# NATURAL DISASTER INTENSITY ANALYSIS AND CLASSIFICATION USING ARTIFICIAL INTELLIGENCE

Project Report

*submitted by*

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## TABLE OF CONTENTS

| | |
|---|---|
| | PROBLEM STATEMENT DEFINITION |
| **3.** | **IDEATION & PROPOSED SOLUTION**<br>EMPATHY MAP CANVAS<br>IDEATION &<br>BRAINSTORMING<br>PROPOSED SOLUTION<br>PROBLEM SOLUTION FIT |
| **4.** | **REQUIREMENT ANALYSIS**<br>FUNCTIONAL REQUIREMENT<br>NON-FUNCTIONAL REQUIREMENTS |
| **5.** | **PROJECT DESIGN**<br>DATA FLOW DIAGRAMS<br>SOLUTION & TECHNICAL<br>ARCHITECTUREUSER STORIES |
| **6.** | **PROJECT PLANNING & SCHEDULING**SPRINT PLANNING<br>& ESTIMATION SPRINT<br>DELIVERY SCHEDULE REPORTS<br>FROM JIRA |

| | |
|---|---|
| **7.** | **CODING & SOLUTIONING**<br>FEATURE 1<br>FEATURE 2 |
| **8.** | **TESTING**<br>TEST CASES |

# CHEPTER 1
# INTRODUCTION

## Project Overview

Natural disasters not only disturb the human ecological system but also destroy the properties and critical infrastructures of human societies and even lead to permanent change in the ecosystem. Disaster can be caused by naturally occurring events such as earthquakes, cyclones, floods, and wildfires. To tackle this problem, we developed a multilayered deep convolutional neural network model that classifies the natural disasterand tells the intensity of disaster of natural The model uses

an integrated webcam to capture the video frame and the video frame is compared with the Pre- trained model andthe type of disaster is identified and showcased on the OpenCV window.

**Purpose**

The purpose of this project to detect the natural disaster and reduce, or avoid, the potential losses from hazards, assure prompt and appropriate assistance to victims of disaster, and achieve rapid and effective recovery.

# CHAPTER 2

# LITERATURE

**TITLE** : A Deep Learning Approach of Recognizing Natural Disasters on Images.

**PROPOSED WORK**

First, this work introduces to the research community a new dataset for the joint classification of natural disaster types and intensity. Moreover, this study primarily aims to explore natural disasters recognition using a convolutional neural network and transfer learning.

An open source tool is used for finding and removing the repeated images for analysis. Wildfire, Earthquake, Flood and Volcanic eruption are taken. In particular, this study attempts to build and train a lightweight convolutional neural network that can jointly recognize natural disaster types and intensity. Based on the intensity, it classifies as Severe, Moderate, Insignificant Lastly, this study attempts to measure the model performance using four performance measures; accuracy, precision, recall, and F1-Score.

**TOOLS USED/ALGORITHM**

- Image Processing
- Slope NDVI
- Location API
- Cloud Architecture
- Google Earth Engine
- K-Means and Classification Algorithm
- RGB Scale

**TECHNOLOGY :** Artificial Intelligence

**TITLE :** Disaster Intensity-Based Selection of Training Samples for Remote SensingBuilding Damage Classification.

**PROPOSED WORK**

In this proposed work, two fully automatic procedures for the detection of severely damaged buildings are introduced. The fundamental assumption is that samples that are located in areas with low disaster intensity mainly represent non-damaged buildings. Furthermore, areas with moderate to strong disaster intensities likely contain damaged and nondamaged buildings. Under this assumption, a procedure that is based on the automatic selection of training samples for learning and calibrating the standard support vector machine classifier is utilized. The second procedure is based on the use oftwo regularization parameters to define the support vectors. These frameworks avoid thecollection of labeled building samples via field surveys and/or visual inspection of optical images, which requires a significant amount of time. The performance of the proposed method is evaluated via application to three real cases. The resulted accuracy ranges between 0.85 and 0.89, and thus, it shows that the result can be used for the rapid allocation of affected buildings.

**TOOLS USED/ALGORITHM**

- Automatic labelling
- Building damage
- Multi regularization parameters
- Demand Parameter
- Support Vector Machine (SVM)

**TECHNOLOGY :** Machine Learning

**TITLE :** Hurricane Damage Detection using Machine Learning and Deep LearningTechniques

**PROPOSED WORK**

In this proposed work, Disaster detection can be done through social media and satellites. Images obtained from satellites are widely used since capturing and processing of these images can be done in a shorter span of time. Satellite images help to recognize damage pattern caused by the disasters. The images from social media are also useful since they provide information on an immediate basis. Since manual methods are error- prone, deep learning and machine learning are used which used for detecting the damagecaused by disasters effectively.

**TOOLS USED/ALGORITHM**

- • Social-media
- • Satellite imagery
- • Deep learning techniques
- • CNN,VGG-16, ResNet
- • Machine learning techniques
- • Support Vector Machine, Decision trees, random forest.

**TECHNOLOGY :** Machine Learning, Deep Learning

**Existing Problem**

Earlier we focus on post disaster relief and rehabilitation measures. Now the focus is shifted. As per sec.2(e) of DM Act 2005, Disaster Management means a coordination and integrated process of planning, organizing, coordinating, and implementing measures which are necessary or expedient for-

- Prevention of danger or threat of any disaster
- Preparedness to deal with any disaster
- Prompt response to any threatening disaster situation or disaster
- Assessing the severity or magnitude of effects of any disaster
- Evacuation, rescue, and relief
- Rehabilitation and reconstruction

**References**


- Mignan, A.; Broccardo, M. Neural network applications in earthquake prediction (1994–2019): Meta-analytic and statistical insights on their limitations. Seism. Res. Lett. 2020, 91, 2330–2342. [CrossRef]
- Tonini, M.; D'Andrea, M.; Biondi, G.; Degli Esposti, S.; Trucchia, A.; Fiorucci, P. A Machine Learning-Based Approach for Wildfire Susceptibility Mapping. The Case Study of the Liguria Region in Italy. Geosciences 2020, 10, 105. [CrossRef]

• • Islam, A.R.M.T.; Talukdar, S.; Mahato, S.; Kundu, S.; Eibek, K.U.; Pham, Q.B.; Kuriqi, A.; Linh, N.T.T. Flood susceptibility modelling using advanced ensemble machine learning models. Geosci. Front. 2021, 12, 101075. [CrossRef]

