NAALAIYA THIRAN PROJECT - 2022
19ECI01-PROFESSIONAL READINESS FOR INNOVATION, EMPLOYABILITY AND ENTREPRENEURSHIP

NATURAL DISASTER INTENSITY ANALYSIS AND CLASSIFICATION USING ARTIFICIAL INTELLIGENCE

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this report **"NATURAL DISASTERS INTENSITY ANALYSIS AND CLASSIFICATION USING ARTIFICIAL INTELLIGENCE "** is the bonafide work of **PRAVEEN KUMAR.S (411519104068),SAICHARAN.G(411519104079),SURESHMANI KANDAN.K(411519104091),TAMILSELVAN.V(411519104094)** who carried out **19ECI01 Professional Readiness for Innovation, Employability and Entrepreneurship** project offered by IBM and Anna University, Chennai.

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CHAPTER 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 disaster and 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 and the 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 SURVEY

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 Sensing Building 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 of two regularization parameters to define the support vectors. These frameworks avoid the collection 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 Learning Techniques

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 errorprone, deep learning and machine learning are used which used for detecting the damage caused by disasters effectively.

TOOLS USED/ALGORITHM

- Social-media
- Satellite imagery
- Deep learning techniques
- CNN,VGG-16, ResNet
- Machine learning tecniques
- 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-

(i) Prevention of danger or threat of any disaster

(ii) Preparedness to deal with any disaster

(iii) Prompt response to any threatening disaster situation or disaster

(iv) Assessing the severity or magnitude of effects of any disaster

(v) Evacuation, rescue, and relief

(vi) Rehabilitation and reconstruction

Problem Statement Definition

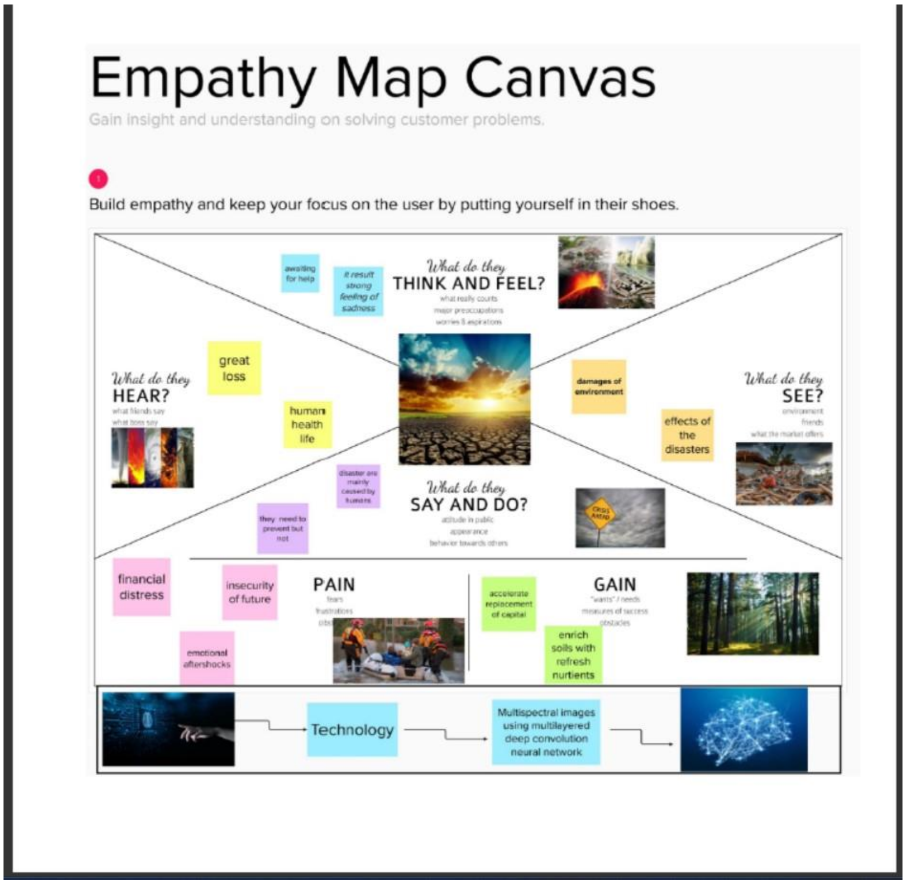
People needs a way to classify and analyse the natural disaster so that they can prevent themselves from losses due to the disaster and millions of lives.

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 andd protect them from such disaster.

