by an automatic process, the postcodes from envelopes. Here is how this may be accomplished:

- **Acquiring the image:** First we need to produce a digital image from a paper envelope. This can be done using either CCD camera, or a scanner.
- **Preprocessing:** This is the step taken before the major image processing task. This problem here is to perfrom some basic tasks in order to render the resulting image more suitable for the job to follow. In this case it may involve enhancing the contrast, removing noise, or identifying regions likely to contain the postcode.
- **Segmentation:** Here is where we actually get the postcode; in other words we extract from the image that part of it which contains just the postcode.
- **Recognition and interpretation:** This mean assigning labels to objects based on their descriptions (from the previous step), and assigning meanings to those labels. So we identify particular digits, and we interpret a string of four digits at the end of the address as the postcode.

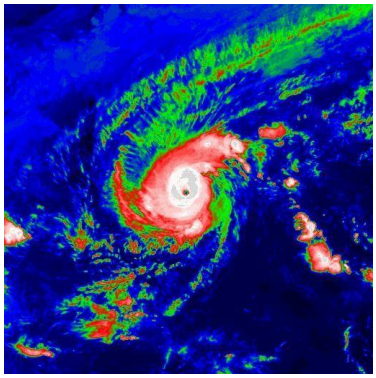
6.7 Tropical Cyclone Estimation based on core size using Image Processing

6.7.1 Libraries

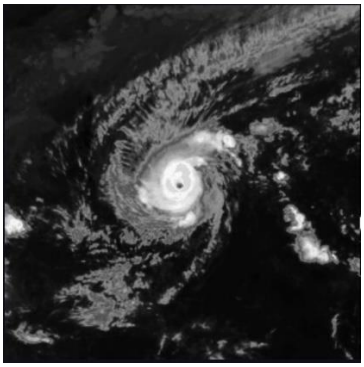
- **Streamlit:** Streamlit is a powerful Python library that enables developers to create interactive and customizable web applications for data science and machine learning projects. It simplifies the creation of user interfaces and data visualization, allowing developers to focus on the core functionality of their application. Streamlit provides a simple and intuitive API for creating web applications and data visualizations using Python, and is compatible with a wide range of popular data science and machine learning libraries such as Pandas, NumPy, Matplotlib, and TensorFlow.
- **PIL:** PIL (Python Imaging Library) is a library for working with images in Python. It provides a wide range of image processing functions, including image loading and saving, basic image manipulation, filtering and transformation, color manipulation, and more.PIL can read and write various image file formats, including BMP, GIF, JPEG, PNG, TIFF, and others. It also supports working with images in different color modes, such as grayscale, RGB, and CMYK.
- **CV2:** OpenCV (Open Source Computer Vision Library) is a popular computer vision library that is widely used for various applications such as object detection, facial recognition, image and video processing, and more. It is an open-source library that contains a large collection of tools and functions for computer vision and machine learning tasks. One of the most important features of OpenCV is its ability to work with images and video data from various sources such as cameras, files, and network streams.
- **Math:** The math library is a built-in Python library that provides various mathematical functions and constants. It includes functions for performing basic mathematical operations such as trigonometry, logarithms, exponents, and factorials. The library also provides constants such as pi and e, which are frequently used in mathematical calculations.The math library can be used by importing it at the beginning of a Python script.
- **Pandas:** Pandas is a powerful and popular open-source data analysis library for Python. It provides data structures for efficiently storing and manipulating large datasets, as well as tools for data cleaning, aggregation, and analysis.The primary data structures in Pandas are the DataFrame and the Series. A DataFrame is a two-dimensional table that stores data in rows and columns, similar to a spreadsheet or SQL table.

- **Numpy:** NumPy is a Python library that provides a powerful array and matrix computation functionality for numerical operations. It is widely used in scientific and data-related applications due to its ability to efficiently perform complex mathematical operations on large multidimensional arrays and matrices.
- **Matplotlib.pyplot:** Matplotlib.pyplot is a plotting library in Python that provides an interface similar to that of MATLAB. It is a powerful tool for creating a wide range of static, animated, and interactive visualizations in Python.
- **Skimage:** The Scikit-Image (skimage) is an open-source image processing library built on the top of NumPy, SciPy, and matplotlib. It is designed to be a user-friendly library for image processing and computer vision tasks. The skimage library provides a comprehensive set of functions for image manipulation, processing, analysis, and visualization.
- **Statistics:** Statistics is the branch of mathematics that deals with the collection, analysis, interpretation, presentation, and organization of data. It provides tools for summarizing and describing large datasets, identifying patterns and relationships within the data, and making predictions based on the available information. Statistics can be divided into two main categories: descriptive statistics and inferential statistics.

