



DisasterNet

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TEAM 8

PRIYANKA SHARMA - ENG21CT0030
SUKRITI SRINIVASA - ENG21CT0039
SUNIDHI KS - ENG21CT0040
SWATHI S - ENG21CT0043
VIDUSHI MODI - ENG21CT0048

BDA



SAVE ENVIRONMENT

INTRODUCTION

Natural disasters such as cyclones, earthquakes, floods, and wildfires cause immense harm to life and property. To address this, our project leverages deep learning with satellite imagery for the detection and classification of these events. Shifting from web camera inputs to satellite data provides greater accuracy and global applicability. By integrating artificial intelligence and convolutional neural networks (CNNs), the project aims to improve disaster prediction, enabling timely interventions to save lives and reduce economic loss.



LITERATURE SURVEY

Paper Title	Author(s)	Year	Journal/Conference	Research Gap	Innovation/Inferences	Link
Disasters Detection from Remote Satellite Images using ML and Deep Learning Approaches	IEEE Authors	2023	IEEE Conference	Insufficient multi-modal data integration for robust prediction.	Integrating geospatial and image-based inputs for better disaster forecasting.	IEEE Xplore [20]
Assessing Damage of Natural Disasters Using Satellite Imagery	Solaiman B	2022	Springer Nature	Overreliance on post-disaster imagery.	Combining pre- and post-disaster data for semantic scene understanding.	Springer
Automated Cyclone Damage Detection Using Sentinel Imagery	Kumar et al.	2022	ISPRS Journal of Photogrammetry	Limited region-specific training data.	Employing transfer learning for cyclone-prone areas.	ISPRS Journal
Real-Time Flood Detection with Satellite Image Processing	Nguyen & Zhang	2023	IEEE Internet of Things Journal	Lack of streaming data capabilities.	Incorporating IoT sensors for near real-time flood predictions.	IEEE IoT Journal
Enhancing Wildfire Detection through Multi-Temporal Satellite Data	Carter et al.	2023	MDPI Remote Sensing	Limited validation with seasonal data.	Using temporal datasets to capture wildfire progression over time.	MDPI



