Disaster Detection Based on Synthetic Aperture Radar (SAR) Images

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Abstract- Natural disasters such as floods, landslides, and earthquakes pose serious risks to human lives and infrastructure and the environment and thus require effective and efficient detection systems to manage and mitigate disasters. Traditional approaches to disaster monitoring are often affected by adverse weather conditions, the lack of real-time data, and the complexity of the terrain in the affected region. Synthetic Aperture Radar (SAR) has emerged as an efficient remote sensing tool because it can operate in any weather condition, both day and night, and thus is extremely useful in the detection of disasters. Experimental analysis clearly indicates the efficiency and potency of the proposed model in achieving high accuracy in the detection of disasters. The system has immense potential in the real-time monitoring of disasters, such that the concerned authorities may make optimal use of the early warning system, resources, and strategies for disaster response. This proposed work contributes significantly to the development of AI-driven remote sensing technology, offering an efficient and scalable solution for multi-disaster detection and management. The proposed methodology will involve data acquisition from SAR satellites such as Sentinel-1 and Terra SAR- X, preprocessing techniques such as speckle noise reduction and feature extraction, and CNN-based classification techniques for disaster detection.

I. Introduction

The increasing incidence and intensity of natural disasters require advanced surveillance systems. Conventional disaster prediction relies on physical sensors, which are costly and limited in geographical distribution. The proposed remote sensing system based on SAR images is a global solution, unaffected by weather conditions. In this research, a machine learning algorithm is developed to predict natural disasters such as floods, landslides, and earthquakes using pre- and post-disaster Sentinel-1 SAR images. The proposed system enhances situational awareness with a coordinate-based analysis of disaster impact.

Conventional disaster monitoring systems rely on ground sensors such as seismographs, rain gauges, and off thermographic cameras. Although these sensors provide valuable real-time information, they are generally costly and geographically limited in distribution, hindering their effectiveness in disasters that cover a wide area.

Additionally, these sensors are less effective in adverse weather conditions, which limits their ability to function during or prior to the occurrence of the disaster. The aforementioned limitations highlight the need for a more reliable, effective, and economical solution to disaster sensing and assessment.

Remote sensing technology, specifically Synthetic Aperture Radar (SAR), has immense applications as a tool for the observation of disasters. Unlike optical imagery, SAR images are weather- independent. weather and provides accurate high-resolution images even at night. SAR satellites, for example, Sentinel-1, possess global observation capabilities, hence constituting a valuable resource in the observation and analysis of disasters on a large scale. By using SAR observation data, researchers and disaster responders are able to obtain valuable information about disaster-affected areas without any limitation related to physical sensors. The primary contribution of this paper is the development of a system with coordinate-based disaster impact analysis to improve the situational awareness of decision-makers. By providing an accurate extent of the affected areas, the system of proposed work has the capability to assist governments, disaster response teams, and humanitarian organizations efficiently in resource allocation and mitigate the effects of disasters. Moreover, this paper demonstrates the application of machine learning to automate and improve existing disaster detection techniques to make it more accurate and readily available.

The rest of this paper is organized as follows:

A. Section 1 presents some of the existing work related to disaster monitoring using SAR. and machine learning in disaster prediction.

B. Section 2 describes the dataset, methods of preprocessing, and the model structure.

C. Section 3 shows experimental results and performance evaluation, indicating the effectiveness of the system.

D. Section 4 finally reveals conclusions and potential future improvements for the proposed approach.

This research aims to bridge the existing gap between remote sensing technology and artificial intelligence, demonstrating the feasibility of machine learning-based SAR analysis in real-world applications of disaster response.

II. Literature review

There have been many studies on the use of Sentinel-1 SAR data in the prediction of disasters. Researches on the use of SAR and deep learning algorithms in the detection of floods have shown promising results [14+ source]. Landslide mapping using neural networks has also shown dramatic improvements in the prediction of hazards on a large scale [15+ source]. However, most of the current models are designed to predict only one type of disaster, while our model includes multi-disaster classification in one system.