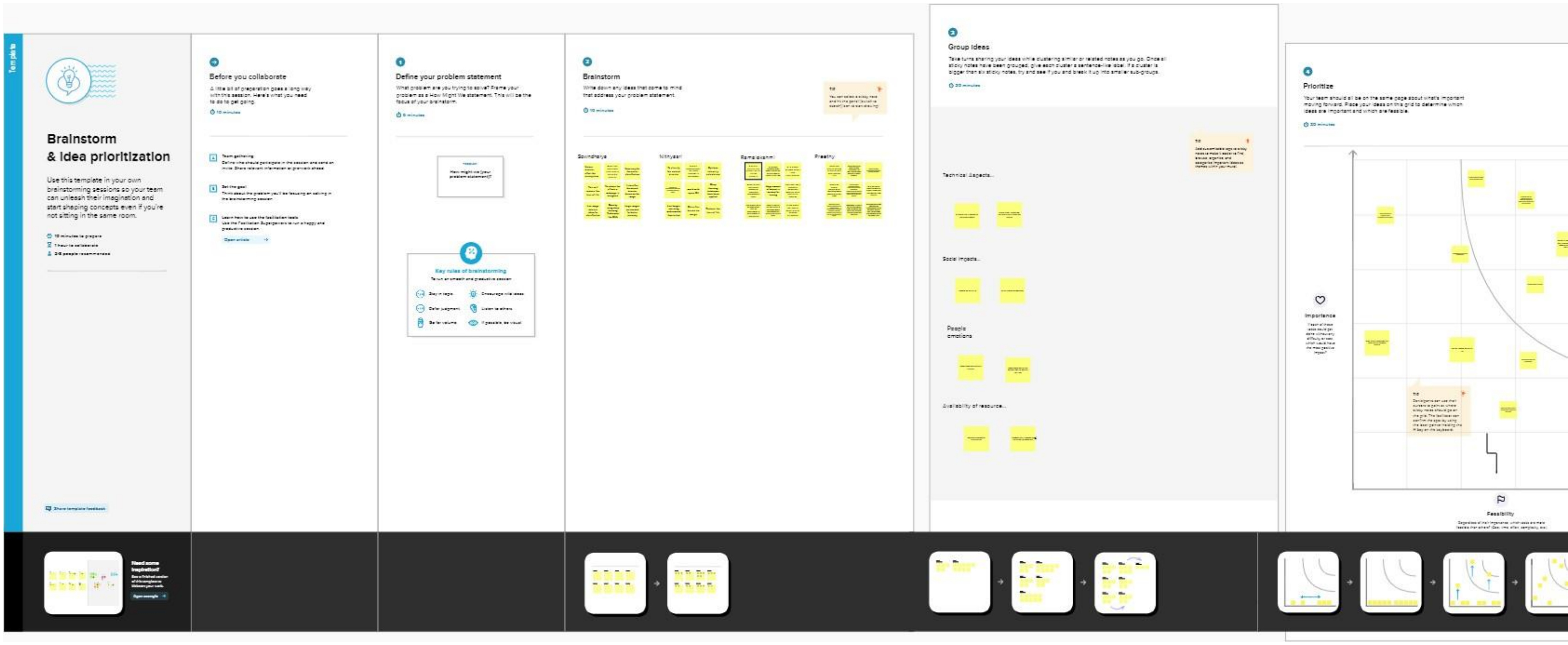
CHAPTER 3

IDEATION & PROPOSED SOLUTION

Empathy Map Canvas



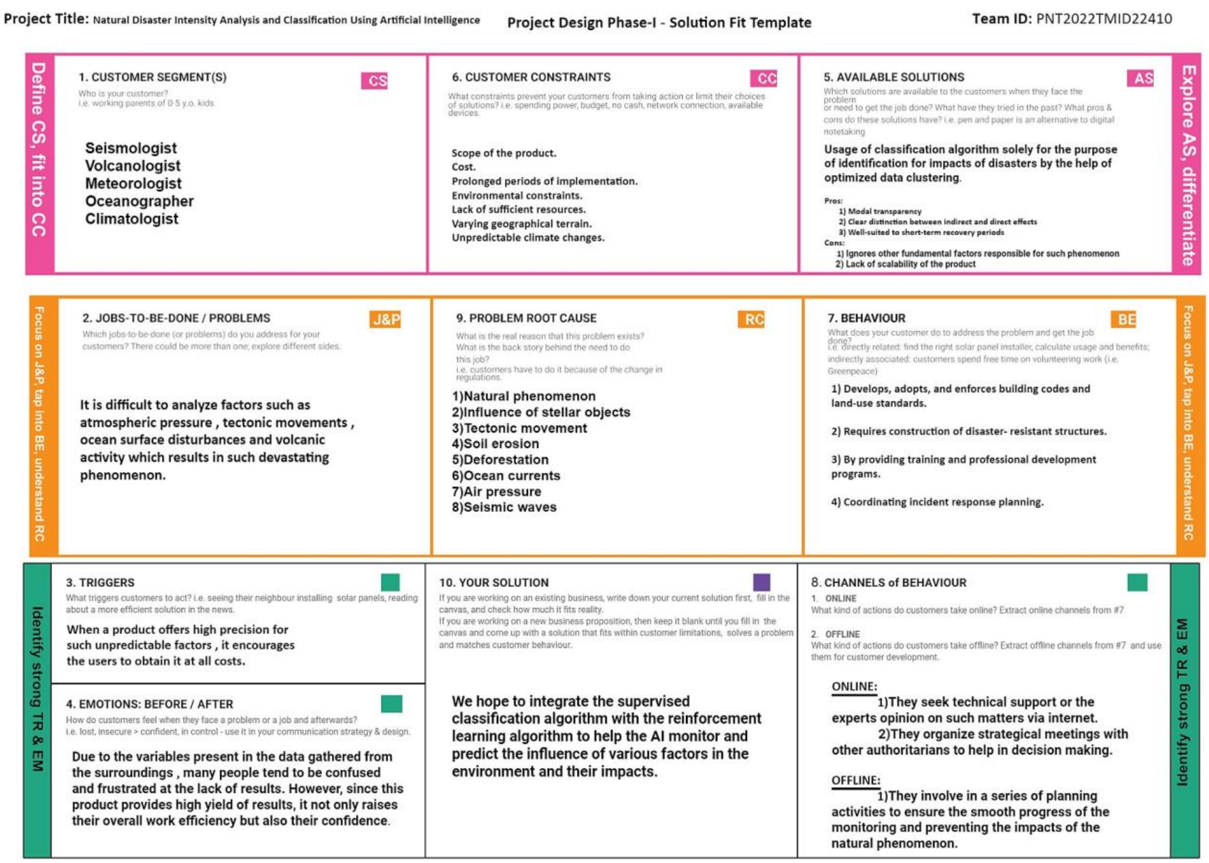
Ideation & Brainstorming



Proposed solution

S. No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	People needs a way to classify and analyse the Disaster priorly so that they can protect themselves from losses due to the Disaster and Millions of Lives.,
2.	Idea/Solution description	This project uses Multi-layered Deep Convolutional Neural Network (pretrained) model to classify Natural Disaster and calculate the intensity of the Disaster
3.	Novelty/Uniqueness	To reduce the issues due to imbalance structure of images, the model uses an integrated webcam to capture the video frame and test data is compared with pretrained data.
4.	Social impact/Customer Satisfaction	By the Application, economic damage caused by Disaster can be reduced. Detection of Natural Disaster will become easier while using videos in Deep CNN instead of images.
5.	Business Model (Revenue Model)	Multi-layered Deep Convolutional Neural Network Model.
6.	Scalability of the Solution	Highly expandible, dependable, reliable, scalable and has robustnes