• • Schlemper, J.; Caballero, J.; Hajnal, V.; Price, A.N.; Rueckert, D. A deep cascade of convolutional neural networks for dynamic MR image reconstruction. IEEE Trans. Med. Imaging 2017, 37, 491–503. [CrossRef] [PubMed]

• • Tang, C.; Zhu, Q.; Wu, W.; Huang, W.; Hong, C.; Niu, X. PLANET:Improved convolutional neural networks with image enhancement for image classification. Math. Probl. Eng. 2020, 2020. [CrossRef]

**Problem Statement Definition**

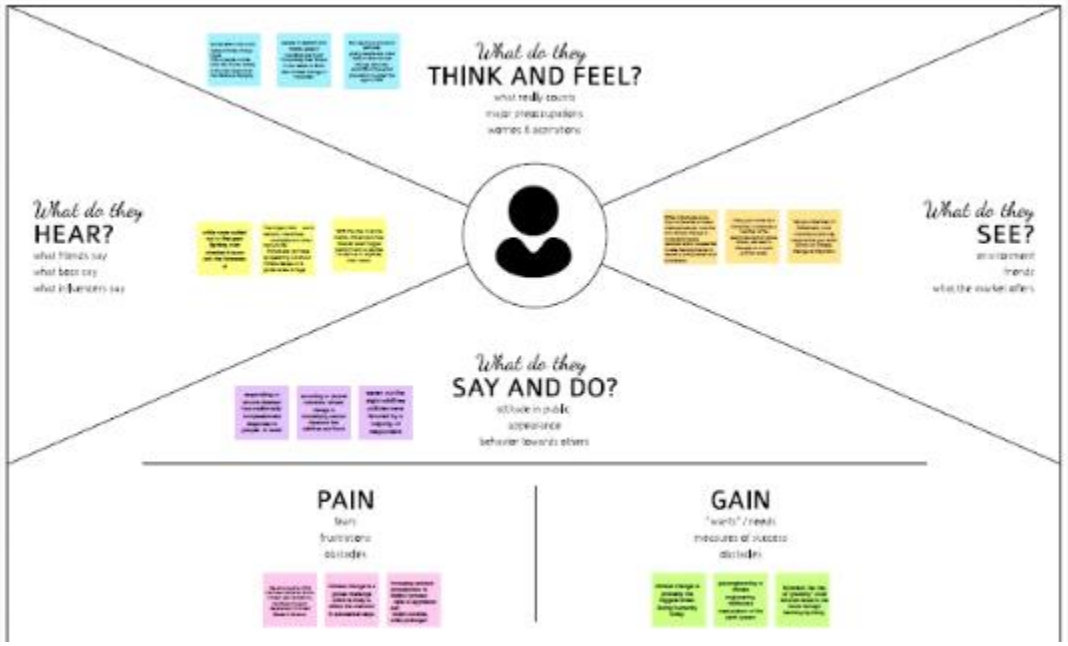
People needs a way to classify and analyse the natural disaster so that they can prevent themselves from losses due to the disaster and millions of lives.

People and animals are facing so many issues like loss of life, property, resources and deterioration of the air quality due to the natural disaster. So we need to analyse and detect natural disaster and protect them from such disaster.

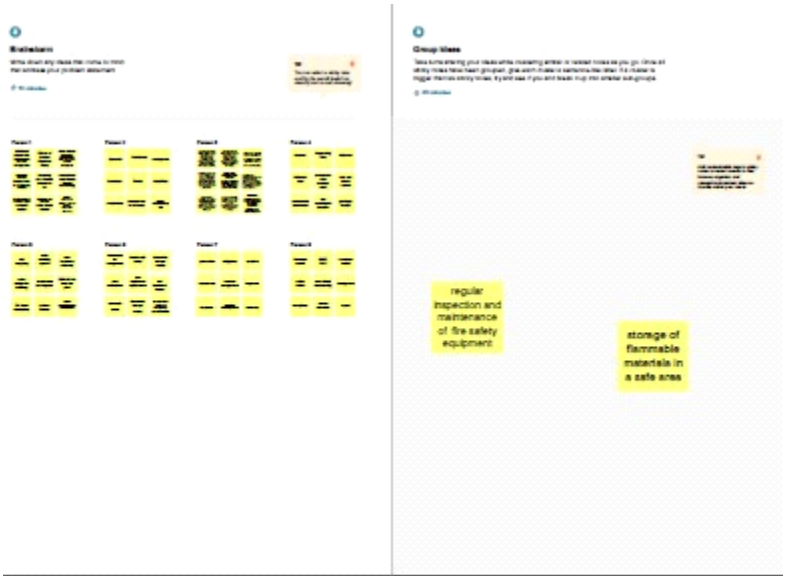
# CHAPTER 3

# IDEATION & PROPOSED SOLUTION

## Empathy Map Canvas




## Ideation & Brainstorming


## Proposed solution

| S. No. | Parameter | Description |
|---|---|---|

| | | |
|---|---|---|
| 1. | Problem Statement (Problem to be solved) | The main purpose of this model is to detect andclassify the type of disaster with a high accuracy rate |
| 2. | Idea/Solution description | Emergency measures, Investments in riskreduction, Information sharing on newestresearch findings, Reforestation, Stablebuildings, EducationTechnology, Governance. |
| 3. | Novelty/Uniqueness | A natural disaster is "the negative impact following an actual occurrence of natural hazardin the event that it significantly harms acommunity".. |
| 4. | Social impact/Customer Satisfaction | Increased mental health issues, alcohol misuse,domestic violence, chronic disease and shortterm unemployment have resulted fromextreme weather events such as bushfires,severe storms, cyclones, floods andearthquakes. |
| 5. | Business Model (RevenueModel) | Be Aware of the Natural Disasters that CouldAffect Your Business, Create a DisasterResponse Plan, Implement CommunicationPlans, Backup Documents and Data, Protect thePower, Plan to Recover, Review Your Commercial Insurance Coverage. |
| 6. | Scalability of the Solution | Scalability: Implementing disaster recoverymeasures involves identifying new and scalablesolutions, such as the cloud. |

**Problem Solution Fit**

# CHAPTER 4

# REQUIREMENT ANALYSIS

## Functional Requirement

| FR No. | Functional Requirement(Epic) | Sub Requirement (Story / Sub-Task) |
|---|---|---|
| FR-1 | Request Permission | Access permission from web camera. |
| FR-2 | Disaster Detection | Based on the webcam image, natural disaster is classified. |
| FR-3 | Accuracy | Since the training and testing images are huge,<br>The accuracy is higher. |
| FR-4 | Speed | The generation of results from the input Images are faster. |
| FR-5 | Resolution | The resolution of the integrated webcamera should be high enough to capturethe video frames. |

| | | |
|---|---|---|
| **FR-6** | User Interface | Maximizing the interaction in Web Designing Service. |