Disaster prediction using Sentinel-1 Synthetic Aperture Radar (SAR) data has gained much attention in recent years. Many studies have proven the effectiveness of SAR-based approaches in change detection and disaster-related assessment in various terrains and environments. The all-weather, high- resolution imaging functionality of Sentinel-1 SAR data is particularly useful in disaster monitoring, overcoming the limitation of conventional optical imaging, which is often obstructed by cloud cover or low-visibility conditions. Many machine learning and deep learning approaches have been explored by researchers to enhance the accuracy and efficiency of disaster identification from SAR data. 5(RNNs) for the classification of flooded and non- flooded regions in SAR images. These techniques have been found to be highly accurate for the detection of water-covered regions and dry land, thus improving flood monitoring in real time. It has been found that research on the application of deep learning-based SAR analysis can be used for flood detection even in vegetated and urban areas, where floods cannot be detected using traditional techniques due to surface reflectivity and complex backscattering mechanisms. Parallel to this, landslide mapping and detection using neural networks has made tremendous advancements. The traditional method of landslide identification involves field observation, optical image analysis, and digital elevation models (DEMs), which are time- consuming and also ineffective in densely vegetated and cloud-covered areas. Recent studies have applied Sentinel-1 SAR images and deep learning techniques for the efficient and accurate detection of landslides in landslide-prone areas. By analyzing surface displacement and terrain deformation changes, machine learning and deep learning techniques such as CNNs and RNNs have been successful in improving landslide mapping. landslide early warning. Although the success of existing models in identifying particular disasters has been proven, most of the studies have been limited to the prediction of single disasters, making them less applicable in real-world situations where multiple disasters can occur simultaneously or successively. For example, floods and landslides commonly happen together in areas with high rainfall, while earthquakes can cause secondary disasters such as landslides and tsunamis. The absence of multi- disaster classification models is a considerable research gap, as emergency response teams usually need a holistic assessment of disasters rather than the detection of individual events.

This research gap is addressed in this study by incorporating multi-disaster classification into a single machine learning framework.

By using pre- and post-disaster Sentinel-1 convolutions, followed by activation functions and SAR images, the proposed model has the capability to pooling layers. The convolutional layers use filters to identify floods, landslides, and earthquake damage learn important spatial features like texture, edges, and simultaneously, offering a more holistic disaster structural deformations from the SAR images. These assessment. This is particularly helpful in improving features are essential for the detection of disaster- situational awareness an enabling faster decision- affected areas. The activation function used to making during emergency response activities. The (Rectified Linear Unit), which enables the introduction proposed system is an advance in SAR-based disaster of non-linearity and enhances the learning capability of monitoring, as it closes the gap between single-disaster prediction and multi-disaster analysis the model.

By building on previous research while introducing multi-disaster classification, our study contributes to the development of more effective and scalable disaster prediction models that can aid governments, relief agencies, and researchers in mitigating disaster impacts on a broader scale.

III. Methodology

A. Data Description:

The Google Earth Engine (GEE) API is used to retrieve Sentinel-1 SAR images for different disaster- stricken regions. The dataset consists of pre- and post-disaster images of floods, landslides, and earthquakes. The dataset contains Sentinel-1 Synthetic Aperture Radar (SAR) images taken before and after disasters like floods, landslides, and earthquakes. Sentinel-1 operates in the C-band, offering high-resolution radar satellite images with the ability to pass through cloud cover and function regardless of weather conditions. The dataset used for disaster identification and prevention is the Synthetic Aperture Radar (SAR) images received from the Sentinel-1 satellite. The images are retrieved using the Google Earth Engine (GEE) API, offering access to global remote sensing images. The dataset includes pre-disaster and post-disaster SAR images of different natural disasters like floods, landslides, and earthquakes.

