Dayananda Sagar University

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Department of
Computer Science & Technology

Big Data and Deep Learning

DisasterNet Report

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CERTIFICATE

This is to certify that the Big Data and Deep Learning project titled **"DisasterNet"** is carried out by **Priyanka Sharma (ENG21CT0030), Sukriti Srinivasa (ENG21CT0039), Sunidhi KS (ENG21CT0040), Swathi S(ENG21CT0043), Vidushi Modi (ENG21CT0048),** Bonafide students of Bachelor of Technology in Computer Science and Technology at the School of Engineering, Dayananda Sagar University, Bangalore in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Technology, during the year **2024-2025**.

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DECLARATION

We, **Priyanka Sharma (ENG21CT0030), Sukriti Srinivasa (ENG21CT0039), Sunidhi KS (ENG21CT0040), Swathi S(ENG21CT0043), Vidushi Modi (ENG21CT0048),** are students of the seventh semester B.Tech in Computer Science and Technology, at School of Engineering, Dayananda Sagar University, hereby declare that the Big Data and Deep Learning project titled "**DisasterNet**" has been carried out by us and submitted in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Technology during the academic year 2024-2025.

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Place : Bangalore
Date :

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1. Introduction

Natural disasters, including cyclones, earthquakes, floods, and wildfires, represent significant threats to human life, infrastructure, and the environment. These calamities often strike with little or no warning, causing substantial loss of life, widespread destruction, and economic upheaval. Traditional disaster monitoring methods typically rely on ground-based sensors, seismographs, weather stations, and web camera inputs. While these tools provide valuable data, they often suffer from limitations, including restricted coverage, slower response times, and challenges in scaling to the vast geographical scope of disasters. As a result, there is a critical need for innovative approaches that can deliver timely and precise detection of such events on a global scale.

This project leverages advancements in artificial intelligence, specifically deep learning techniques combined with satellite imagery, to address these challenges. By employing convolutional neural networks (CNNs), a specialized class of deep learning models designed for image analysis, the system is capable of detecting and classifying natural disasters with high accuracy. High-resolution satellite images provide comprehensive and detailed views of affected areas, enabling the system to analyze features such as cloud patterns, terrain changes, and temperature variations to identify disaster events in real-time.

Satellite-based monitoring offers several key advantages. First, it ensures global coverage, making it possible to monitor both urban and remote regions with equal efficiency. Second, the real-time processing capabilities of deep learning models allow for quicker identification and response, reducing the time between disaster detection and emergency action. Lastly, the system's adaptability allows it to work in diverse environments and across different types of natural disasters, making it a versatile tool for disaster management.

The project aims to enhance disaster preparedness by integrating satellite data into predictive models, enabling authorities to issue timely warnings and implement mitigation strategies. This not only minimizes the loss of human lives but also reduces the economic and environmental impact of disasters. By harnessing the power of artificial intelligence and satellite technology, this approach represents a significant leap forward in global disaster monitoring and response, offering a scalable and reliable solution to one of humanity's most pressing challenges.

2. Literature Survey

The detection and classification of natural disasters using satellite imagery have gained significant attention in recent years, with various studies addressing the limitations of existing systems and proposing innovative solutions. These efforts aim to enhance the accuracy, scalability, and real-time applicability of disaster monitoring systems, leveraging advancements in deep learning and remote sensing technologies.

In "Disasters Detection from Remote Satellite Images using ML and Deep Learning Approaches" (IEEE Authors, 2023), researchers identified insufficient multi-modal data integration as a critical gap. The study proposed combining geospatial and image-based inputs to improve disaster prediction accuracy and robustness. This integration enables better forecasting by utilizing diverse data sources, ensuring that predictions are not solely reliant on a single modality. Similarly, Solaiman B. (2022) in "Assessing Damage of Natural Disasters Using Satellite Imagery" highlighted the overreliance on post-disaster imagery. The study suggested incorporating both pre- and post-disaster data to enhance semantic scene understanding, enabling a more comprehensive analysis of disaster impact and progression.