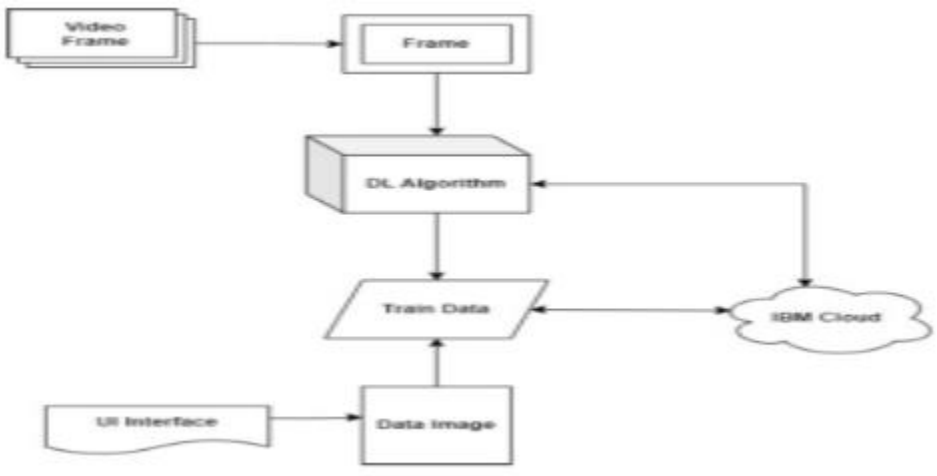
## Non-Functional Requirement

| **NFR. No.** | **Non-Functional Requirement** | **Description** |
|---|---|---|
| **NFR-1** | Usability | User friendly and classify the disaster easily. |
| **NFR-2** | Security | The model is secure due to the cloud deployment models and also there is nologin issue. |
| **NFR-3** | Reliability | Accurate prediction of the natural disaster and the website can also be fault tolerant. |
| **NFR-4** | Performance | It is shown that the model gives almost 95 Percent accuracy after continuous training. |
| **NFR-5** | Availability | The website will be made available for 24 hours. |
| **NFR-6** | Scalability | The website can run on web browsers like Googlechrome, Microsoft edge and also itcan be extended to the NDRFand customers. |

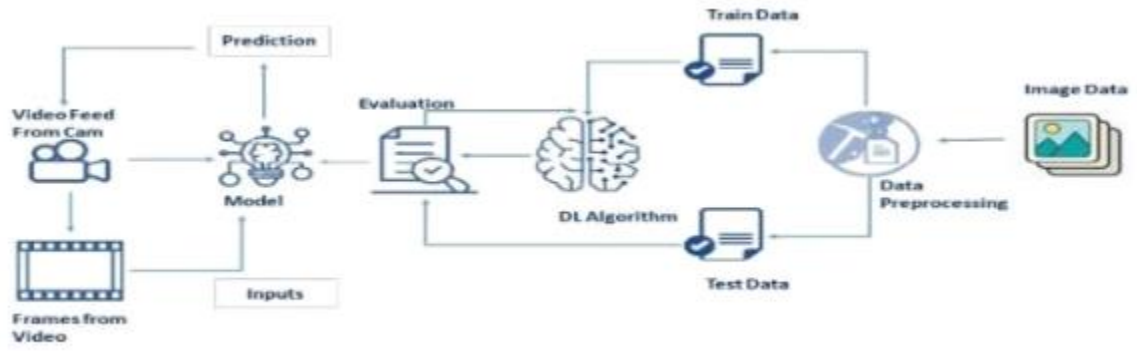
# CHAPTER 5
# PROJECT DESIGN

## Data Flow Diagrams

A Data Flow Diagram (DFD) is a traditional visual representation of the information flows within a system. A neat and clear DFD can depict the right amount of the system requirement graphically. It shows how data to be enter and leaves thesystem, what changes the information, and where data is stored.