Problem Solution Fit



Project Title: Natural Disaster Intensity Analysis and Classification Using Artificial Intelligence

Project Design Phase-I - Solution Fit Template

Team ID: PNT2022TMID22410

Define CS, fit into CC

1. CUSTOMER SEGMENT(S) CS

Who is your customer?
i.e. working parents of 0-5 y.o. kids

Seismologist
Volcanologist
Meteorologist
Oceanographer
Climatologist

6. CUSTOMER CONSTRAINTS CC

What constraints prevent your customers from taking action or limit their choices of solutions? i.e. spending power, budget, no cash, network connection, available devices.

Scope of the product.
Cost.
Prolonged periods of implementation.
Environmental constraints.
Lack of sufficient resources.
Varying geographical terrain.
Unpredictable climate changes.

5. AVAILABLE SOLUTIONS AS

Which solutions are available to the customers when they face the problem or need to get the job done? What have they tried in the past? What pros & cons do these solutions have? i.e. pen and paper is an alternative to digital notetaking

Usage of classification algorithm solely for the purpose of identification for impacts of disasters by the help of optimized data clustering.

Pros:
1) Modal transparency
2) Clear distinction between indirect and direct effects
3) Well-suited to short-term recovery periods

Cons:
1) Ignores other fundamental factors responsible for such phenomenon
2) Lack of scalability of the product

Explore AS, differentiate

Focus on J&P, tap into BE, understand RC

2. JOBS-TO-BE-DONE / PROBLEMS J&P

Which jobs-to-be-done (or problems) do you address for your customers? There could be more than one; explore different sides.

It is difficult to analyze factors such as atmospheric pressure , tectonic movements , ocean surface disturbances and volcanic activity which results in such devastating phenomenon.

9. PROBLEM ROOT CAUSE RC

What is the real reason that this problem exists? What is the back story behind the need to do this job?
i.e. customers have to do it because of the change in regulations.

1)Natural phenomenon
2)Influence of stellar objects
3)Tectonic movement
4)Soil erosion
5)Deforestation
6)Ocean currents
7)Air pressure
8)Seismic waves

7. BEHAVIOUR BE

What does your customer do to address the problem and get the job done?
i.e. directly related: find the right solar panel installer, calculate usage and benefits; indirectly associated: customers spend free time on volunteering work (i.e. Greenpeace)

1) Develops, adopts, and enforces building codes and land-use standards.

2) Requires construction of disaster- resistant structures.

3) By providing training and professional development programs.

4) Coordinating incident response planning.

Focus on J&P, tap into BE, understand RC

Identify strong TR & EM

3. TRIGGERS

What triggers customers to act? i.e. seeing their neighbour installing solar panels, reading about a more efficient solution in the news.

When a product offers high precision for such unpredictable factors , it encourages the users to obtain it at all costs.

4. EMOTIONS: BEFORE / AFTER

How do customers feel when they face a problem or a job and afterwards?
i.e. lost, insecure > confident, in control - use it in your communication strategy & design.

Due to the variables present in the data gathered from the surroundings , many people tend to be confused and frustrated at the lack of results. However, since this product provides high yield of results, it not only raises their overall work efficiency but also their confidence.

10. YOUR SOLUTION

If you are working on an existing business, write down your current solution first, fill in the canvas, and check how much it fits reality.
If you are working on a new business proposition, then keep it blank until you fill in the canvas and come up with a solution that fits within customer limitations, solves a problem and matches customer behaviour.

We hope to integrate the supervised classification algorithm with the reinforcement learning algorithm to help the AI monitor and predict the influence of various factors in the environment and their impacts.

8. CHANNELS of BEHAVIOUR

1. ONLINE
What kind of actions do customers take online? Extract online channels from #7

2. OFFLINE
What kind of actions do customers take offline? Extract offline channels from #7 and use them for customer development.

ONLINE:
1)They seek technical support or the experts opinion on such matters via internet.
2)They organize strategical meetings with other authoritarians to help in decision making.

OFFLINE:
1)They involve in a series of planning activities to ensure the smooth progress of the monitoring and preventing the impacts of the natural phenomenon.

Identify strong TR & EM

CHAPTER 4

REQUIREMENT ANALYSIS

Functional Requirement

FR No.	Functional Requirement(Epic)	Functional Requirement(Epic)
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, 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 web camera should be high enough to capturethe video frames
FR-6	User Interface	Maximizing the interaction in Web Designing Service.