Region-specific challenges were addressed by Kumar et al. (2022) in "Automated Cyclone Damage Detection Using Sentinel Imagery." The study emphasized the limited availability of training data for specific regions prone to cyclones and proposed employing transfer learning to overcome this limitation. Transfer learning allows models trained on global datasets to adapt to localized conditions, improving their effectiveness in cyclone-prone areas.

Real-time capabilities were a major focus of Nguyen and Zhang (2023) in "Real-Time Flood Detection with Satellite Image Processing." They identified the lack of streaming data capabilities as a bottleneck in flood detection systems. To address this, the study proposed incorporating IoT sensors for near real-time flood prediction, enabling faster and more accurate responses to flood events. Carter et al. (2023), in "Enhancing Wildfire Detection through Multi-Temporal Satellite Data," tackled the challenge of limited validation with seasonal data. By using temporal datasets, the study captured wildfire progression over time, providing insights into fire behavior and enabling better resource allocation for firefighting.

Other studies have focused on addressing variability and multi-modal integration. Siti Nor Khuzaimah Binti Ami et al. (2016) emphasized the need to incorporate weather data variability in satellite image analysis for disaster detection. This approach ensures that models are robust across different weather conditions, improving their reliability. Ilkay Cinar (2023) proposed a multi-modal framework combining satellite and social media image data. This integration leverages the strengths of both data types, allowing for more comprehensive disaster monitoring.

Romany F. Mansour et al. (2023) developed the Progressive Image Classification Algorithm (PICA) to address delays in processing large-scale satellite images. This innovation enhances the real-time monitoring of disasters by reducing processing time. Taiwo H. Agbaje et al. (2024) explored the use of crowdsourced data from social media combined with GeoAI models for building damage assessment, while Abdullah M. Braik et al. (2024) proposed integrating satellite imagery, GIS, and deep learning to automate large-scale mapping and damage assessment.

These studies collectively demonstrate the potential of advanced technologies in addressing existing gaps in disaster detection and mitigation. By leveraging deep learning, multi-modal data integration, and real-time processing, these innovations pave the way for more accurate, scalable, and efficient disaster management solutions.

3. Project Requirement Specification

1. **Mobile Application Interface**

   Develop a user-friendly mobile application interface that allows users to capture images or stream video directly from their mobile camera.Implement a real-time detection system to display disaster detection results promptly on the device screen.

2. **Image Processing and Detection Module**

   Leverage convolutional neural networks (CNNs) for the detection of disaster elements such as smoke, fire, floods, or structural damage.Process camera input efficiently to identify and classify visual disaster markers with high accuracy.

3. **Satellite Data Integration**

   Integrate disaster-related satellite data, including weather patterns and heatmaps, using publicly available APIs such as NASA Earth Data and Sentinel Hub.Combine satellite data with real-time camera input to enhance the accuracy of disaster classification and provide a comprehensive situational analysis.

4. **Notification System**

   Implement a robust notification system to alert users immediately upon the detection of a disaster.Provide actionable recommendations for safety measures or evacuation based on detected risks.

4. Problem Definition

Natural disasters such as cyclones, earthquakes, floods, and wildfires pose a grave threat to human life, property, and the environment. Most of these natural disasters strike without warning and can cause great damage in little time, making it challenging to take effective action against them. Current disaster detection systems depend on satellite imagery or ground-based sensors, which may lack real-time responsiveness, localized insights, or integrated analysis.

Traditionally, disaster detection and classification will pose serious problems in combining the on-ground observation with satellite data, thereby limiting the use of satellite data. The necessity lies in a system which has exploited the widespread mobile device for real-time data capturing by integrating it with the capabilities of satellite imagery towards deriving comprehensive and actionable insights.

It caters to the important demand of disaster detection systems that must be real-time, scalable, and robust by combining both satellite data and mobile camera inputs. The system identifies the disaster markers using advanced deep learning models and CNNs in order to enhance accuracy levels in prediction and, most importantly, provide prompt warnings for reducing loss of lives and property.