6.7.2 Grayscale Conversion



(a) Infrared Image



(b) Grayscale Image

Fig 6.9: Conversion from Infrared to Grayscale image

Grayscale conversion is a common step in image processing. A grayscale image is a black-and-white image where the intensity of each pixel is represented by a single value between 0 and 255. In a color image, each pixel is composed of three color channels - Red, Green, and Blue (RGB). In contrast, in a grayscale image, each pixel has only one channel, which represents the intensity of the color.

- **Luminance method:** This method calculates the intensity of each pixel by taking the weighted average of the RGB channels. The weights are based on the human eye's sensitivity to different colors, with green having the highest weight and blue having the lowest weight.
- **Average method:** This method calculates the intensity of each pixel by taking the average of the RGB channels.
- **Lightness method:** This method calculates the intensity of each pixel by taking the maximum and minimum values of the RGB channels and averaging them.

6.7.3 Image Thresholding

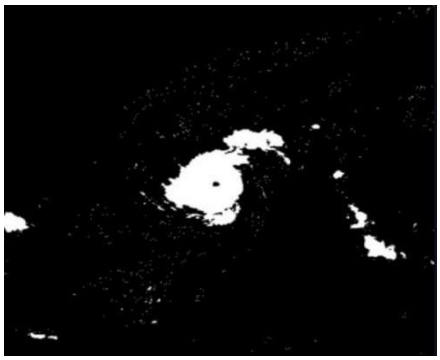


Fig 6.10: Tropical Cyclone image after performing Thresholding operation

Image thresholding is a technique used in image processing to convert an image into a binary image. In a binary image, each pixel is either black (0) or white (255) based on a threshold value. This threshold value is used to separate the foreground pixels from the background pixels in an image.

There are different methods for thresholding an image, such as global thresholding, adaptive thresholding, and Otsu's thresholding.

Once the threshold value is selected, each pixel in the image is compared to this value. If the pixel value is greater than the threshold, it is set to white (255), otherwise, it is set to black (0). This results in a binary image where the foreground pixels are white and the background pixels are black.

The second step in our model is converting greyscale image into binary image after performing image thresholding. Image thresholding is performed using the cv2.threshold function. the cv2.threshold function is used to convert the grayscale image obtained in the previous step into a binary image. The function takes the grayscale image as input and applies a threshold value to each pixel in the image.

6.7.4 Morphological Operation

Fig 6.11: Image after performing morphological operations on binary image

Morphological operations are a fundamental set of image processing techniques used to analyze and manipulate the geometric structure of objects in digital images. These operations are based on the shapes and sizes of the objects in the image and the way they are arranged.

The main purpose of morphological operations is to extract information about the shape and structure of objects, as well as to enhance or remove specific features from the image.

- **Erosion:** erosion operation is performed using cv2.erode() function. Erosion is a morphological operation that shrinks the foreground pixels and expands the background pixels, thereby removing small regions or thin lines from the image.
- **Dilation:** dilation operation is performed using cv2.dilate() function. Dilation is the opposite of erosion, it expands the foreground pixels and shrinks the background pixels, thereby filling in gaps and making the object boundaries more defined. It is achieved by sliding a structuring element (kernel) over.

6.7.5 Clear border regions

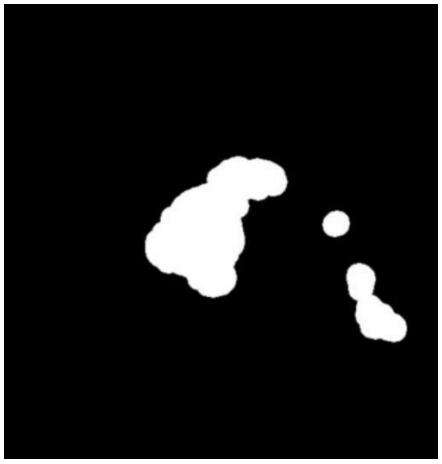


Fig 6.12: Image after clearing border regions

In image processing, the "clear border region" refers to the process of removing or erasing the objects or features that are touching or intersecting with the image's border or edges. This process is often performed to separate the foreground objects or features from the background and to remove the artifacts that can interfere with the analysis or interpretation of the image.