Non-Functional Requirement

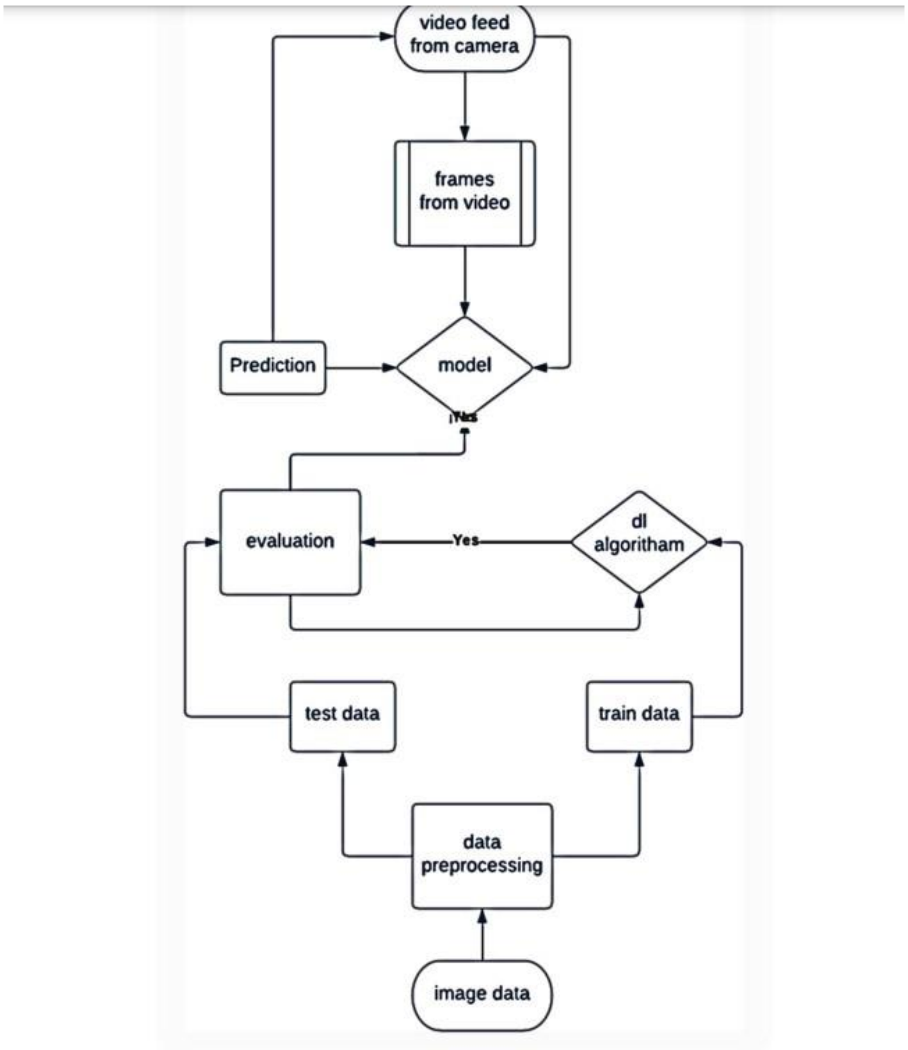
NFR. No.	NonFunctional Requirement	Description
NFR-1	Usability	User friendly and classify the disaster easily.
NFR-2	Security	The model is secure due to the cloud deployment models and also there is no login issue.
NFR-3	Reliability	Accurate prediction of the natural disaster and the website can also 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 it can beextended to the NDRFand customers.

CHAPTER 5 PROJECT

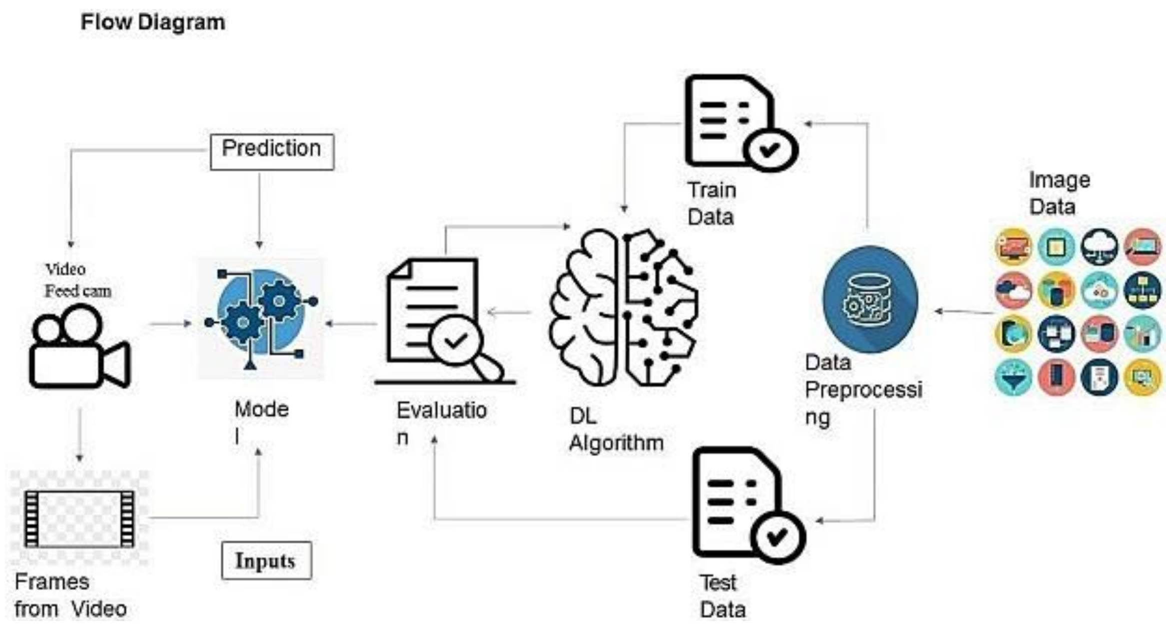
DESIGN

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 the system, 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 are to:

● Find the best tech solution to solve existing business problems.