4.1 Problem Statement

Natural disasters such as cyclones, earthquakes, floods, and wildfires destroy a lot of life, property, and infrastructure. Successful disaster management requires timely and accurate detection, prediction, and communication of risk. However, current disaster detection systems suffer from several limitations:

- Limited Real-Time Responsiveness: Many existing systems rely solely on satellite imagery or ground-based sensors, which often involve delays in data acquisition, processing, and dissemination.
- Fragmented Data Sources: The lack of integration between satellite data and ground-level observations reduces the overall accuracy and contextual understanding of disaster events.
- Accessibility Challenges: High-end disaster detection systems are not readily accessible to the general public, especially in remote or underserved regions.

There may also be inadequate localized insights into various disasters because satellite images take a bird's-eye view, failing to observe subtle structural damage, localized floods, or even minor ignitions that are otherwise only visible at ground-level exposures. Given the widespread availability of smartphones equipped with high-quality cameras, there is an untapped opportunity to enhance disaster detection by combining real-time inputs from mobile devices with satellite data. Such an approach would not only increase detection accuracy but also provide actionable insights tailored to specific locations.

This project seeks to address these challenges by developing an integrated disaster detection system. The system will:

1. Utilize live inputs from mobile cameras to capture visual markers of disasters such as smoke, fire, floods, and structural damage.
2. Integrate satellite data such as weather patterns and heatmaps to provide a more holistic view of disaster scenarios.
3. Utilize advanced deep learning techniques, specifically convolutional neural networks (CNNs), to process and analyze both ground-level and satellite data for accurate disaster classification.
4. Provide real-time alerts along with recommendations and actions that allow users to take preventive or responsive action.
5.

4.2 Relevance of the Problem

Natural disasters are increasingly becoming a global concern as they are more frequent and intense, which is partly caused by climate change. Events such as cyclones, floods, wildfires, and earthquakes not only result in significant loss of life and property but also have devastating effects on economies, communities, and ecosystems. According to UNDRR, it has predicted that economic losses resulting from disasters are going to surge, mainly in the developing countries without adequate infrastructural facilities for early warnings and responses.

Detection of such disasters should occur timely because that is where mitigation and its impact is best prevented. Traditional detection systems often delay data processing in regard to satellite imagery, sensors, or ground-based detectors, and reporting, allowing opportunities for early intervention. Such systems usually work isolated in either focus on remote satellite data or local observation.

In this respect, it can be seen why satellite data and mobile camera inputs would be relevant for each other. Smartphones, as ubiquitous and technologically equipped devices, may allow capturing real-time information regarding the disaster in that local environment. The inclusion of this information with a more comprehensive view of satellite data about the scope and the nature of the conditions could offer a more effective disaster detection framework. In contrast to most prediction systems, this approach promotes timeliness and accuracy about disaster predictions while making it accessible to the general public, especially in regions that lack advanced disaster management infrastructure.

Furthermore, deep learning techniques, such as CNNs, can be integrated into this system to enhance the accuracy of disaster detection. CNNs are particularly efficient in processing visual data and are therefore ideal for identifying disaster markers such as smoke, fire, or floodwater from both satellite images and mobile camera feeds. The system can analyze these data sources simultaneously to provide more reliable and actionable insights, leading to quicker and more informed responses.

Essentially, in line with current needs, the importance of this problem lies in discovering a more efficient, integral, and accessible disaster-detection system that provides a real-time, localized information source. By using mobile camera data and satellite imagery, this project strives to fill an important gap in disaster management, working towards saving lives, bringing down economic loss, and improving the overall resilience of communities to natural disasters as a whole.