Clearing the border region can be achieved using several techniques such as morphological operations, image erosion, and image dilation.

In our model the "clear_border" function from the "skimage.segmentation" module is used to remove objects that touch the border of the image. This is done because objects that touch the border may not be fully captured in the image, which can lead to errors in subsequent processing steps.

6.7.6 Blob Detection

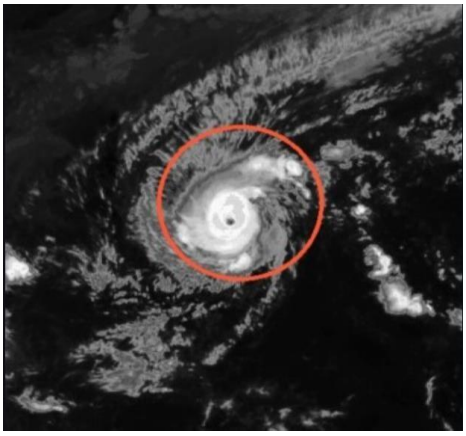


Fig 6.13: Blob detection

Blob detection is a fundamental operation in computer vision that involves identifying and locating regions or objects in an image that have homogeneous pixel values or color. Blobs can be described as connected components or regions that are distinguished from their surroundings by a significant difference in intensity, color, or texture. Blob detection can be used for a wide range of applications, including object recognition, tracking, and image segmentation.

The process of blob detection involves thresholding an image to produce a binary image, followed by grouping adjacent pixels or regions into connected components. The size, shape, and other features of each blob can then be analyzed and used for further processing or decision- making.

In our model blob detection is performed using the cv2.findContours() function. This function finds contours (i.e., the boundaries) of white objects in a binary image. In this case, the binary image is the output of the thresholding step performed earlier.

6.8 Implementation of IoT Flood Detection Module

6.8.1 Hardware Setup

The hardware model consists of:

- NodeMCU ESP8266
- Water level sensor
- Active buzzer
- LED indicator
- USB power supply

6.8.2 MQTT Communication Logic

ESP8266 connects to Wi-Fi and subscribes to a specific MQTT topic, for example:

Topic: floodsystem/alert

When the flood threshold is crossed, the backend publishes:

Payload: "1"

On receiving this payload, ESP8266 triggers:

- digitalWrite(buzzer, HIGH)
- digitalWrite(LED, HIGH)
- digitalWrite(LED, LOW)

6.8.3 Flutter Mobile Alert Integration

The mobile application subscribes to the same MQTT topic or receives REST-based push notification.

The alert screen displays:

- Flood detection timestamp
- Water level
- Suggested action
- Emergency contact button

6.8.4 ESP8266 Sample Code Snippet

```
if (message == "1") {
  digitalWrite(buzzer, HIGH);
  digitalWrite(led, HIGH);
}
```

CHAPTER 7

RESULTS AND ANALYSIS

7.1 Results

The results provides an opportunity to demonstrate the effectiveness of the developed model. It includes metrics such as accuracy, precision, and others that provide a quantitative measure of the performance of the model. It provides a means to verify the validity of the approach taken in developing the model. By analyzing the results, it may become clear that certain features or parameters could be modified to improve the performance of the model.

7.2 Validation

Validation is a crucial step in the development of deep learning models. It involves assessing the accuracy and reliability of the model, and ensuring that it performs well on a variety of data. The first step in validating a deep learning model is to prepare the data.

7.3 Confusion Matrix

A confusion matrix is a table that is often used to evaluate the performance of a deep learning model in classification tasks. It compares the predicted class labels with the actual class labels to calculate various performance metrics.

- True Positive (TP): This is when the model correctly predicts the positive class for a given sample. For example, if the actual class is high, and the model correctly predicts high, it would be a true positive for High.
- False Positive (FP): This is when the model predicts the positive class for a sample, but the actual class is negative. For example, if the actual class is Low, but the model predicts High, it would be a false positive for High.
- False Negative (FN): This is when the model predicts the negative class for a sample, but the actual class is positive. For example, if the actual class is High, but the model predicts Low, it would be a false negative for High.
- True Negative (TN): This is when the model correctly predicts the negative class for a given sample. For example, if the actual class is Low, and the model correctly predicts Low, it would be a true negative for High.