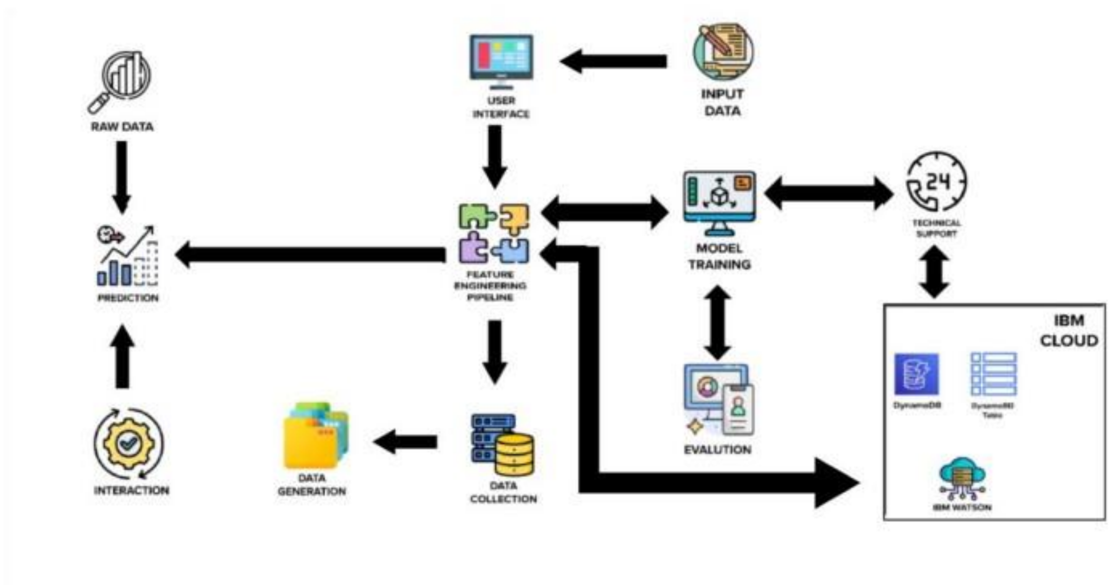
● Describe the structure, characteristics, behavior, and other aspects of the software to project stakeholders.

● Define features, development phases, and solution requirements.

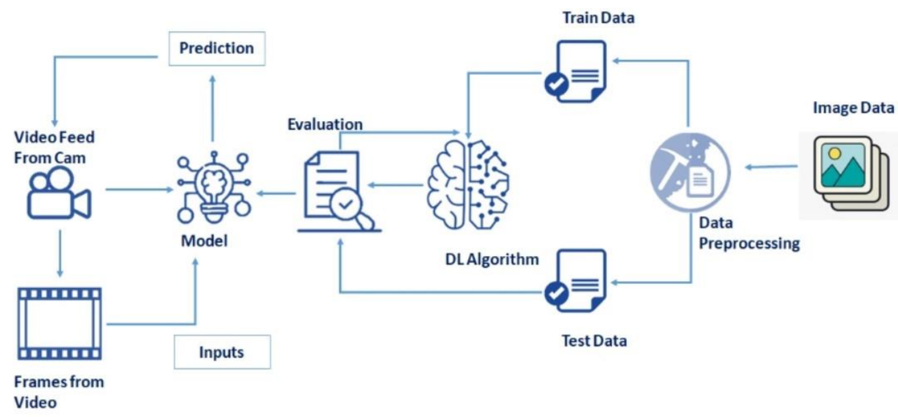
● Provide specifications according to which the solution is defined, managed, and delivered.

Solution Architecture Diagram

Example - 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 just before.	HTML, CSS, JavaScript, Django, Python.
2.	Disaster Detection	This function is used to detect, Decision Outcomes , the new trained data to perform tasks and solve new problems.	Decision trees, Regression, Convolutional Neural networks
3.	Evaluation system	It monitors that how Algorithm performs on data as well as during training.	Chi-Square, Confusion Matrix, etc.
4.	Input data	To interact with our model and give it problems to solve. Usually this takes the form of an API, auser interface, or a command line interface.	Application programming interface, etc
5.	Data collection unit	Data is only useful if it’s accessible, so itneeds to be stored ideally in a consistent structure and conveniently inone place.	IBM Cloud, SQLServer.
6.	Database management system	An organized collection of data stored in database, 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 development that is designed by a social network of software developers. These frameworks are free for public use and provide the foundation for building a software application.	Keras, Tensorflow.
2.	Authentication	This keep sour models secure and makes sure only those who havepermission can use them	Encryption and Decryption (OTP)
3.	Application interface	User uses mobile application and web 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-todate. 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, colour themes, etc. which make a software interface 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 can collect the dataset for monitoring and analyzing	I can get the idea about the Application.
Intro page	USN-3	As a user, I want to about the 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 the webcam 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 the required algorithm for specific analysis.	Selection must give the better accuracy and better output
Training and Testing	USN-7	As a user, I can train and test the model using the algorithm.	Training the model to classify and analyze the intensity
Detection and analysis of data	USN-8	As a user, I can detect and visualize the data effectively.	I can capture a video or image of particular disaster to analyze and detect.
Model building	USN-9	As a user I can build with the web application.	Model should be predicting occurrence of the disaster and intensity level of disaster

Integrate the web app with the AI Model	USN-10	As a user, I can use Flask app 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 can deploy the AI model in IBM Cloud.	Model’s prediction should be 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 about the 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 and report on past event analysis.	**5**
Sprint-2	Algorithm selection	USN-6	As a user, I can choose the required Algorithm for specific analysis.	**5**
Sprint-2	Training and Testing	USN-7	As a user, I can train and test the model 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-10	As a user, I can use Flask app to use model easily through web app.	**10**
Sprint-4	Model deployment	USN-11	As an administrator, I can deploy the AI model in IBM Cloud.	**10**

Sprint Delivery schedule

Sprint	Total Story Points	Duration	Sprint Start Date	Story Points Completed (as on 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 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 giving precautionary measures for the people living in the Danger zone.

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

Feature 2

The accuracy of the project is improved more better than the previously submitted models. The accuracy is improved by training and testing more images in the dataset.

CHAPTER 8
TESTING

Test cases

Test Case ID	**Component**	**Test Scenario**	**Expected Result**	**Actual Result**	**Status**
TC_001	Home Page	Verify user is able to see the Home page	Home page should Display	Working as expected	Pass
TC_002	Home Page	Verify the UI elements in Home page	Application should show below UI elements: Home page button Intro page button Open webcam button	Working as expected	Pass
TC_003	Home Page	Verify user is able to see the cards about Disaster	Application should show the cards about Disaster.	Working as expected	Pass
TC_004	Home Page	Verify user is able to navigate to the required page	Application should navigate to the Intro page	Working as expected	Pass
TC_005	Intro Page	Verify user is able to see the Intro page	Intro page should display	Working as expected	Pass
TC_006	Intro Page	Verify the UI Elements in Intropage	Application should show below UI elements: Home page Intro page Open webcam button	Working as expected	Pass
TC_007	Intro Page	Verify the user is able to see the introduction of the Disaster	Application should show the sentences about the Disaster	Working as expected	Pass

TC_008	Intro Page	Verify user is able to 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 should show below UI elements: a. Emergency pull button	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 real time 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	3	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, and untested.