LITERATURE SURVEY

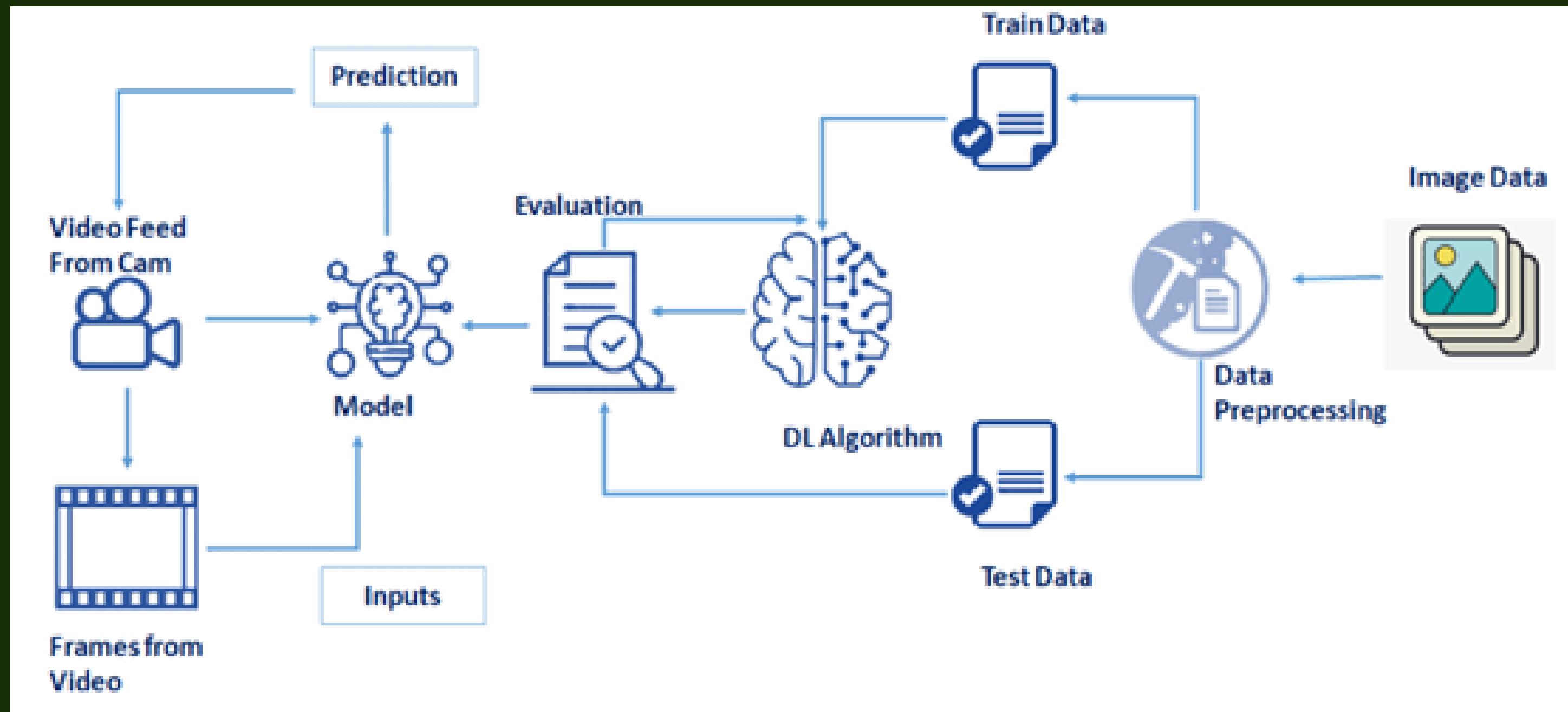
Paper Title	Author(s)	Year	Journal/Conference	Research Gap	Innovation/Inferences	Link
Analysis of Satellite Images for Disaster Detection	Siti Nor Khuzaimah Binti Ami et al.	2016	IEEE Conference	Limited Weather Variations in Training Data	Incorporate Weather Data Variability	Link6
Disaster Detection Using Machine Learning Methods with Deep Features	Ilkay CINAR	2023	International Conference on Intelligent Systems and New Applications	Satellite image analysis often lacks integration with social media image classification	Combine satellite and social media image data using multi-modal deep learning frameworks that can process and integrate visual data from both sources.	Link7
Disaster Monitoring of Satellite Image Processing Using Progressive Image Classification	Romany F. Mansour et al.	2023	CCSE Journal Vol.44	Current systems struggle with real-time monitoring due to delays in processing large-scale satellite images	Using Progressive Image Classification Algorithm (PICA)	Link8
Building Damage Assessment in Aftermath of Disaster Events by Leveraging GeoAI	Taiwo H. Agbaje et al.	2024	World Journal of Advanced Research & Reviews	High-quality, annotated datasets are required to train GeoAI models	Innovating the use of crowdsourced data from social media platforms, combining deep learning with traditional GIS data	Link9
Automated building damage assessment and large-scale mapping by integrating satellite imagery, GIS, and deep learning	Abdullah M. Braik et al.	2024	Computer-Aided Civil and Infrastructure Engineering Journal	Integration of GIS with other data sources like drones, social media, or IoT-based sensors is still limited.	Innovative integration of satellite imagery, GIS, and deep learning enables the automation of the building damage assessment process	Link10



METHODOLOGY

1. **Data Collection:** Satellite images from sources like Sentinel or Landsat are used.
2. **Preprocessing:** Images undergo augmentation, noise reduction, and normalization.
3. **Model Design:**
 - A convolutional neural network (CNN) is enhanced for satellite image analysis.
 - Multi-class classification predicts disaster types: cyclone, flood, wildfire, and earthquake.
4. **Training:**
 - Models are trained using labeled disaster datasets.
 - Fine-tuning is done with hyperparameter optimization.
5. **Validation and Testing:** Accuracy is evaluated using metrics like precision and recall.
6. **Deployment:** Real-time satellite data integration for disaster monitoring and alert systems