5. System Architecture

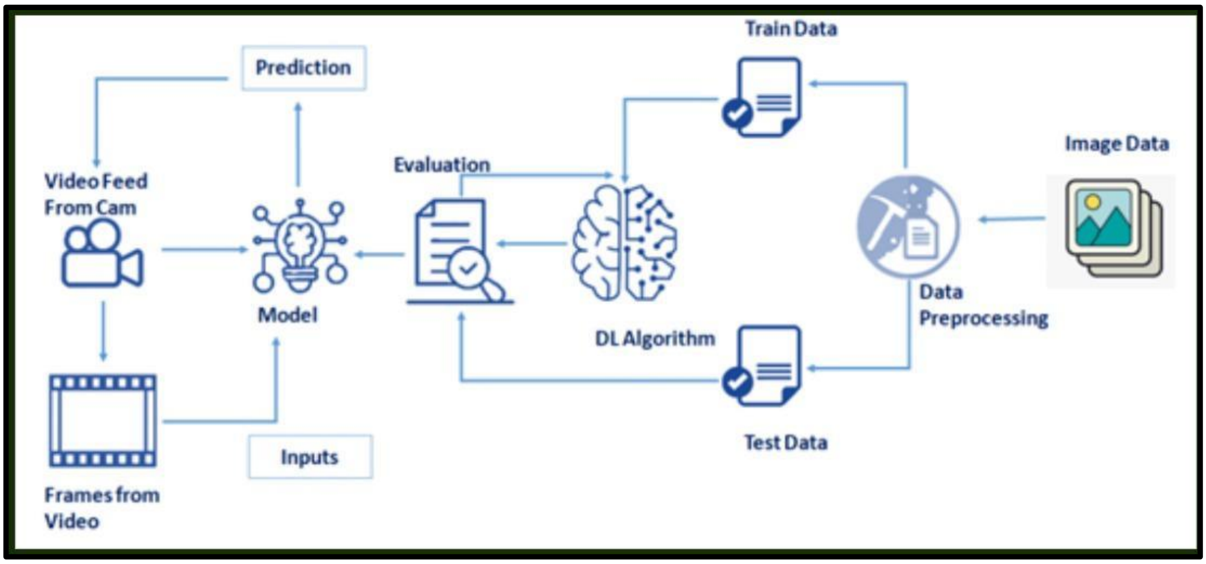


Figure 1

This system is a representation of a DL-based pipeline to be used for processing and processing video feeds. This consists of a combination of several stages, including data preprocessing, training, evaluation, and prediction. Each step is explained in detail followed by its role in the main workflow:

Input Sources

1. Video Feed from Camera :

A live video stream captured by a camera is the principal input to the system. The video feed provides continuous data that can be analyzed in real-time.

2. Frames from Video

The video stream is split into individual frames. These static images serve as the core units of analysis for the deep learning model. Extracting frames allows the system to focus on specific snapshots of the video, ensuring the model processes and evaluates the visual data effectively.

Model Development and Training

1. Image Data:

Data in pre-existing images are used for the training of this deep learning model. There are labeled images in a dataset, thus enabling that model to learn the related patterns and features for this specific task: for instance, object detection, motion tracking, or anomaly detection.

2. Data Preprocessing

   Before training, preprocessing is done on image data. This stage contains processes such as resizing, normalization, data augmentation which involves flipping, rotation, etc., and noise removal that improves the quality of the data and increases the richness of the data. A correctly preprocessed model can only ensure good generalization capabilities over unseen data.

3. Training and Test Data:

   The preprocessed image data is split into two halves.

   - Training Data: For training the deep learning model, in which the model learns to find the features and relations within the data.

   - Test Data: This set is left out for the evaluation and ensures that the model will be good at predicting unseen data, not overfitting to the training set.

4. DL Algorithm (Deep Learning Algorithm):

   This system primarily relies on the DL algorithm. The most common types of algorithms are CNN for image-based tasks or RNN for time-series analysis. The algorithm processes train data, extracting features and mapping input data to the desired outputs.

Evaluation and Prediction

1. Evaluation:

   After training, the model's performance is evaluated using the test data. Metrics like accuracy, precision, recall, and F1-score are calculated to measure the model's ability to correctly classify or predict outcomes. This step ensures the model meets the desired performance criteria before deployment.

2. Model:

   The trained and evaluated model is then deployed for inference tasks. It represents the final version of the DL system capable of making predictions or identifying patterns in new data.

3. Inputs and Predictions:

   Frames from the live feed of video are fed in the model as inputs; real-time predictions are thereby made by processing these inputs from the model. Real-time predictions may include finding out objects within the frames to detect particular activities or unusual situations.