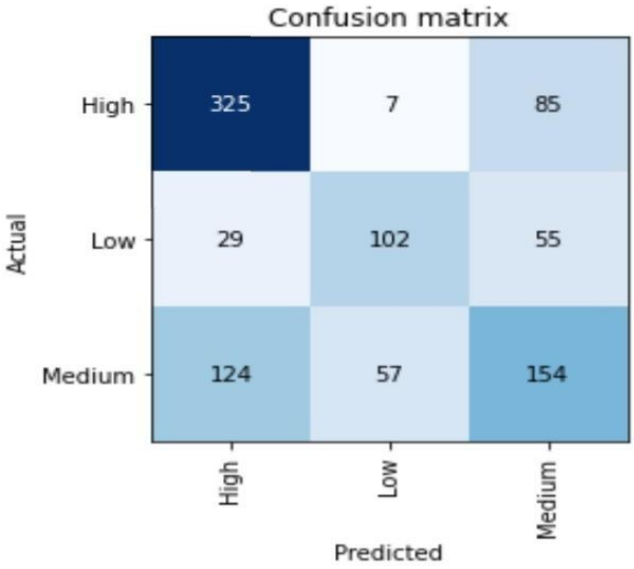


Fig 7.1: Confusion Matrix.

7.4 Learning Rate and Accuracy curve

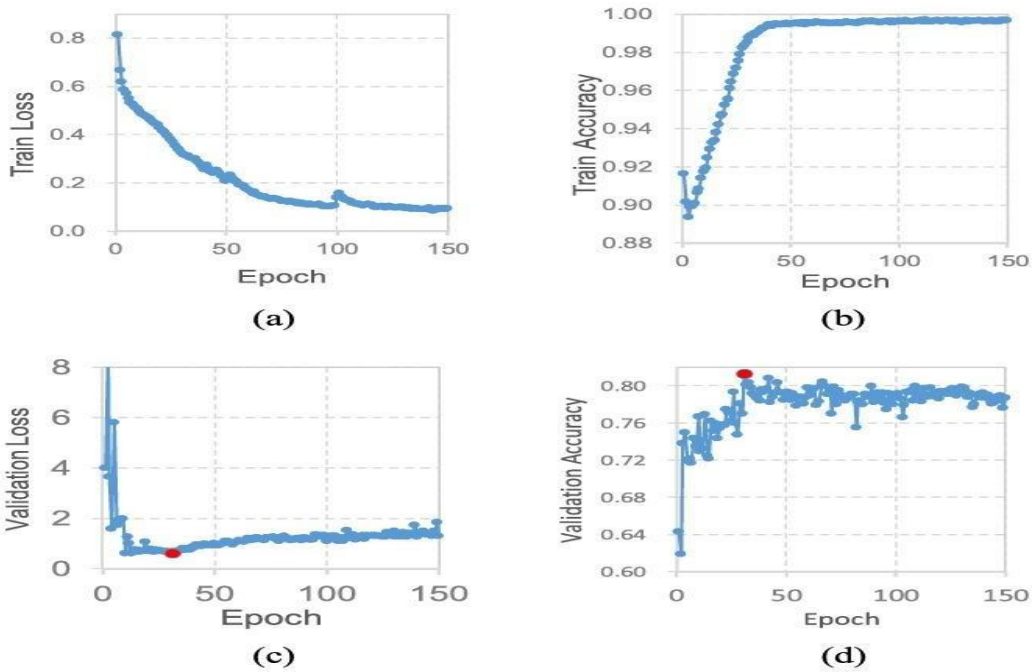


Fig 7.2 :Accuracy curve and loss function curve for the TCIC module.

a. loss function curve
b. Training accuracy curve
c. Validation loss function curve
d. Validation accuracy curve