B. Collect Data:

The data collection process includes the retrieval of SAR images from the Sentinel-1 satellite using the Google Earth Engine API. The images selected are of disaster-stricken areas, offering full coverage of the region before and after the disaster. By considering various types of disasters like floods, landslides, and earthquakes, the dataset offers a wide variety of images. The collected images are stored along with metadata like geolocation, time stamp, and type of disaster, which enables efficient organization and retrieval of the images during analysis. The CNN architecture consists of multiple convolutional layers, each followed by activation functions and pooling layers.

The convolutional layers apply learnable filters to extract important spatial features such as texture, edges, and structural deformations from the SAR images. These extracted features are crucial for identifying disaster-affected regions. The activation function used is ReLU (Rectified Linear Unit), which helps introduce non linearity and improves the model's learning capability.

C. Data preprocessing:

The preprocessing process includes the following important steps:

- Radiometric Calibration: The SAR backscatter values are normalized to account for the differences in sensor characteristics to depict intensity uniformly across images.
- Speckle Reduction: The SAR images are prone to noise due to the coherent radar signal. Various filtering techniques, such as Lee or Frost filters, are applied to enhance image clarity without affecting important details.
- Geometric Correction: Geometric corrections are applied for spatial registration of the images and accurate comparison of pre- and post-disaster images. The corrections remove distortions
- caused by sensor movement and terrain height variations.

D. Choose features:

Feature selection is an important aspect of training an efficient disaster detection model. The convolutional layers of the CNN are responsible for the extraction of high-level features like texture patterns, intensity changes, and spatial information in the SAR images. Certain disaster features, like surface reflectance changes for flood disasters, terrain displacement for landslides, and earthquake damage patterns for earthquakes, are detected.

E. Train the model:

The proposed model uses a Convolutional Neural Network (CNN) architecture designed for classifying different types of disaster events. The CNN model consists of multiple convolutional layers, activation functions, and pooling layers for