**Flow Diagram**




**Solution & Technical**

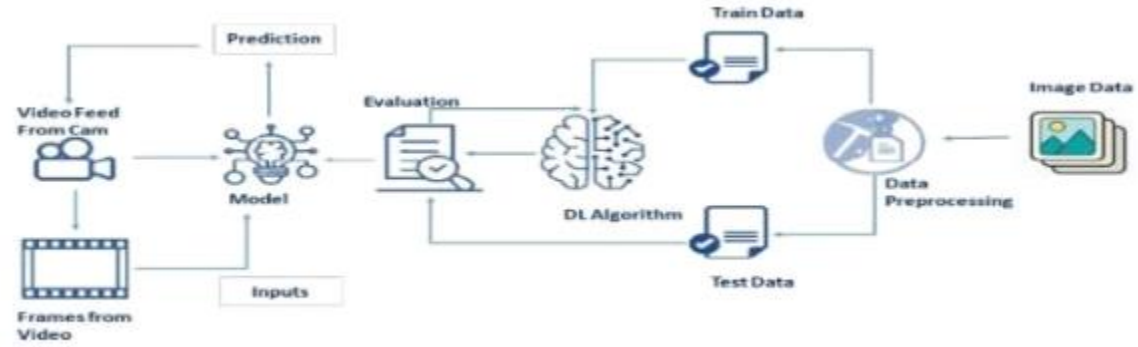
**Architecture Solution**

**Architecture**

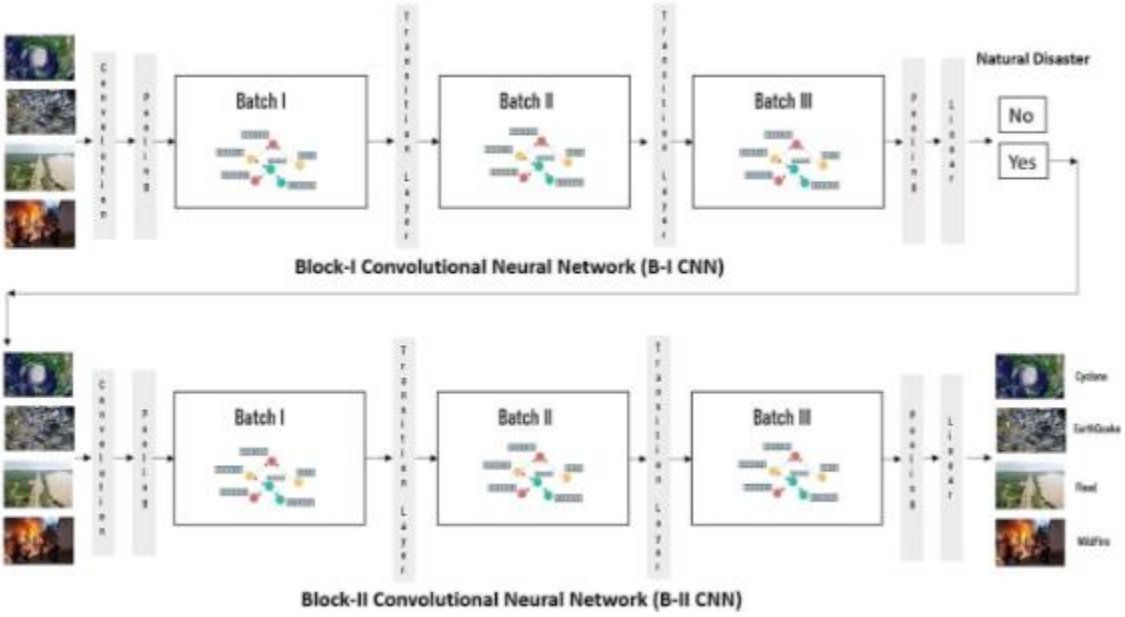
Solution architecture is a complex process – with many sub-processes – that bridges the gap between business problems and technology solutions. Its goals areto:

- • Find the best tech solution to solve existing business problems.
- • Describe the structure, characteristics, behavior, and other aspects of thesoftware to project stakeholders.
- • Define features, development phases, and solution requirements.
- • Provide specifications according to which the solution is defined, managed,and delivered.

**Solution Architecture Diagram**




## Technical Architecture




## Components &Technologies:

| S.No | Component | Description | Technology |
|---|---|---|---|

| | | | |
|---|---|---|---|
| 1. | User Interface | User interacts with application for the detection of any Natural disaster's intensity and classify which happened justbefore. | HTML, CSS, JavaScript, Django, Python. |
| 3. | Disaster Detection | This function is used to detect, Outcomes from | Decision trees, Regression, |
| | | the new trained data to perform new | Convolutio |
| | | tasks and solve new problems. | nal Neural |
| | | | networks. |
| 4. | Evaluation system | It monitors that how Algorithm performson data as well as during training. | Chi-Square, Confusion Matrix, etc. |
| 5. | Input data | To interact with our model and give itproblems to solve. Usually this takes the formof an API, auser interface, or a command-line interface. | Application programming interface, etc. |

| | | | |
|---|---|---|---|
| 6. | Data collection unit | Data is only useful if it's accessible, soitneeds to be stored ideally in a consistent structure and conveniently inone place. | IBM Cloud, SQLServer. |
| 7. | Database management system | An organized collection of data stored indatabase, so that it can be easily accessedand managed. | MySQL, DynamoDB etc. |

**Application Characteristics:**

| S.No | Characteristics | Description | Technology |
|---|---|---|---|
| 1. | Open-Source Frameworks | An open source framework is a template for software developmentthat is designed by a social networkof software developers. These frameworks are free for public useand provide the foundation for building a software application. | Keras, Tensorflow. |

| | | | |
|---|---|---|---|
| 2. | Authentication | This keep sour models secure andmakes sure only those who havepermission can use them. | Encryption and Decryption (OTP). |

| | | | |
|---|---|---|---|
| 3. | Application interface | User uses mobile application andweb application to interact with model | Web Develop ment (HTML,C SS) |
| 4. | Availability (both Online and Offline work) | Its include both online and offline work. As good internet connection is need for online work to explore the software perfectly. Offline work includes the saved data to explore for later time. | Caching, backend server. |

| | | | |
|---|---|---|---|
| 5. | Regular Updates | The truly excellent software product needs a continuous process of improvements and updates. Maintain your server and make sure that your content is always up-to- date. Regularly update an app and enrich it with new features. | Waterfall Approach, Incremental Approach, Spiral Approach |
| 6. | Personalization | Software has features like flexible fonts, backgrounds, settings, colourthemes, etc. which make a softwareinterface looks good and functional. | • • CSS |

**User Stories**

| **Functional Requirement (Epic)** | **User Story Number** | **User Story / Task** | **Acceptance criteria** |
|---|---|---|---|
| Collection of dataset | USN-1 | As a user, I can collect the dataset for monitoring and analyzing. | Enough data collected for training Model. |

| | | | |
|---|---|---|---|
| Home Page | USN-2 | As a user, I want to knowto about the basics of frequently occurring Disasters. | I can get the idea about theApplication. |
| Intro page | USN-3 | As a user, I want to aboutthe introduction of Disaster in particular areas. | I can get idea about the disaster and where it occurs. |
| Open webcam | USN-4 | As a user, I adapt with thewebcam to analyze and classify the Disaster from video capturing | I can capture a video or image of particular disaster to analyze and classify. |
| Analysis of required phenomenon | USN-5 | As a user, I can regulate certain factors influencing the action and report on past event analysis. | Model should be easy to use & working fine from the web app. |

| | | | |
|---|---|---|---|
| Algorithm selection | USN-6 | As a user, I can choose therequired algorithm for specific analysis. | Selection must give the better accuracy and better output. |
| Training and Testing | USN-7 | As a user, I can train andtest the model using the algorithm. | Training the model intensity |
| Detection and analysis of data | USN-8 | As a user, I can detect andvisualize the data effectively. | I can capture a video or image of particular disasterto analyze and detect. |
| Model building | USN-9 | As a user I can build withthe web application. | Model should be predicting occurrence of the disaster and intensity level of disaster. |
| Integrate the web app with theAI Model | USN-10 | As a user, I can use Flaskapp to use model easily through web app. | Model should be easy to use and working fine from the web app. |
| Model deployment | USN-11 | As an administrator, I candeploy the AI model in IBM Cloud. | Model's prediction shouldbe available for users to make decision. |