CHAPTER 8

SNAPSHOTS

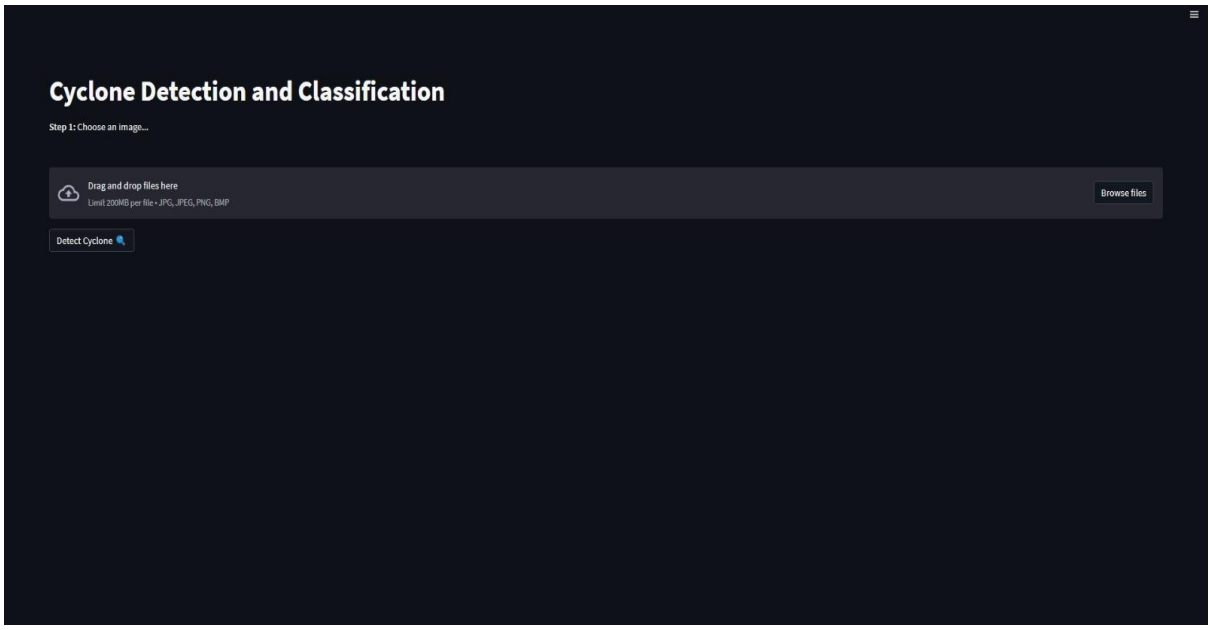


Fig 8.1: Browse files to detect Cyclone.