Block Diagram



Implementation

The screenshot shows a Jupyter Notebook interface with two code cells. The first cell, labeled [3], contains Python code for setting up image data augmentation parameters:

```
# Setting parameter for Image Data augmentation to the traing data
train_datagen = ImageDataGenerator(rescale = 1./255, shear_range = 0.2, zoom_range = 0.2, horizontal_flip = True)

# Image Data augmentation to the testing data
test_datagen = ImageDataGenerator(rescale = 1./255)
```

The second cell, labeled [4], contains code for performing data augmentation on training and testing sets:

```
# Performing data augmentation to train data
x_train = train_datagen.flow_from_directory(r'C:\Users\srini\Project Files\dataset\train_set', target_size = (64, 64),
                                             batch_size = 5, color_mode = 'rgb', class_mode = 'categorical')

# Performing data augmentation to test data
x_test = test_datagen.flow_from_directory(r'C:\Users\srini\Project Files\dataset\test_set', target_size = (64, 64),
                                             batch_size = 5, color_mode = 'rgb', class_mode = 'categorical')
```

Output from cell [4] shows:

```
... Found 742 images belonging to 4 classes.
Found 198 images belonging to 4 classes.
```

The terminal window displays the output of a Flask application running on port 5000. It includes a warning about using Werkzeug in production, followed by logs for incoming requests:

```
Loaded model from disk
 * Serving Flask app 'app'
 * Debug mode: off
INFO:werkzeug:WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
INFO:werkzeug:Press CTRL+C to quit
INFO:werkzeug:127.0.0.1 - - [12/Dec/2024 23:20:09] "GET / HTTP/1.1" 200 -
INFO:werkzeug:127.0.0.1 - - [12/Dec/2024 23:20:18] "GET /upload HTTP/1.1" 200 -
1/1 ██████████ 0s 320ms/step
INFO:werkzeug:127.0.0.1 - - [12/Dec/2024 23:21:00] "POST /predict HTTP/1.1" 200 -
1/1 ██████████ 0s 46ms/step
INFO:werkzeug:127.0.0.1 - - [12/Dec/2024 23:26:17] "POST /predict HTTP/1.1" 200 -
```

Implementation

The screenshot shows a web browser window with the URL `127.0.0.1:5000` in the address bar. The page title is "AI-based Natural Disaster Analysis". The navigation bar includes links for "Home", "Introduction", and "Open Web Cam".