# CHAPTER 6

# PROJECT PLANNING & SCHEDULING

## Sprint planning & Estimation

| Sprint | Functional Requirement (Epic) | User Story Number | User Story / Task | Story Points |
|---|---|---|---|---|
| Sprint-1 | Collection of Dataset | USN-1 | As a user, I can collect the dataset for monitoring and analysing. | 5 |
| Sprint-1 | Home page | USN-2 | As a user, I want to know to aboutthe basics of frequently occurring Disasters. | 5 |
| Sprint-1 | Intro page | USN-3 | As a user, I want to about the introduction of Disaster in particular areas. | 5 |

| | | | | |
|---|---|---|---|---|
| Sprint-1 | Open webcam | USN-4 | As a user, I adapt with the webcam to analyse and classify the Disaster from video capturing. | 5 |
| Sprint-2 | Analysis of required phenomenon | USN-5 | As a user, I can regulate certain factors influencing the action andreport on past event analysis. | 5 |

| | | | | |
|---|---|---|---|---|
| Sprint-2 | Algorithm selection | USN-6 | As a user, I can choose therequired Algorithm for specific analysis. | 5 |
| Sprint-2 | Training and Testing | USN-7 | As a user, I can train and test themodel using the algorithm. | 10 |
| Sprint-3 | Detection and analysis of data | USN-8 | As a user, I can detect and visualise the data effectively. | 10 |
| Sprint-3 | Model building | USN-9 | As a user, I can build with the web application. | 10 |

| | | | | |
|---|---|---|---|---|
| Sprint-4 | Integrate the web app with the AI model | USN-11 | As a user, I can use Flask app touse model easily through web app. | 10 |
| Sprint-4 | Model deployment | USN-12 | As an administrator, I can deploythe AI model in IBM Cloud. | 10 |

**Sprint Delivery schedule**

| Sprint | Total Story Points | Duration | Sprint Start Date | Story Points Completed (ason Planned End Date) | Sprint Release Date (Actual) |
|---|---|---|---|---|---|
| Sprint-1 | 20 | 6 Days | 24 Oct 2022 | 20 | 29 Oct 2022 |
| Sprint-2 | 20 | 6 Days | 31 Oct 2022 | 20 | 05 Nov 2022 |
| Sprint-3 | 20 | 6 Days | 07 Nov 2022 | 20 | 12 Nov 2022 |
| Sprint-4 | 20 | 6 Days | 14 Nov 2022 | 20 | 19 Nov 2022 |

**Reports from Jira**

**Velocity:**

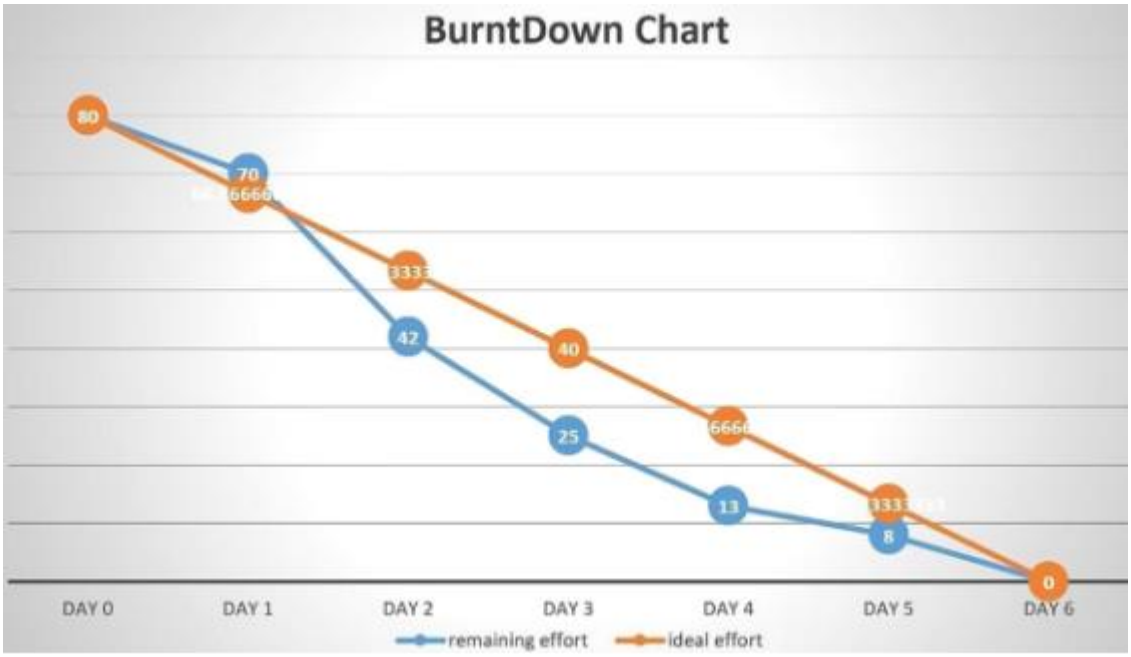
Imagine we have a 10-day sprint duration, and the velocity of the team is 20(points per sprint). Let's calculate the team's average velocity (AV) per iteration unit (story points per day)

**Average velocity = Sprint duration / velocity**

**=20/6**

**=3**

**Burndown Chart:**




A burn down chart is a graphical representation of work left to do versus time. It is often used in agile software HYPERLINK "https://www.visual-paradigm.com/scrum/what-is-agile-software-development/"_ HYPERLINK "https://www.visual-paradigm.com/scrum/what-is-agile-software-development/"developmen HYPERLINK "https://www.visual-paradigm.com/scrum/what-is-agile-software-development/"t HYPERLINK "https://www.visual-paradigm.com/scrum/what-is-agile-software-

development/"_ HYPERLINK "https://www.visual-paradigm.com/scrum/what-is-agile-software-development/"methodologies such as Scrum.However, burn down charts can be applied to any project containing measurable progress over time.

# CHAPTER 7

## CODING & SOLUTIONING

### Feature 1

The project focuses on the analysis of intensity of Disaster for givingprecautionary measures for the people living in the Danger zone.

It focuses on classifying the type of Disaster which oftenly occurs in thatparticular zone.

### Feature 2

The accuracy of the project is improved more better than the previouslysubmitted models.

The accuracy is improved by training and testing more images in the dataset.