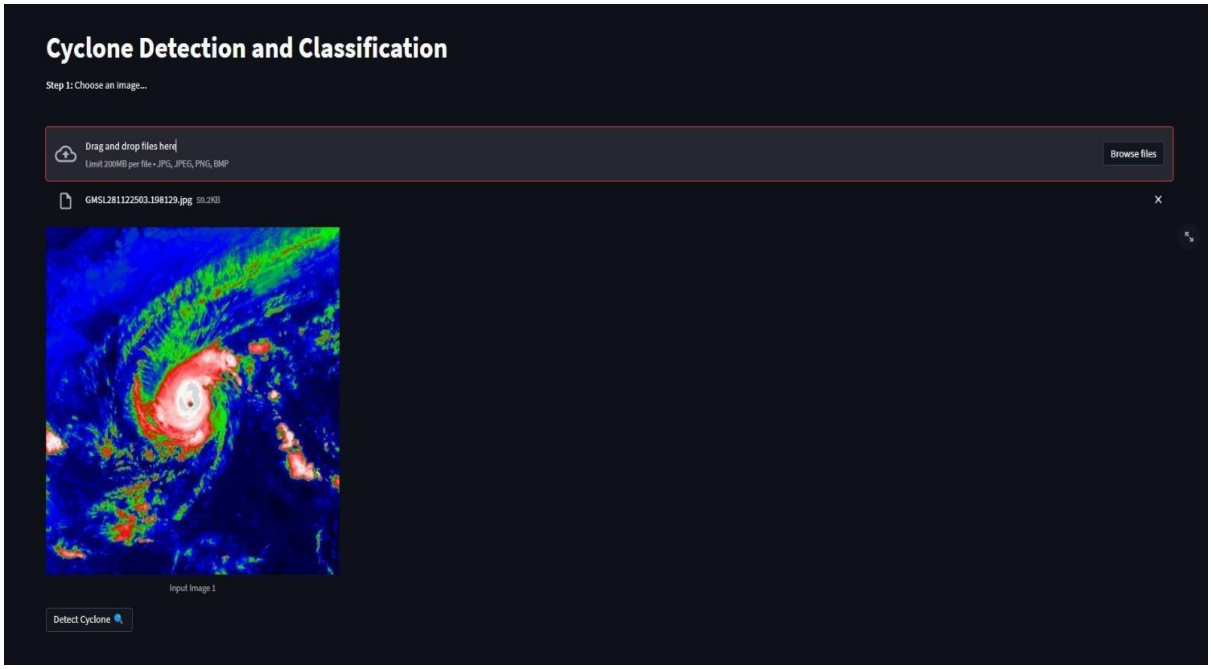


Fig 8.2: Selected a Tropical Cyclone to detect cyclone.

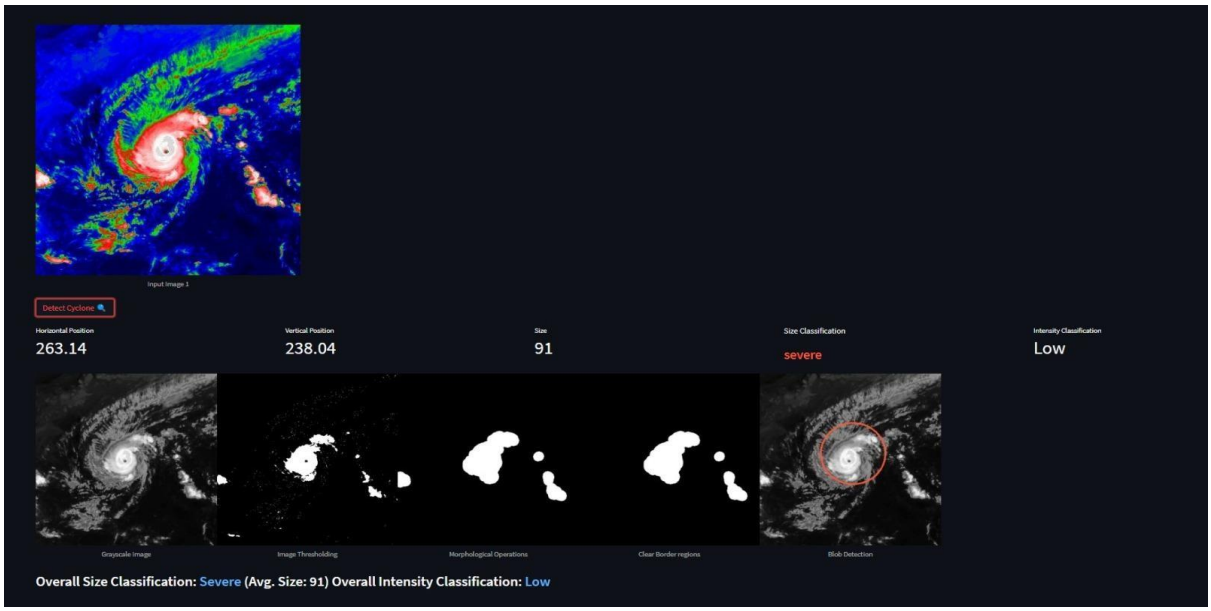


Fig 8.3: Intensity Classification of a single Tropical Cyclone.