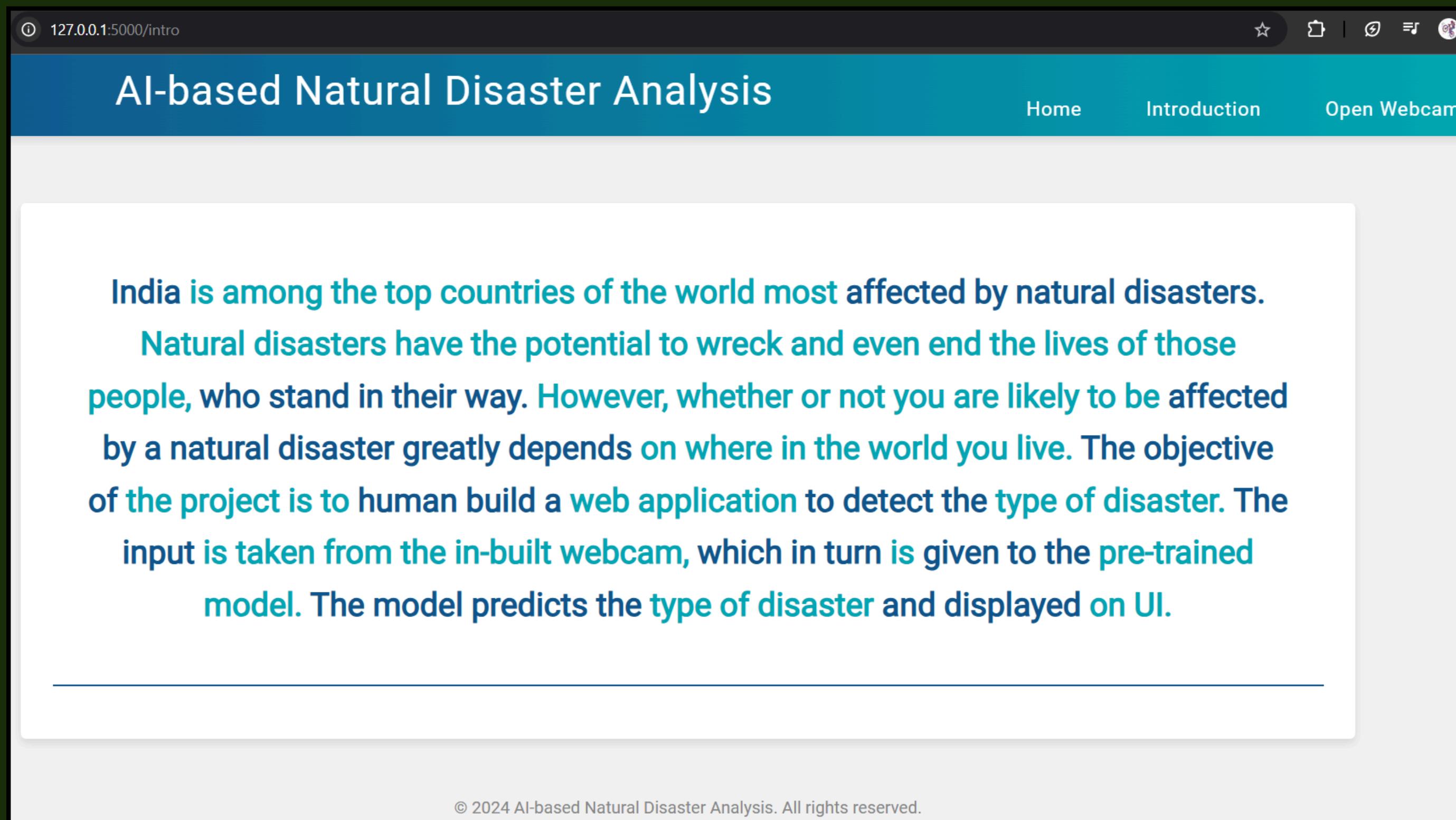
Earthquake Section:

- Image: A close-up photograph of a large, jagged crack in asphalt.
- Section Title: `//Earthquake`
- Caption: "Earthquake"
- Description: "Sudden release of stored energy in the Earth's crust that creates seismic waves."

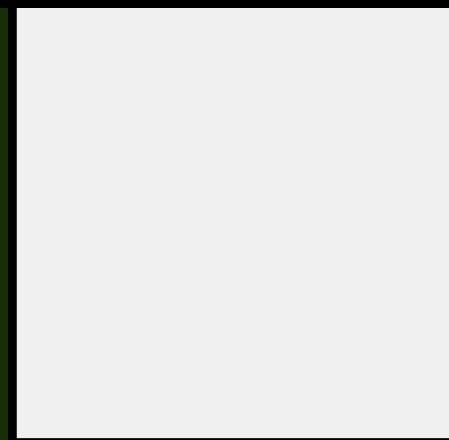
Flood Section:

- Image: A photograph of a flooded street with several cars submerged up to their roofs. A green emergency exit sign is visible on a pole.
- Section Title: `//Flood`
- Caption: "Flood"
- Description: "An overflow of water on normally dry ground"