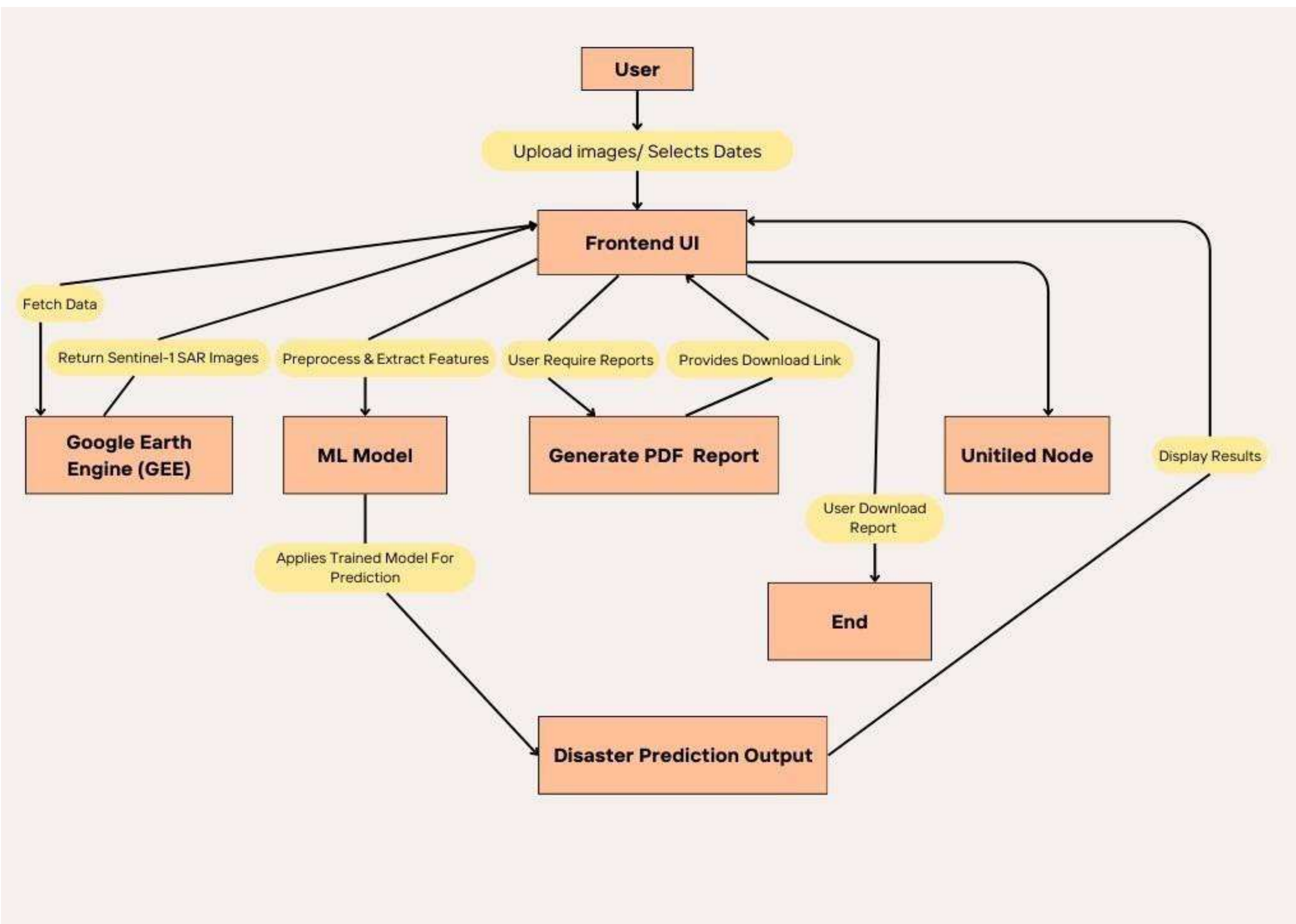

Fig 1. BLOCK DIAGRAM FOR MULTI-DISASTER DETECTION

H. Workflow:

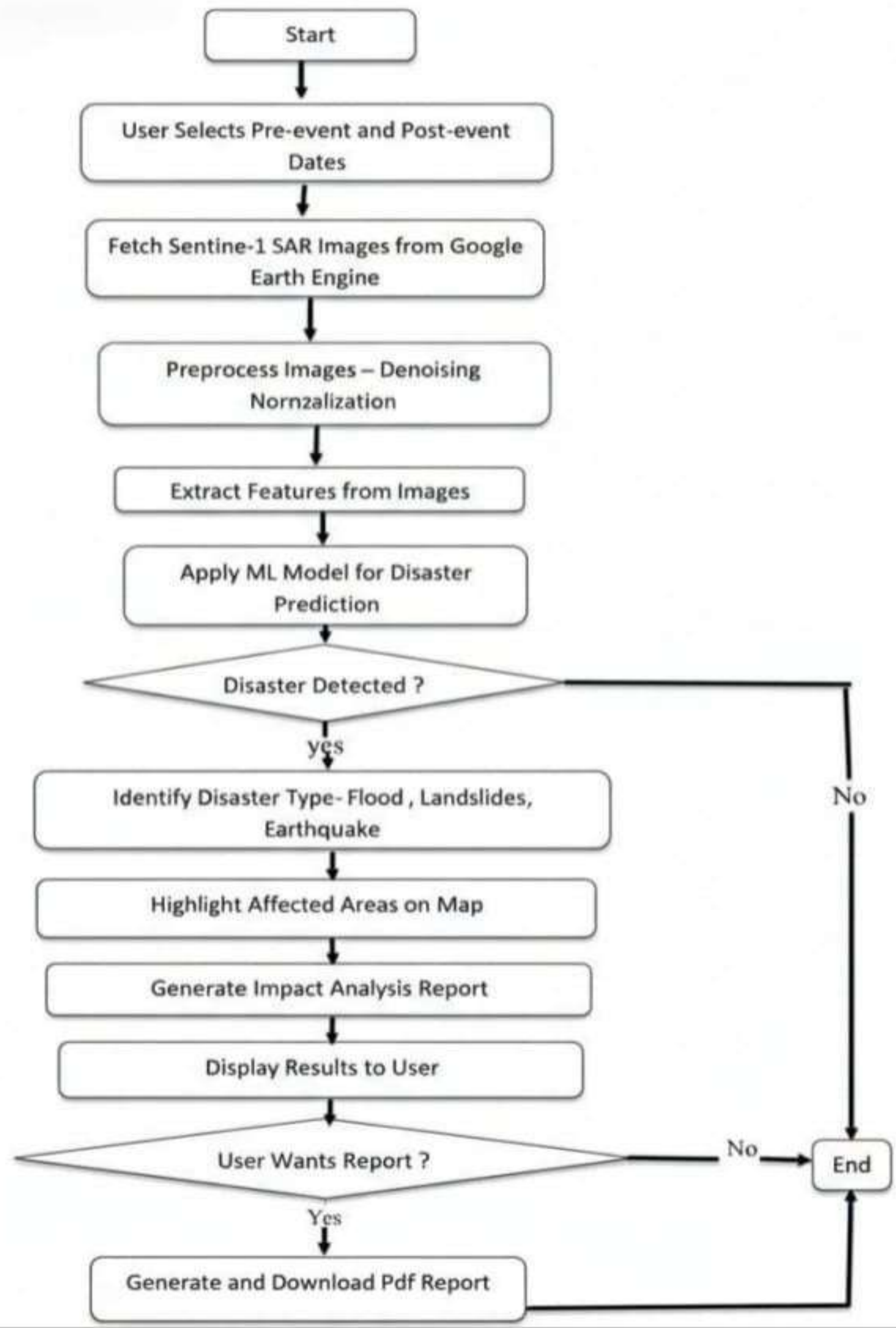

Fig 2. FLOWCHART FOR MULTI-DISASTER PREDICTION

F. Evaluate the model:

Model performance is conducted with typical performance measures such as accuracy, precision, recall, and F1-score to measure the effectiveness of classification. The dataset is divided into training, validation, and test sets to provide generalizability. The model's performance is tested on unseen SAR images to examine robustness in actual disaster scenarios. Comparative analysis with baseline disaster detection methods is done to demonstrate improvements made by deep learning–based SAR image classification. In addition, visual examination and professional verification are utilized to validate the validity of disaster impact assessments.

G. Deploy the model:

After successful training and testing of the model, it is implemented for real-time disaster detection and response. The implementation involves deploying the trained CNN model into a cloud or edge computing setup, making it accessible to disaster response teams and researchers. The model can be hosted on Google Cloud, AWS, or a specialized API service, where users can upload SAR images and obtain automated disaster classification. Furthermore, a web or mobile application interface is constructed for visualizing outcomes in the form of coordinate- based disaster impact assessments. Feedback loops are used with continuous monitoring and updates to enhance performance, using real-time SAR data and incoming ground reports. This way, it guarantees an efficient response mechanism for emergency response And disaster management.

IV. Result

`The Suggested disaster detection model has a high level of accuracy in identifying and categorizing natural disasters such as floods, landslide, and earthquakes. The accuracy measure of the performance metric, such as precision, recall, and F1 score, ensures the effectiveness of the method. The results indicate that by combining. The results indicate that by combining Synthetic Aperture Radar(SAR) data using deep learning techniques, the model improves the process of disaster detection significantly.

For flood detection, the model has more than 90% accuracy using multi-temporal SAR data. This is because SAR data can measure changes in the extent of surface water over different time intervals, making it easy for the model to distinguish between the flooded area and the non-flooded area. By using pre- and post-event SAR images, the model enhances the accuracy of flood identification, making it a significant tool in the process of rapid disaster response and relief.