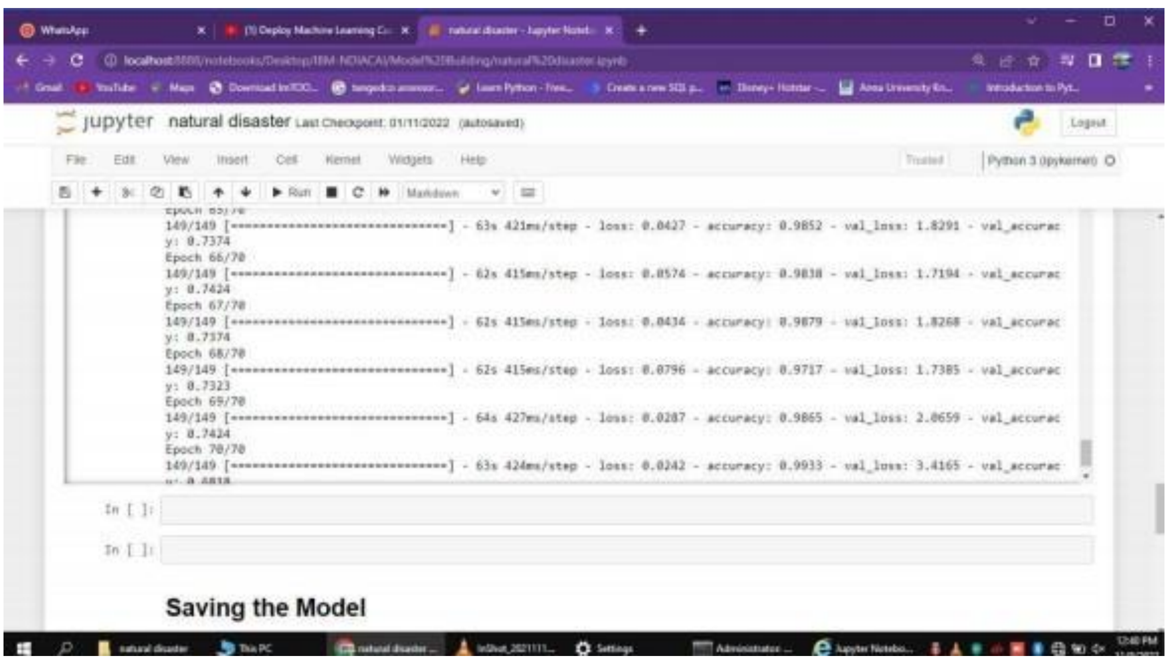
Section	Test Cases	Not Tested	Fail	Pass
Home Page	4	0	0	4
Intro Page	4	0	0	4
Open Webcam	3	0	0	3

CHAPTER 9
RESULTS

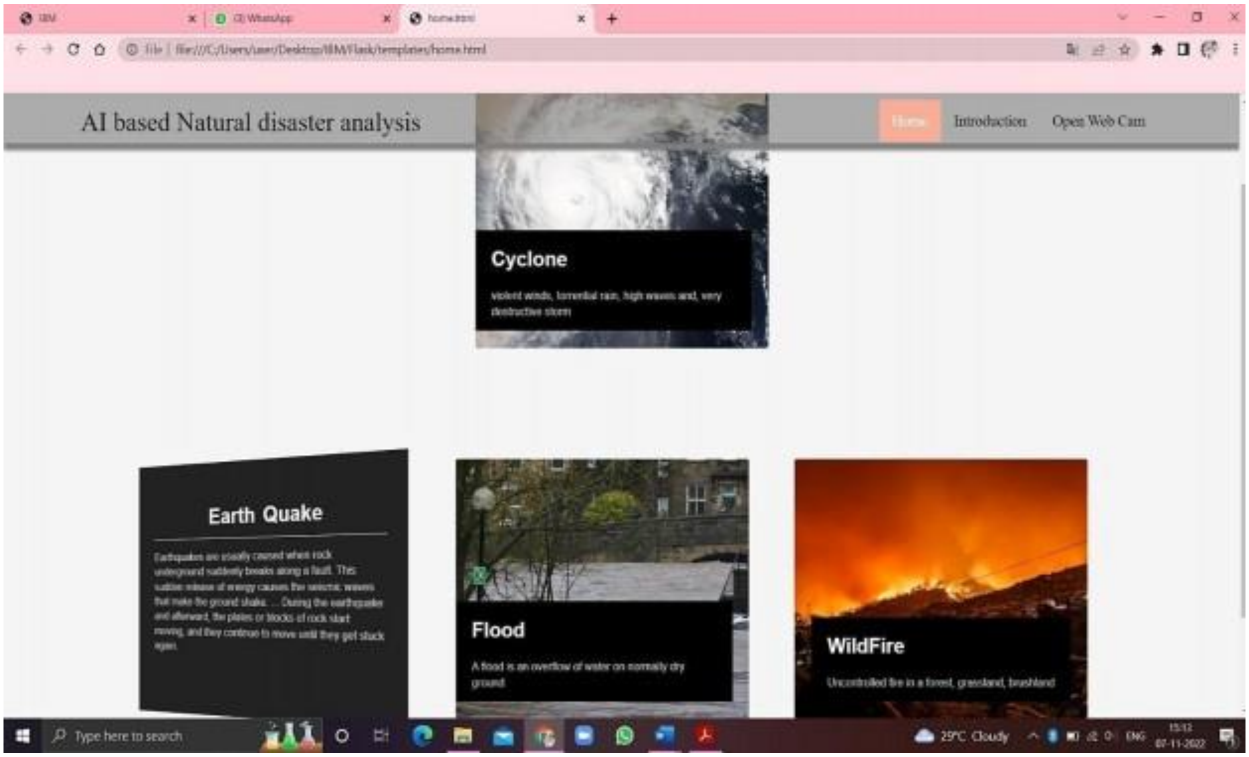
Performance Metrics

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.