# CHEPTER 8
# TESTING

## Test cases

| Test Case ID | Component | Test Scenario | Expected Result | Actual Result | Status |
|---|---|---|---|---|---|
| TC_001 | Home Page | Verify user is ableto see the Home page | Home page should Display | Working as expected | Pass |
| TC_002 | Home Page | Verify the UI elements in Home page | Application shouldshow below UI elements:<br>Home page button<br>Intro page button<br>Open webcam button | Working as expected | Pass |
| TC_003 | Home Page | Verify user is ableto see the cards about Disaster | Application should show the cards about Disaster. | Working as expected | Pass |
| TC_004 | Home Page | Verify user is ableto navigate to the required page | Application should navigate to the Intro page | Working as expected | Pass |
| TC_005 | Intro Page | Verify user is ableto see the Intro | Intro page should display | Working as expected | Pass |

| | | | | | |
|---|---|---|---|---|---|
| | | page | | | |
| TC_006 | Intro Page | Verify the UI Elements in Intropage | Application shouldshow below UI elements:<br>Home page<br>Intro page<br>Open webcam button | Working as expected | Pass |
| TC_007 | Intro Page | Verify the user is able to see the introduction of theDisaster | Application should show the sentences about the Disaster | Working as expected | Pass |
| TC_008 | Intro Page | Verify user is ableto navigate to the required page | Application should navigate to the Open webcam page | Working as expected | Pass |
| TC_009 | Webcam page | Verify user is able to see the webcam page | Webcam page is displayed | Working as expected | Pass |
| TC_010 | Webcam page | Verify the Emergency pull button is visible while the webcam is not connected | Application shouldshow below UI elements:<br>a. Emergency pullbutton | Working as expected | Pass |

| | | | | | |
|---|---|---|---|---|---|
| TC_011 | Webcam page | Verify user is able to see the output window | Application should detect the type of Disaster from the realtime video | Working as expected | Pass |

**User Acceptance Testing**

It is to briefly explain the test coverage and open issues of the natural disasters intensity analysis and classification using artificial intelligence project at the time of the release to User Acceptance Testing (UAT).

**Defect Analysis:**

This report shows the number of resolved or closed bugs at each severity level, and how they were resolved

| Resolution | Severity 1 | Severity 2 | Severity 3 | Severity 4 | Subtotal |
|---|---|---|---|---|---|
| By Design | 1 | 0 | 0 | 2 | 3 |
| Duplicate | 1 | 0 | 0 | 0 | 1 |
| External | 0 | 0 | 0 | 0 | 0 |
| Fixed | 1 | 0 | 0 | 2 | 3 |

| | | | | | |
|---|---|---|---|---|---|
| Not Reproduce | 0 | 0 | 0 | 0 | 0 |
| Skipped | 0 | 0 | 0 | 1 | 1 |
| Won't Fix | 0 | 0 | 0 | 0 | 0 |
| Totals | 3 | 0 | 0 | 5 | 8 |

**Test Case Analysis:**

This report shows the number of test cases that have passed, failed, anduntested.

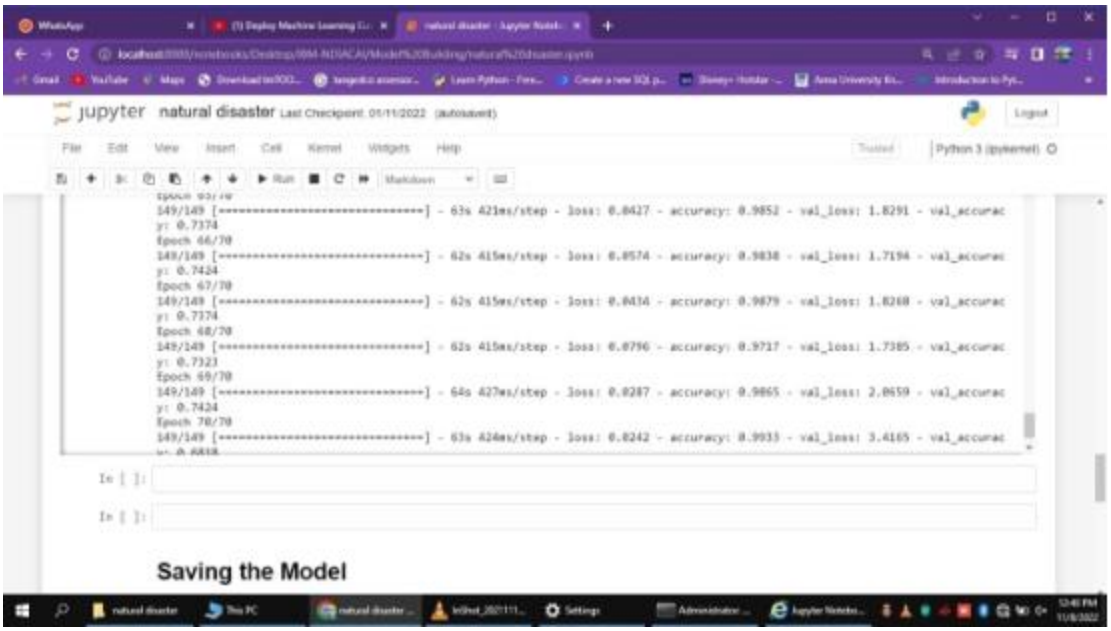
| Section | Test Cases | Not Tested | Fail | Pass |
|---|---|---|---|---|
| Home Page | 4 | 0 | 0 | 4 |
| Intro Page | 4 | 0 | 0 | 4 |
| Open Webcam | 3 | 0 | 0 | 3 |