6. Implementation

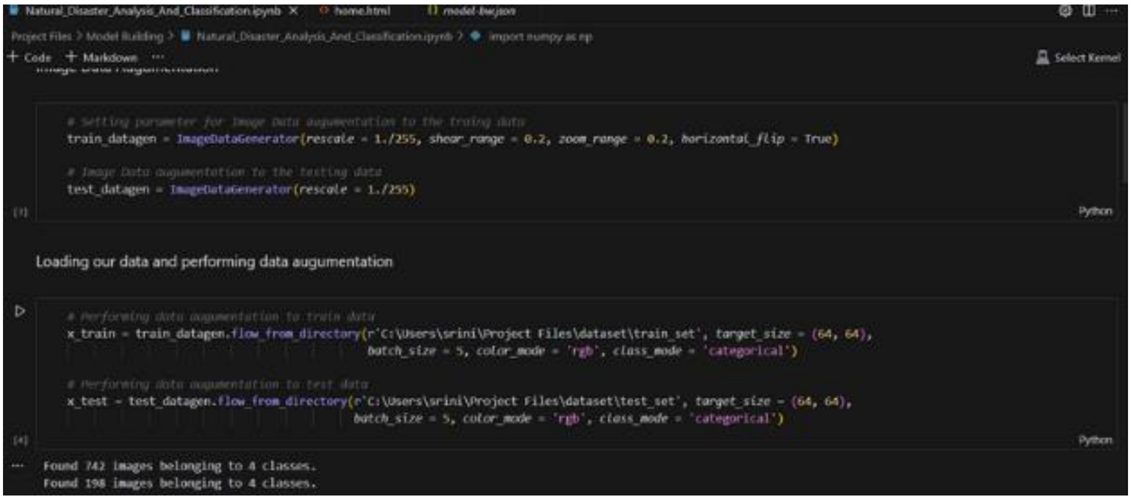


Figure 2

A. Data Preprocessing and Augmentation:

Data augmentation was performed using the ImageDataGenerator class from Keras, which includes the following steps:

a. Image rescaling
b. Zoom, shear transformations, and horizontal flipping to enhance model robustness

Preparation of training and testing datasets using the flow_from_directory method with the following parameters:

- Target image size: 64x64 pixels.
- Class mode: Categorical for multi-class classification.

B. Model Training:

The model was trained on the augmented training dataset. Testing data were used to test the performance of the model after training.

C. Web Application Development:

Developed a Flask-based application to deploy the trained model.

-Application endpoints:

a. /upload: Input images for classification.
b. /predict: Process uploaded images and return predictions.
c. The application was run locally in a development server environment for testing.
d. Server Logs: Logs showed successful handling of HTTP requests (GET and POST) during the prediction process, as shown in Figure 2.2.

7. Output

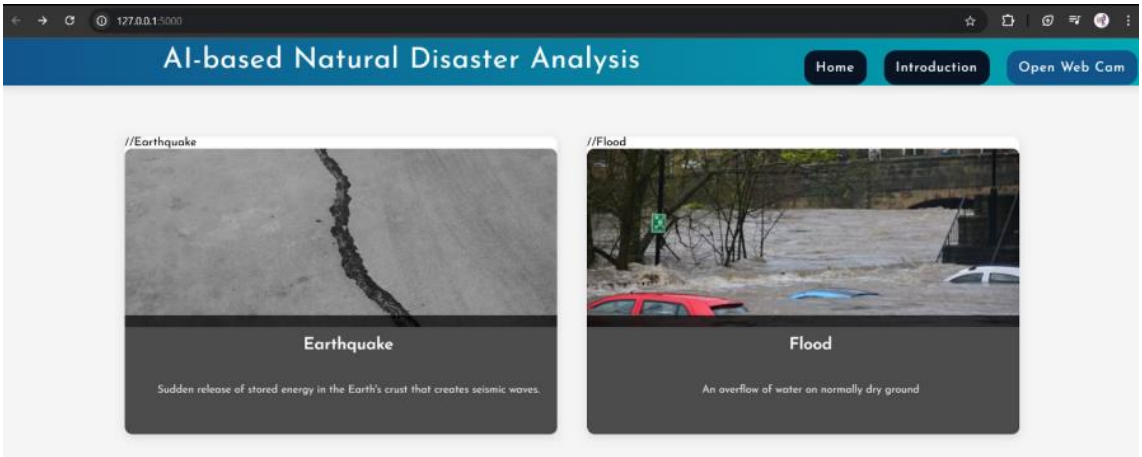
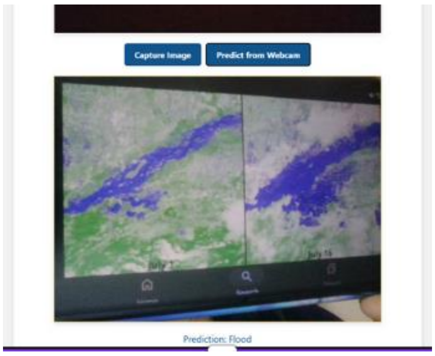