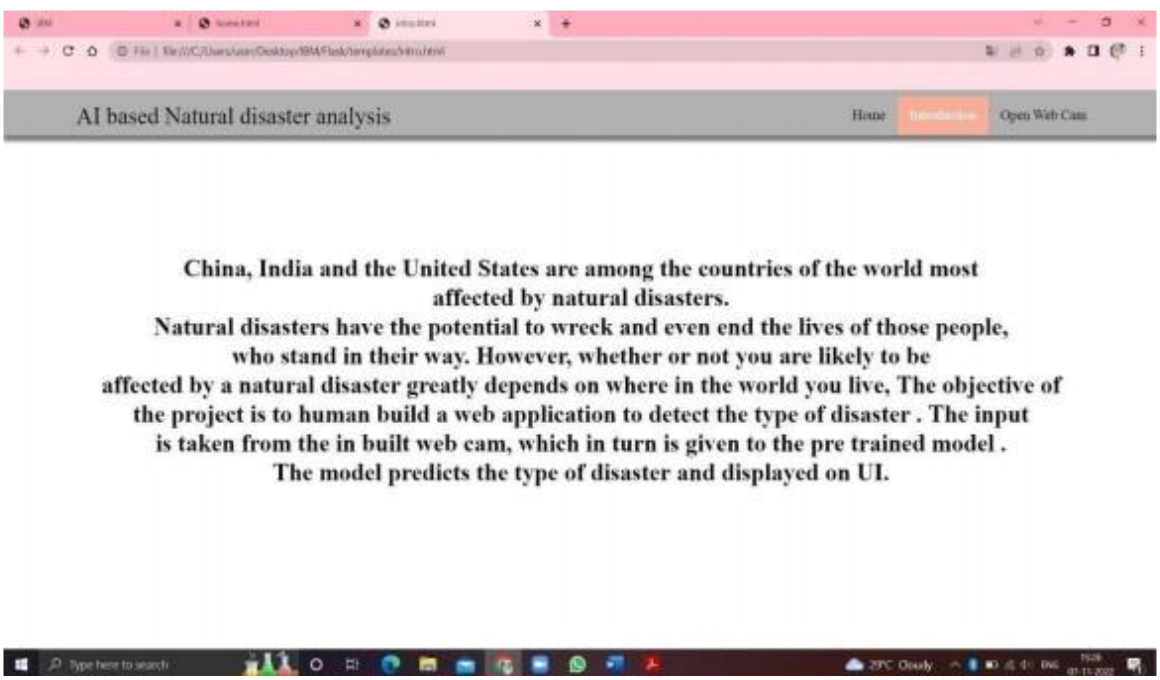
Output of application



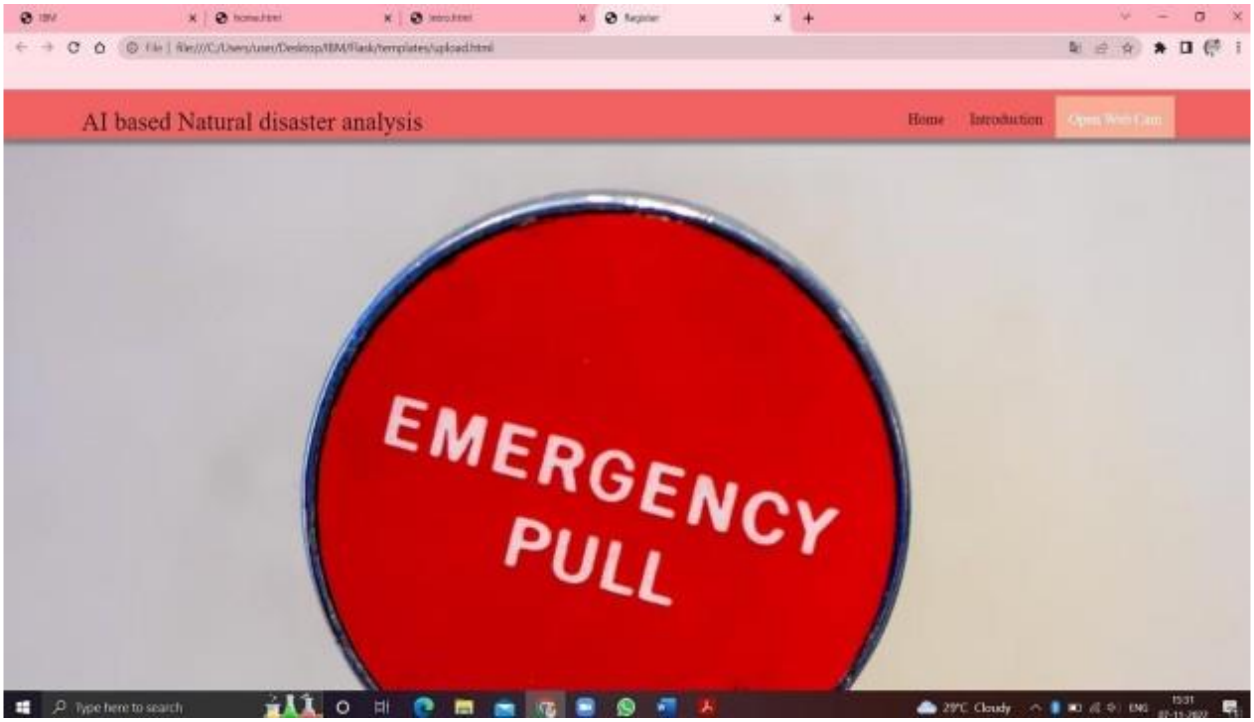
HOME PAGE



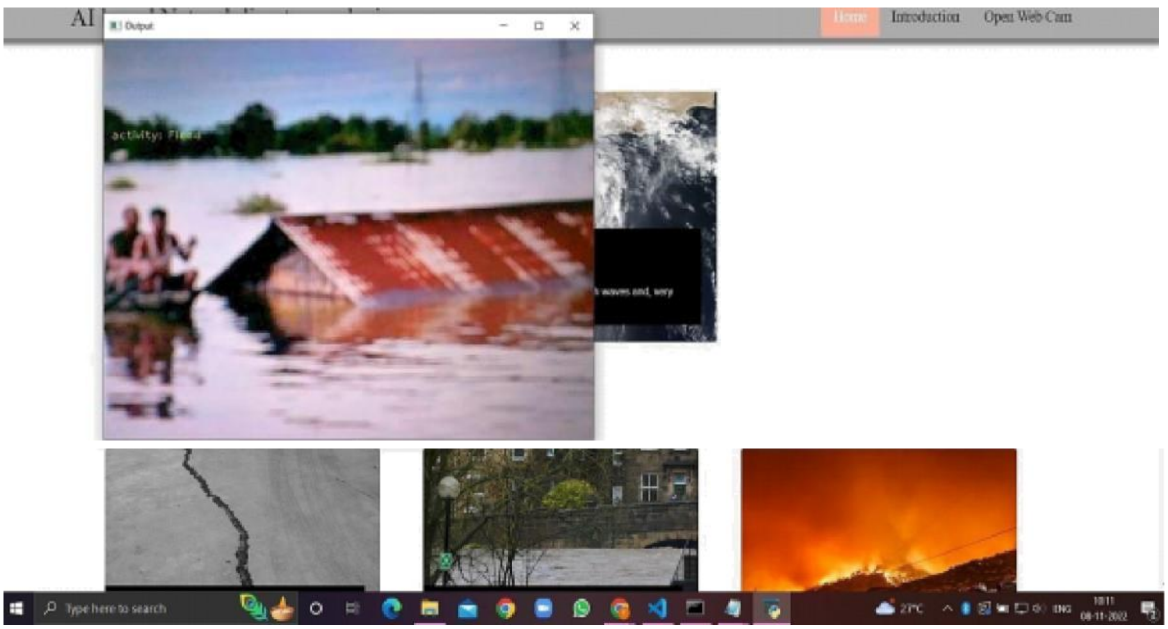
INTRODUCTION PAGE



WEB CAM


AI based Natural disaster analysis
Home
Introduction
EMERGENCY
PULL
Type here to search
29°C Cloudy

DETECTION OF NATURE DISASTER


Output
Home
Introduction
Open Web Cam
Type here to search
ENG
08-11-2022

CHAPTER 10

ADVANTAGES & DISADVANTAGES

ADVANTAGES

1. The proposed model will be used as a real time natural disaster detection model and provide some upcoming predictions for future disasters.

2. The model is to detect and classify the type of disaster and The model have a high accuracy rate (99.33).

3. 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 heavy loss of human ecological systems and property.

4. The proposed system helps to reduce the impact of hazards occur during natural disaster. This provides an efficient way to warn and educate people about disaster prone areas.

5. It will help us be prepared in times of disaster.

DISADVANTAGES

1. The resultant model unable to validate the model performance under uncontrolled conditions.

2. The model cannot be used for various natural disaster

CHAPTER 11

1 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. Many researchers have attempted to use different deep learning methods for detection of natural disasters. However, the detection of natural disasters by using deep learning techniques still faces various issues due to noise and serious class imbalance problems. To address these problems, we proposed a multilayered deep convolutional neural network for detection and intensity classification of natural disasters. The proposed method works in two blocks—one for detection of natural disaster occurrence and the second block is used to remove imbalanced class issues. The results were calculated as average statistical values: sensitivity, 97.54%; specificity, 98.22%; accuracy rate, 99.92%; precision, 97.79%; and F1-score, 97.97% for the proposed model. The proposed model achieved the highest accuracy as compared to other state-of-the-art methods due to its multilayered structure. The proposed model performs significantly better for natural disaster detection and classification, but in the future the model can be used for various natural disaster detection processes. The reason for this is that the proposed technique works in two parts: one for natural disaster occurrence detection and the second one for natural disaster classifications. The overall proposed model works on an image dataset to detect and classify the natural disasters. As the model is evaluated on a