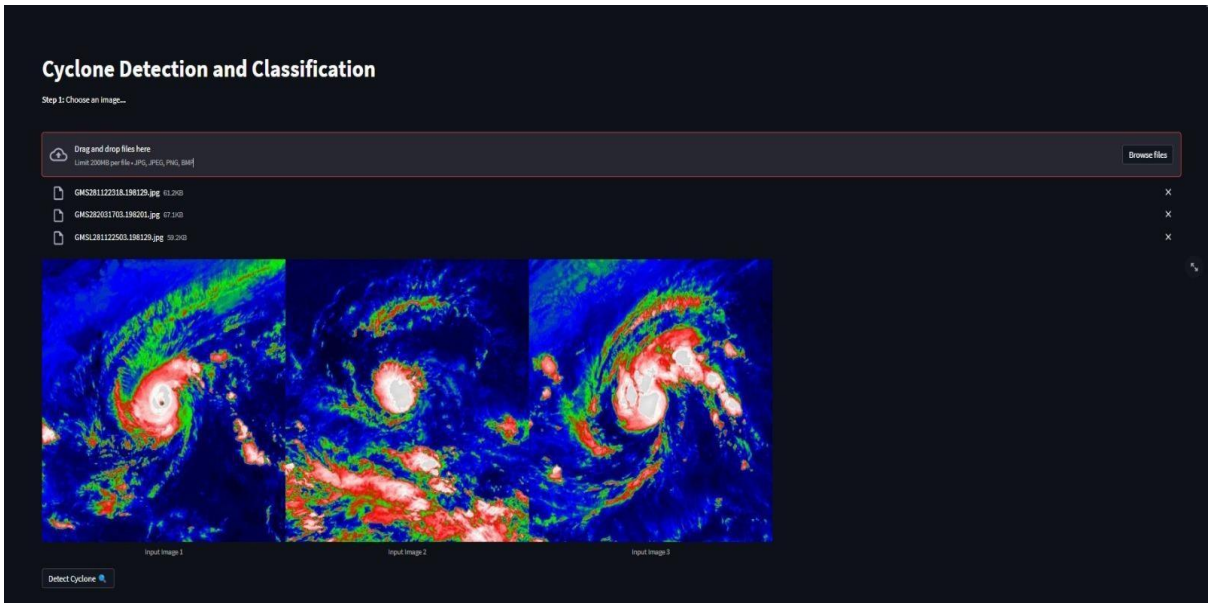


Fig 8.4: Selecting multiple Tropical Cyclones at a time for classification.

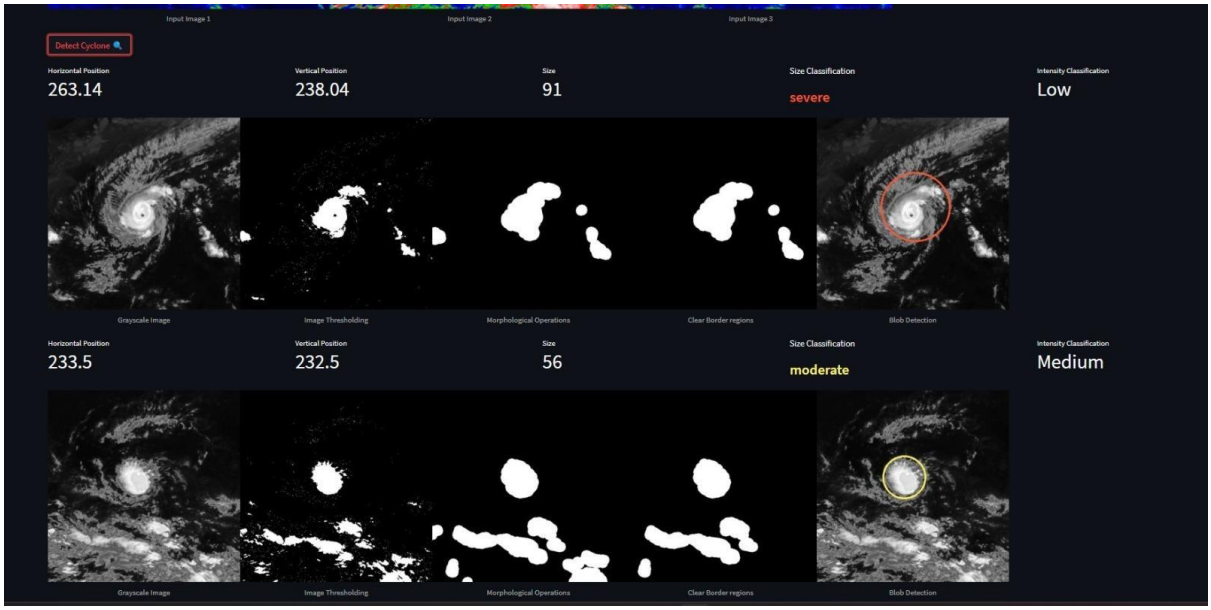


Fig 8.5: Classification of the first to Tropical cyclones.