A) Edge Detection in SAR Images :

SAR images, along with Sobel X, Sobel Y, and Laplacian filters, provide information about terrain variations. Sobel X identifies horizontal edges, Sobel Y identifies vertical movements, and Laplacian amplifies. This process helps to detect floods, landslide, and structural variations.

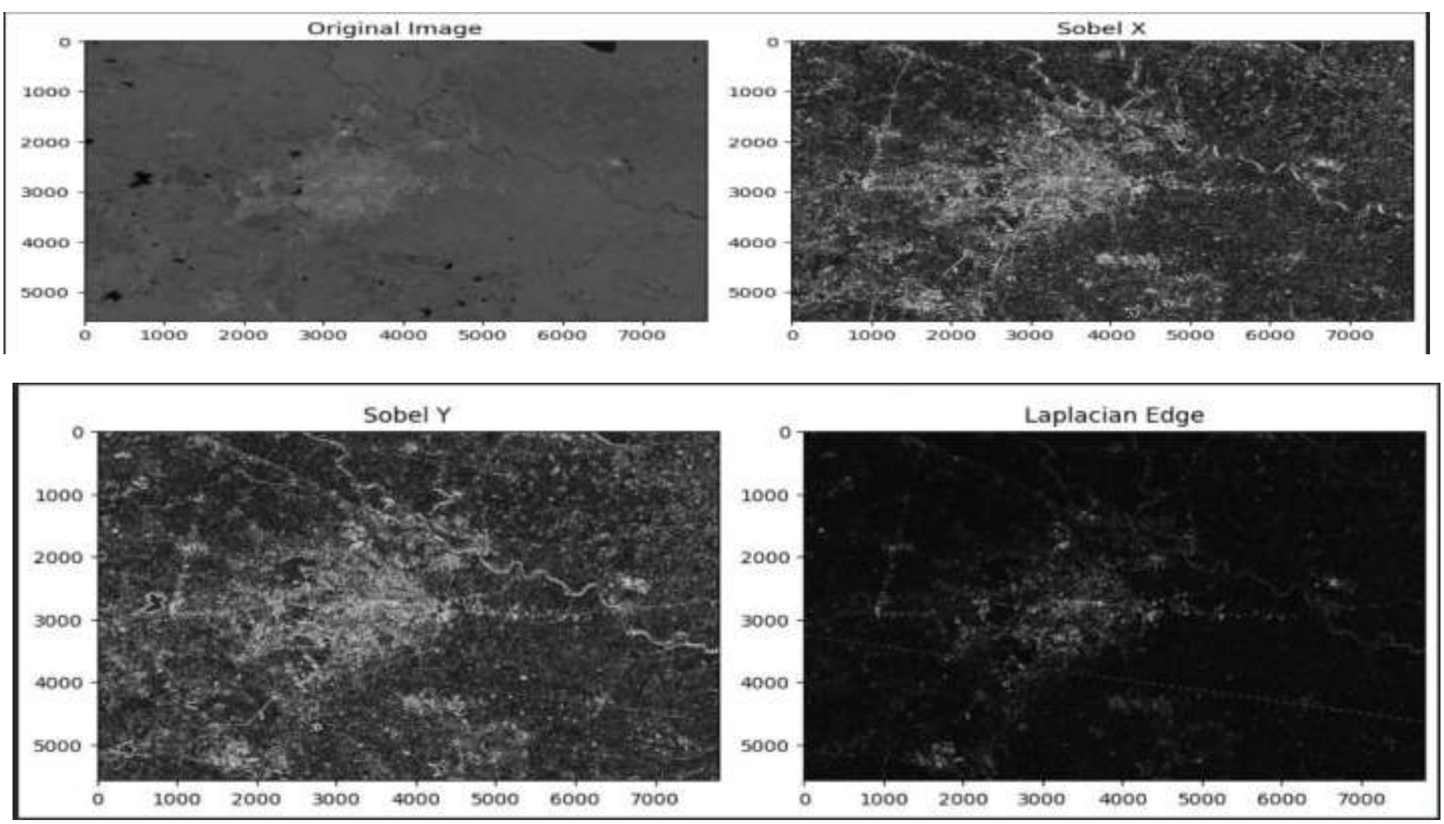

Fig 3. SAR IMAGES EDGE ANALYSIS