Figure 3



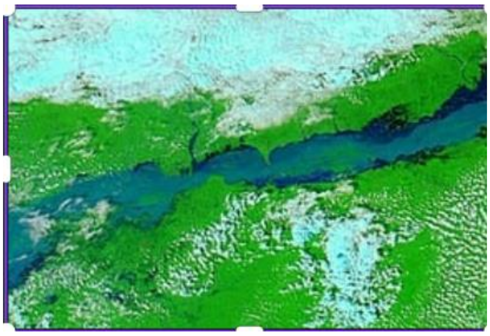


Figure 3.1 ***Figure 3.2***

Satellite image integration and deep learning utilization of real-time video feeds have dramatically transformed the processes of disaster prediction and monitoring systems, particularly with flood detection. This system, working on high-resolution satellite images and camera-captured video frames, allows accurate prediction of disasters in its best performance. The model can make predictions of flood-affected areas and distinguish overflow areas of water from the rest by making use of CNNs. The satellite imagery covers an extensive geographical area and therefore enables macro-level analysis, whereas real-time camera inputs facilitate the generation of instantaneous predictions. The system is very responsive to this combination of analysis pre- and post-disaster. It tracks flood progress and assesses damage over time. Data augmentation techniques include zooming, rotation, and noise reduction for enhancement of model robustness and adaptability to diverse geographic and environmental conditions.

This allows for the processing of video streams in a split form as frames, maintaining the capability to process at a computational efficiency level with real-time predictive capabilities. This can be generalized across datasets in different areas, such as both urban and remote regions. Challenges in its dependency on resolution, cloud cover, and overheads in computation will present potential avenues for improvement in low-resource settings. Despite these challenges, combining satellite imagery with real-time data feeds has proved quite effective in giving actionable information for early warnings, focused responses, and resource utilization during disasters. Such innovative methodology holds significant potential to save lives, reduce economic losses, and make disasters more resilient globally. Future development might focus on IoT sensors and edge computing to enhance scalability, accuracy, and responsiveness in real time.

8. Conclusion

The integration of mobile camera inputs with satellite data allows for the detection of disasters-a huge advancement in the way disaster monitoring and response take place in real-time systems. This system has integrated mobile devices and satellite images into a more accurate and accessible solution for identifying or classifying natural disasters: fires, floods, structural damage, and so forth. Use of CNNs for image processing helps ensure accuracy in disaster identification, and the use of satellite data helps to add more context to the situation, providing macro-level insights critical to understanding the broader scenario.

This will improve the timeliness of detecting disasters and empower users to have immediate alerts and actionable recommendations to save lives and minimize economic losses. In addition, the integration of mobile and satellite data enables more effective and comprehensive disaster response in areas that lack a high-level disaster management infrastructure.

The system has an architecture that is cloud-based; therefore, it provides for scalability, data storage, and continuous improvement by retrains and fine-tunes models. By processing real-time data coming from both mobile cameras and satellite sources, it produces more accurate predictions and classifications, making the system more adaptable to any kind of disaster scenario.

This project is, therefore, a step forward in disaster detection technology, as it offers innovative solutions in terms of the integration of mobile and satellite data, deep learning models, and real-time notifications. It will have an important role to play in disaster management and will reduce the effects of natural disasters on communities all over the world.

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