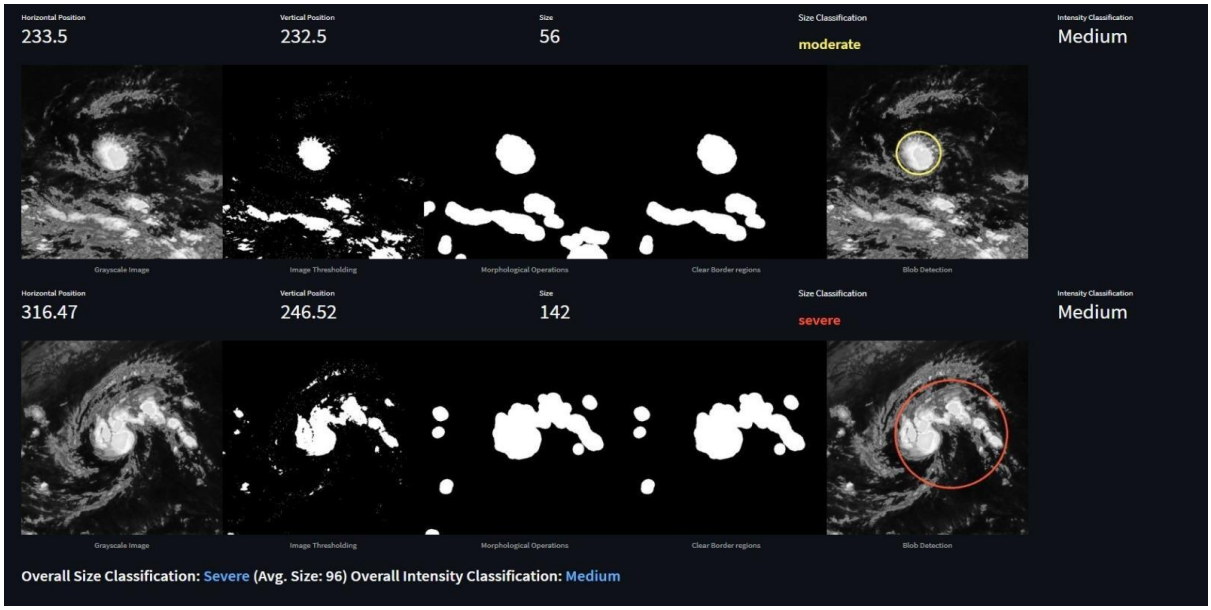


Fig 8.6: Taking average of all three to classify their intensity.

CONCLUSION

The use of image processing and deep learning techniques for tropical cyclone intensity estimation and classification is a promising area of research. By analyzing satellite images, these methods can extract important features of the storm, such as cloud patterns, size to accurately estimate its intensity and track its movements.

Deep learning models, such as Convolutional Neural Networks (CNNs), have shown excellent performance in recognizing and classifying tropical cyclones based on their intensity, with good accuracy and reliability, providing valuable information for disaster management and evacuation planning.

However, there are still challenges in this area, including the need for large datasets of high-quality satellite images, the complexity of deep learning models, and the difficulties of interpreting their results.

In conclusion, the use of image processing and deep learning for tropical cyclone intensity estimation and classification holds great potential for improving our understanding these dangerous weather events. However, further research is needed to address the remaining challenges and ensure that these methods can benefit all communities at risk.

FUTURE ENHANCEMENTS

There are several potential avenues for future enhancement of image processing and deep learning techniques for tropical cyclone intensity estimation and classification:

1. Increase the accuracy and reliability of the deep learning models: This can be achieved by developing more sophisticated deep learning architectures that can extract more meaningful features from satellite images, and by training these models on larger and more diverse datasets.

2. Incorporate other types of data: In addition to satellite images, other types of data such as weather station data, oceanic data, and atmospheric data can be used to enhance the accuracy of the models.

3. Improve the interpretability of the models: Deep learning models are often considered "black boxes" because they are difficult to interpret. Researchers can work on developing new techniques that enable better understanding of how the models arrive at their predictions.

4. Make the technology more accessible: Currently, the use of image processing and deep learning techniques for tropical cyclone intensity estimation and classification is limited to researchers with access to specialized equipment and software. Future enhancements can focus on making these techniques more accessible to a wider audience by developing user-friendly software and making the data and models freely available.

5. Improve the ability to predict the impact of tropical cyclones: In addition to predicting the intensity of tropical cyclones, image processing and deep learning techniques can also be used to predict the potential impact of these events on specific areas. This could help authorities and communities better prepare for and respond to tropical cyclones.

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