Implementation

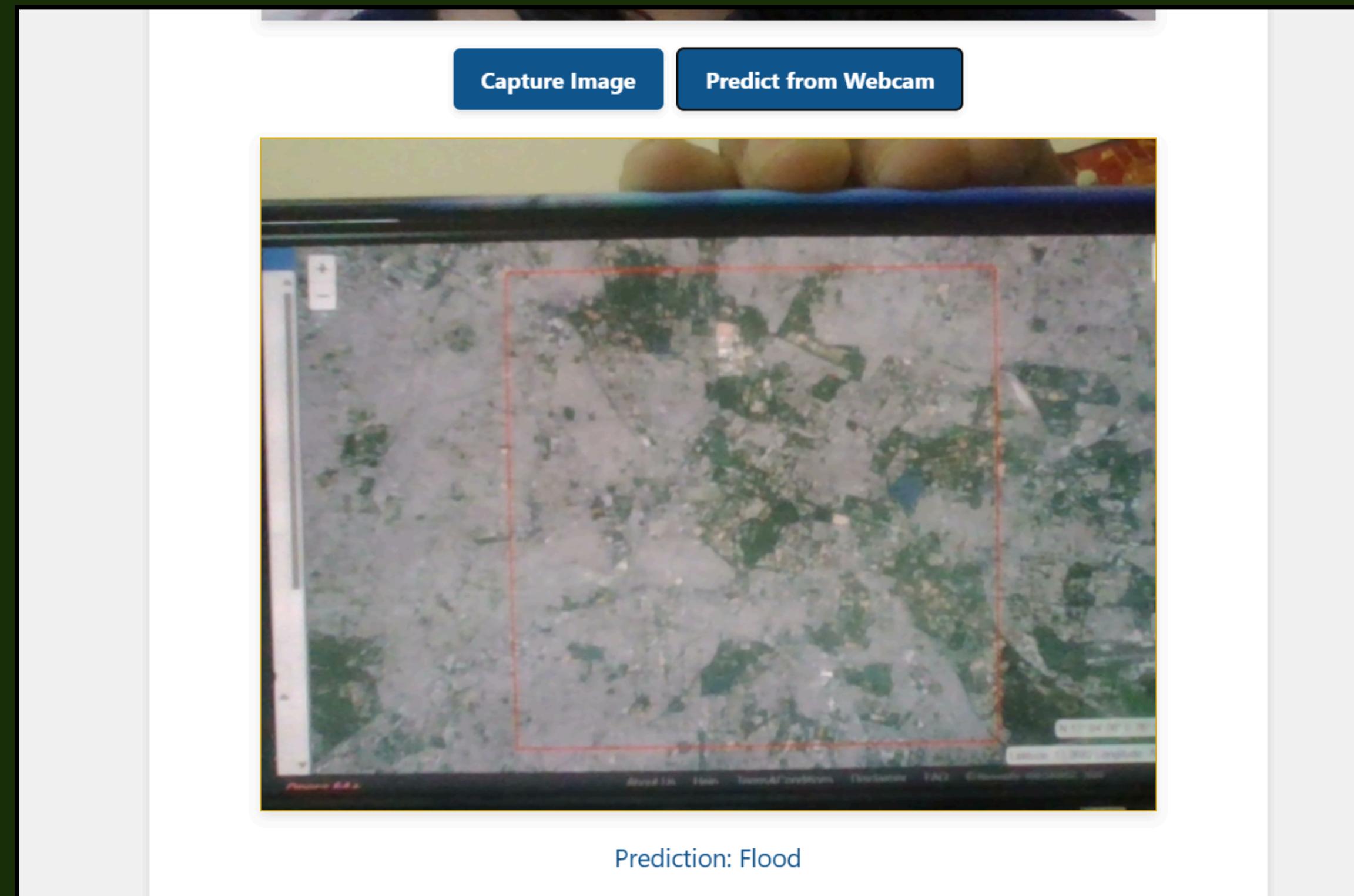


Results

A screenshot of a software application window. At the top, there are two blue buttons: "Capture Image" and "Predict from Webcam". Below them is a dark rectangular area. The main content area contains two side-by-side satellite images of a river. The left image is labeled "July 1" and the right image is labeled "July 16". Both images show a river flowing through a landscape. A blue polygonal shape is overlaid on both images, indicating a predicted flood area. At the bottom of the window, there is a dark footer bar with icons for "Search" and "Save".

Prediction: Flood

Results





Thank You