# CHEPTER 9
# RESULTS

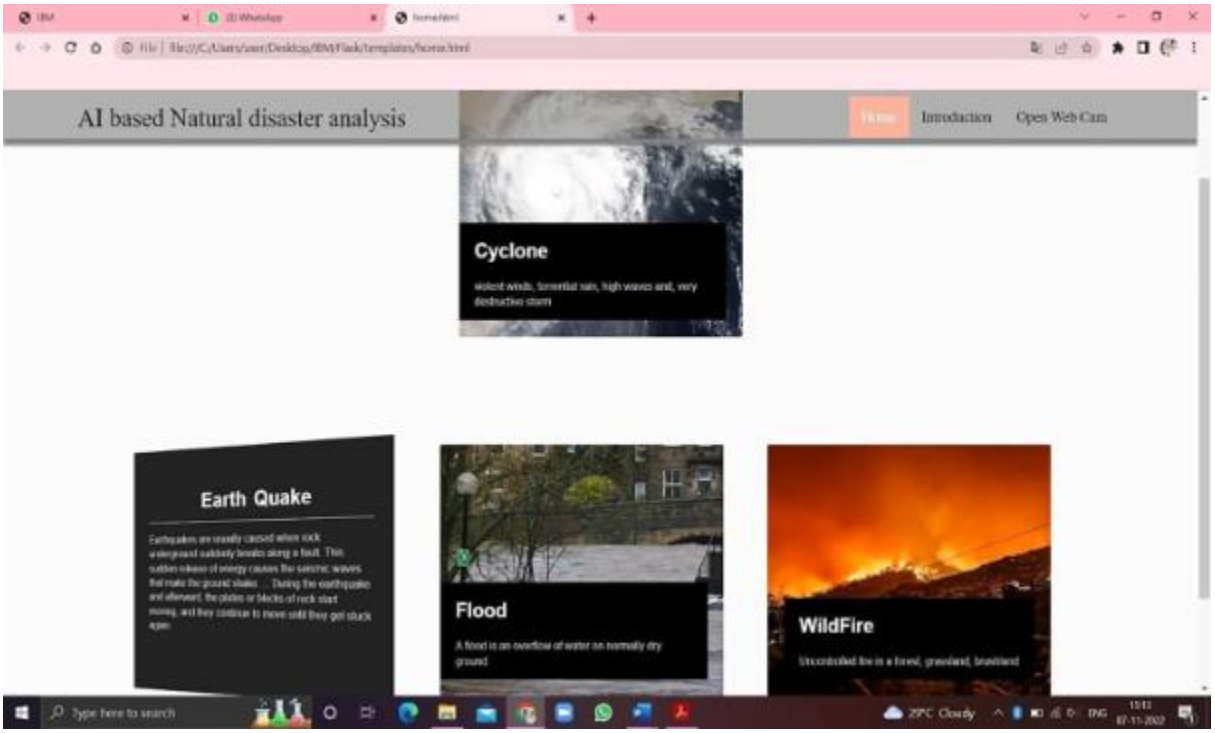
## Performance Metrics

The nature disaster intensity analysis and classification with test data and train data has been executed successfully. The model has been trained over 1000+ images and the model have an accuracy of nearly 99% and the model has been tested withthe data which is separate from the trained data and has predicted the data well.

## Output of application




## HOME PAGE

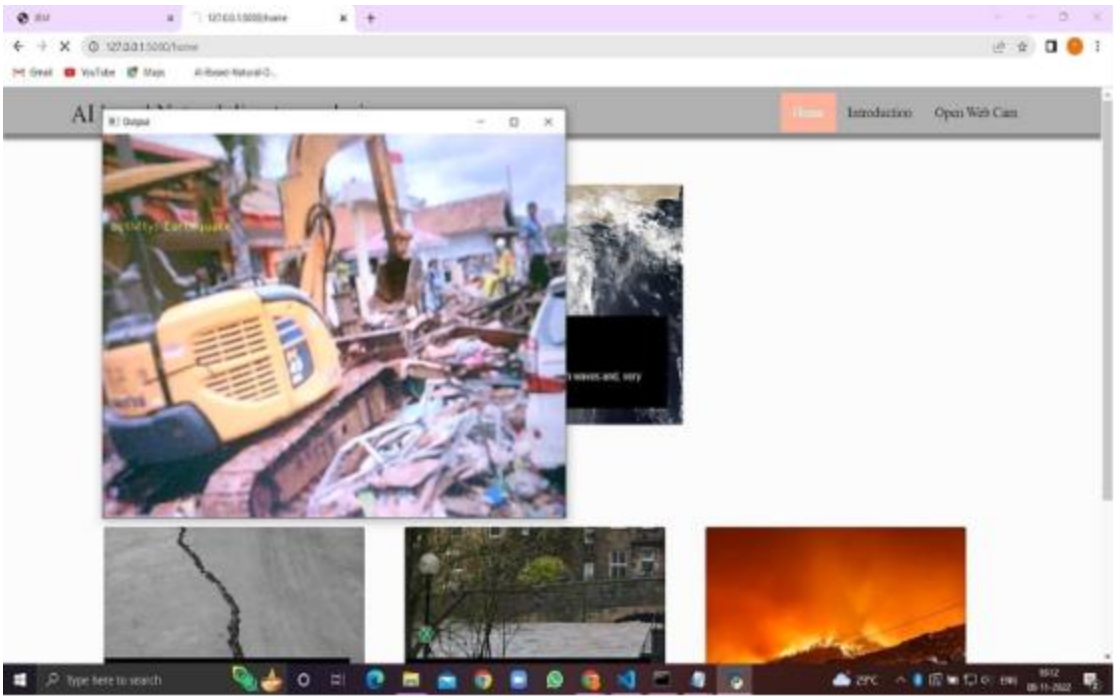


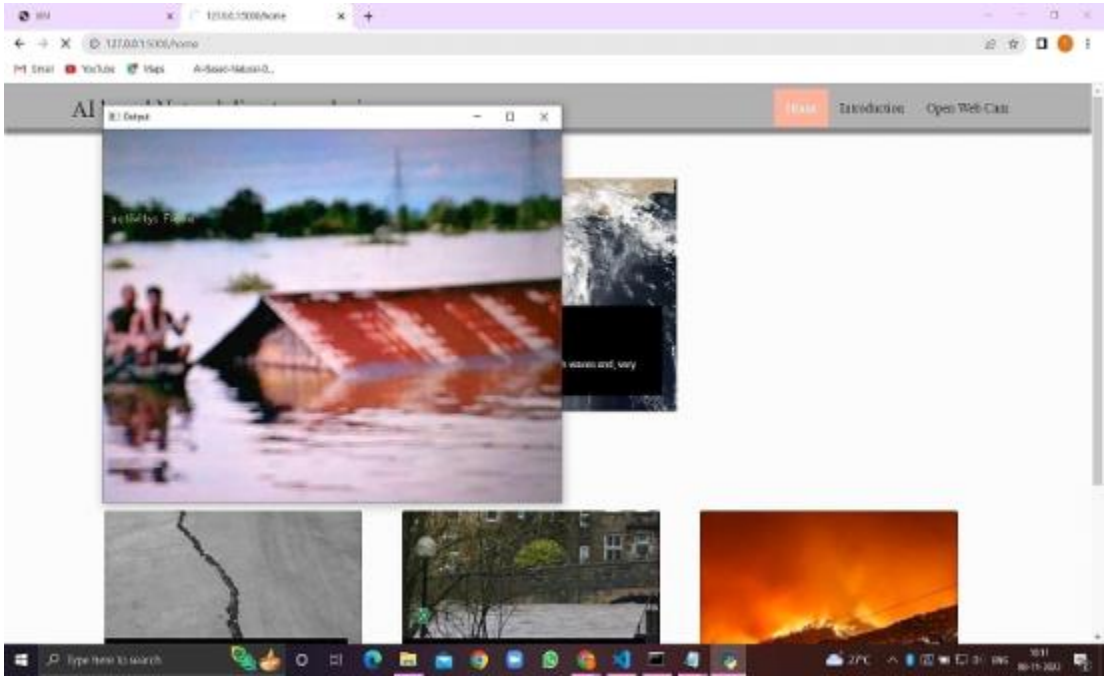

## INTRODUCTION PAGE


**China, India and the United States are among the countries of the world most affected by natural disasters.**
**Natural disasters have the potential to wreck and even end the lives of those people, who stand in their way. However, whether or not you are likely to be affected by a natural disaster greatly depends on where in the world you live, The objective of the project is to human build a web application to detect the type of disaster . The input is taken from the in built web cam, which in turn is given to the pre trained model . The model predicts the type of disaster and displayed on UI.**