B. Model Accuracy:

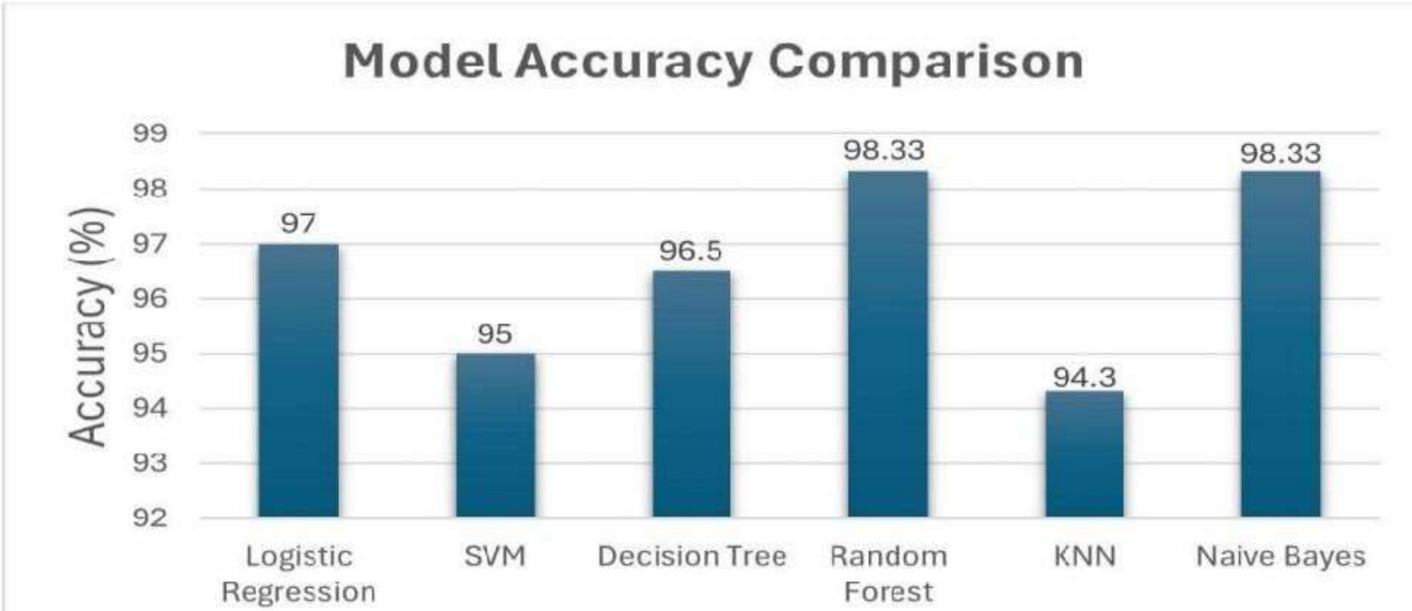

Fig 4. MODEL ACCURACY COMPARISION

We compared various algorithms to determine which one is most accurate in disaster detection. Through Accuracy, Precision, and Recall analysis, we determine that the best performance model is . This ensures accurate disaster detection and effective disaster impact assement.