simple central processing unit (CPU)-based system, it only detects disaster types and then classifies them into cyclone, earthquake, flood and wildfire classes. However, if this model is run on a graphic processing unit (GPU)-based system in the future with real time sensors and monitoring power, then the proposed model will be used as a real time natural disaster detection model and provide some upcoming predictions for future disasters. The main purpose of this model is to detect and classify the type of disaster with a high accuracy rate. To prevent natural disasters in the future, said model can be used to predict future disasters and take some action against heavy loss of human ecological systems and property.

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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. The proposed model performs significantly better for natural disaster detection and classification, but in the future the model can be used for various natural disaster detection processes. The reason for this is that the proposed technique works in two parts: one for natural disaster occurrence detection and the second one for natural disaster classifications. The overall proposed model works on an image dataset to detect and classify the natural disasters. 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. Many researchers have attempted to use different deep learning methods for detection of natural disasters. However, the detection of natural disasters by using deep learning techniques still faces various issues due to noise and serious class imbalance problems

CHAPTER 13

APPENDIX

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 **#Convolutional layer**

#MaxPooling2D-for downsampling the image

from keras.preprocessing.image import ImageDataGenerator

tensorflow.__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_range=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\rajeshwari\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\rajeshwari\Desktop\IBM

Project\dataset\test_set',target_size=(64, 64),batch_size=5,

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

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 c

c(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), act

 # 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 previous convolution 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 of images 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_model from

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','Flood','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-8518-1658922234

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