## WEB CAM


## DETECTION OF NATURE DISASTER


Introduction
Open Web Cam


Introduction
Open Web Cam

# CHAPTER 10

# ADVANTAGES & DISADVANTAGES

## ADVANTAGES

- • The proposed model will be used as a real time natural disaster detectionmodel and provide some upcoming predictions for future disasters.
- • The model is to detect and classify the type of disaster and The modelhave a high accuracy rate ( 99.33).
- • The model was used to prevent natural disasters in the future and model can be used to predict future disasters and take some action against heavyloss of human ecological systems and property.
- • The proposed system helps to reduce the impact of hazards occur during natural disaster. This provides an efficient way to warn and educate peopleabout disaster prone areas.
- • It will help us be prepared in times of disaster

## DISADVANTAGES

- • The resultant model unable to validate the model performance underuncontrolled conditions.
- • The model cannot be used for various natural disaster

# CHEPTER 11

# CONCLUSION

It focused how image from given dataset (trained dataset) in field and past data set used predict the pattern of different nature disaster using CNN model. In the system had applied different type of CNN compared the accuracy. The natural disaster in Indonesia frequently happened, due to the geographical position of the country. Thus, natural disasters mostly occurred as an impact of the natural condition. However, the weather and climate condition has also influenced and triggered the disasters.

# CHAPTER 12
# FUTURE SCOPE

In the future, the research will be continued to obtain the data from all over the country, not only west java province, and with the use of more complete analysis, so that the government or related institution could make a better anticipation work as a mitigation effort.

# CHAPTER 14
# PEAD IX

**Inserting necessary libraries**

import numpy as np **#used for numerical analysis**

import tensorflow **#open source used for both ML and DL for computation**

from tensorflow.keras.models import Sequential **#it is a plain stack of layers**

from tensorflow.keras import layers **#A layer consists of a tensor-in**

**tensor-outcomputation function**

**#Dense layer is the regular deeply connected neural network layer**

from tensorflow.keras.layers import Dense,Flatten

#Faltten-used fot flattening the input or change the dimension

from tensorflow.keras.layers import Conv2D,MaxPooling2D

**#Convolutionallayer**

**#MaxPooling2D-for downsampling the image**

from keras.preprocessing.image import

ImageDataGeneratortensorflow.__version

_____

tensorflow.keras._version_____

**Image Data Augumentation**

**#setting parameter for Image Data agumentation to the training data**

train_datagen =

ImageDataGenerator(rescale=1./255,shear_range=0.2,zoom_ra

nge=0.2,horizontal_ flip=True)

**#Image Data agumentation to the testing data**

test_datagen=ImageDataGenerator(rescale=1./255)

**Loading our data and performing Data**

**Augumentation#performing data agumentation**

**to train data**

x_train=train_datagen.flow_from_directory(r'C:\Users\vasanth

\Desktop\IBM Project\dataset\train_set',target_size=(64,

64),batch_size=5,

color_mode='rgb',class_mode='categorical')

**#performing data agumentation to test data**

x_test=test_datagen.flow_from_directory(r'C:\Users\vasanth\
Desktop\IBM Project\dataset\test_set',target_size=(64,
64),batch_size=5,

color_mode='rgb',class_mode='cat

egorical') print(x_train.class_indices**)#checking the number**

**of classes**

print(x_test.class_indices)#**checking the number of classes**

from collections import

Counter as cc(x_train

.labels)

**Creating the Model**

**# Initializing the CNN**

classifier = Sequential()

**# First convolution layer and poolingo**

```
classifier.add(Conv2D(32, (3, 3), input_shape=(64, 64, 3), activation='relu'))

classifier.add(MaxPooling2D(pool_size=(2, 2)))

classifier.add(Conv2D(32, (3, 3), input_shape=(64, 64, 3), activation='relu'))

# Second convolution layer and pooling

classifier.add(Conv2D(32, (3, 3), activation='relu'))

# input_shape is going to be the pooled feature maps from the previousconvolution layer

classifier.add(MaxPooling2D(pool_size=(2, 2)))

classifier.add(Conv2D(32, (3, 3), input_shape=(64, 64, 3), activation='relu'))

# Flattening the layers

classifier.add(Flatten())

# Adding a fully connected layer
```

```
classifier.add(Dense(units=128,   activation='relu'))

classifier.add(Dense(units=4,  activation='softmax')) #
```

**softmax for more than 2**

```
classifier.summary()
```

#**summary of our model#**

**Compiling the Model**

**# Compiling the CNN**

**# categorical_crossentropy for more than 2**

```
classifier.compile(optimizer='adam',
loss='categorical_crossentropy',metrics=['accuracy'])
```

**# Fitting the Model**

```
classifier.fit_generator(

      generator=x_train,steps_per_epoch

      =  len(x_train),

           epochs=10, validation_data=x_test,validation_steps =
len(x_test))
```
**# No ofimages in test set**

**# Saving the Model**

```
classifier.save('disaster.

h5') model_json =

classifier.to_json()

with open("model-bw.json", "w")

   as json_file:

   json_file.write(model_json)
```

**# Predicting Results**

```
from tensorflow.keras.models

import load_modelfrom

keras.preprocessing import

image

model = load_model("disaster.h5") #loading the model for testing

img=image.load_img(r"C:\Users\vasanth\Desktop\IBMProject\dataset\test_
set\Cyc lone\921.jpg",grayscale=False,target_size= (64,64)) #loading of the
image\n

x = image.img_to_array(img)#image to array\n",

x = np.expand_dims(x,axis = 0)#changing the shape\n",

pred = model.predict_classes(x)#predicting the classes\n",
```

```
pred

index=['Cyclone','Earthquake','F

lood','Wildfire']

result=str(index[pred[0]])

result
```

**Links to find files, documents and result related to this project, GitHub: https://github.com/IBM-EPBL/IBM-Project-47709-1660801736**