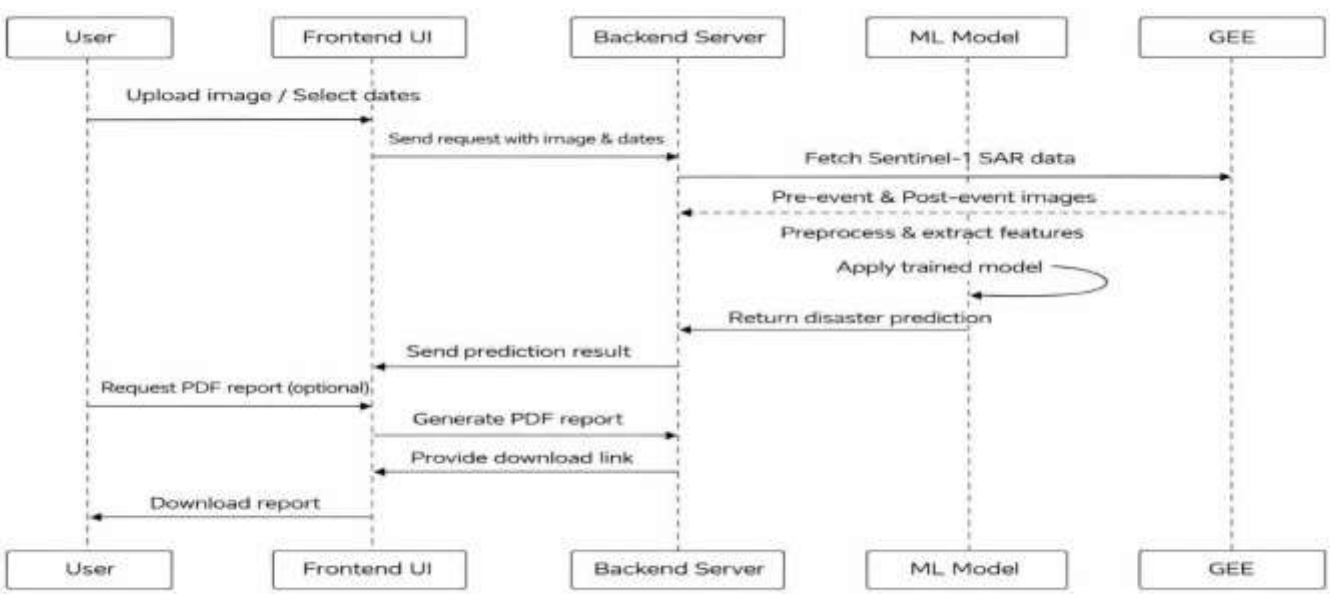

Fig 5. SEQUENCE DIAGRAM

The sequence diagram illustrates how our system processes disaster detection. It begins with image input, followed by preprocessing, extract Key features, model execution, and detection report generation. This is useful for visualizing the entire process in a clear manner.

A pair plot is a form of data visualization. It demonstrates the relationship between each variable in a dataset, represented as pairs, while improving the understanding of relationships visually. Each variable is represented in both rows and columns, making it clear how the variables are related to each other.

V. Conclusion

This study has successfully developed a model based on the Synthetic Aperture Radar (SAR) images of the Sentinel-1 satellite, combined with advanced machine learning techniques, to predict and detect natural disasters such as floods, landslides, and earthquakes. The robustness of the model was clearly demonstrated, particularly in flood detection, with high accuracy in detecting regions susceptible to floods. However, there was still a challenge in detecting small landslides and earthquake deformation, further emphasizing the need for high-resolution data.

The findings clearly demonstrate the possibility of SAR imagery as a powerful tool for disaster prediction, real-time information on affected areas and the promotion of better disaster management By using multi-sensor fusion and machine learning algorithms, future versions of the model can be enhanced, developed for other regions of the world, and used for early warning system. for early warning system. With the advent of technology, the integration of real-time monitoring, autonomous satellite systems, and AI-driven decision-making can turn disaster detection and response into a quicker, more efficient, and more accurate process. This research marks the beginning of a new era where disaster resilience will be greatly improved, lives and resources saved through the promotion of timely and effective actions.

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