AI-Based Change Detection for Disaster Identification utilizing Bi-temporal Satellite Images

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Abstract - *Globally, hundreds of natural disasters happen every year. Identifying high-impact areas and conducting an accurate analysis of the post-disaster landscape are critical for disaster relief and recovery efforts. It would enable damage assessment and the identification of routes for early response to affected areas. Currently, after natural disasters that cause humanitarian crises, the mapping to be done is carried out by volunteer initiatives all over the world using satellite imagery. However, because the volunteers are mostly inexperienced and follow different processes, the process takes time and is inconsistent across the various initiatives. Comparing the pixel values of satellite images before and after the disaster could help identify changed areas. The Change Detection method can be used to compare pixel values more effectively compared to the human initiatives. Change detection examines changes in a region's spectral characteristics over time to determine the processes that lead to changes in land use or land cover. The purpose of change detection is to analyse the variability in images captured over a specific time period related to a specific area. This change in the image is used to detect the occurrence and amount of damage. In this project, a change detection-based model is implemented for identifying disaster occurrence and predicting the percent probability of occurrence based on an analysis of a change map generated with the VGG-19 pre-trained model as a feature extractor. In addition, a pre-trained InceptionV3 model is used to perform binary classification in order to predict the type of disaster between hurricane and earthquake.*

Key Words**: *natural disasters, change detection, bi-temporal satellite images, pixel values, buildings, change maps***

1. INTRODUCTION

A disaster is a serious issue that happens over a short or long period of time and results in significant losses to people, property, the economy, and the environment that exceeds the capacity of the affected community to manage the use of its resources. Disasters can be caused by natural, man-made, and technical dangers as well as several other factors that influence how exposed and vulnerable depending on the population. Developing nations bear the brunt of the costs associated with natural disasters, and these nations also account for over 95% of all deaths resulting from hazards. A quick and prompt response is necessary during natural catastrophes to reduce damage and preserve lives. The scale and impact of disasters must be addressed by effective and knowledgeable disaster management.

Identification and application of diverse ways to reduce disaster-related losses are part of the ongoing, integrated process known as disaster management. Standardizing, organizing, and managing the data and information about disaster management is mostly done with the benefit of current technology. Quick data collection during or before to a disaster, the creation of maps and statistical data, and the presentation of the data in various mediums for many users as well as on the Internet are necessary to accomplish this.

Governments commonly employ traditional disaster management techniques, such as search and rescue teams, field survey teams, and local governing bodies, to analyze the damages and the disaster's nature. Damage assessment is usually done considerably later than anticipated, which can hinder quick relief efforts and deprive rescuers and the people without the knowledge necessary to comprehend the severity of the disaster and take precautions. These survey methods are very risky. Information from social media platforms can be utilized in these situations because it is affordable and quick. Data can be shared using social media in a variety of ways, including text, photos, and video. These media can be helpful for determining the extent of damage after disasters; the condensed nature of social media posts makes it simple to swiftly compile crucial information.

Deep learning is a subset of machine learning. It uses artificial neural networks, which are created to mimic how humans think and learn, whereas machine learning uses simpler principles. Larger, more complicated neural networks are now possible thanks to developments in big data analytics, which enable computers to learn and respond to difficult situations faster than people. Speech recognition, language translation, and image categorization have all benefited from deep learning. The most common natural disasters are earthquakes, wildfires, floods, droughts, and landslides that cause damage to man-made structures such as buildings and roads. Identifying affected and degraded areas at an early stage is a crucial issue for mitigating the negative impacts of destructive events and managing them.

A vision-based disaster detection system that uses deep learning algorithms can be used to quickly extract features from damaged areas from outdoor satellite imagery. The use of satellite imagery for disaster monitoring and response has grown in popularity. Monitoring of the environment and climate, particularly in the detection and management of natural disasters, depends more and more on the analysis of satellite imagery. Prioritizing rescue operations, humanitarian assistance, and coordinating relief activities are important after a disaster. Since resources are often scarce in disaster-affected areas, these must be carried out quickly and effectively, and it is critical to pinpoint the places that have sustained the most damage. However, the majority of current disaster mapping efforts are manual, which takes time and frequently produces inaccurate results.

Change detection (CD) is a technique for identifying differences in the state of an object or phenomenon by observing it at different times. To compare and evaluate two or more remote sensing images captured in the same area at various intervals to learn more about changes to the ground object, change detection (CD) based on remote sensing data is an essential application of remote sensing image interpretation. This technique has been extensively applied in a variety of sectors, including scene classification, ecological environment monitoring, disaster assessment, agricultural study, and land planning. Deep learning techniques are currently being extensively studied in the field of remote sensing picture target extraction.

2. SATELLITE IMAGES FOR DISASTER IDENTIFICATION

In the recent decades, because of the significant human casualties that follow disasters, disaster detection has emerged as one of the most intriguing scientific topics. Using sensors and straightforward image processing methods, researchers have examined the effects of changes brought about by disasters. Disaster detection systems, according to a previous study, have several serious flaws, including the inability to observe disasters beyond a certain distance. This is a result of the low accuracy and a limited number of catastrophe detection sensors that only receive verbal input. Due to the enormous number of satellite images that must be viewed in a short amount of time, operators also struggle with disaster detection. Therefore, this could result in a calamity being missed or misjudged. It is essential to develop an automatic disaster detection system that monitors the occurrence of disasters over a greater area using satellite images, with the use of deep learning techniques.

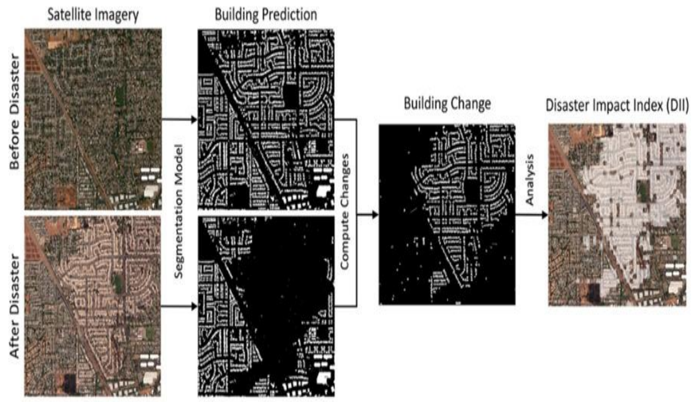

Fig - 1: Disaster identification using Satellite image

Trained models on CNN detect human-made features, such as buildings. In order to train on existing methodologies for disaster impact assessments, new classes of structures damaged by fire must be manually annotated, which can be time-consuming and expensive to develop **[1]**. Only building data sets are used in this new approach. Figure 1 depicts disaster identification using building predictions in satellite images that are processed using a segmentation model to obtain an accurate disaster analysis. These are easily accessible and expandable to address other, comparable natural calamities. The models are initially trained to recognize these high-level traits because variations owing to the seasons, the time of day, or other circumstances may result in inaccurate findings (i.e., buildings) and then produce prediction masks in disaster-affected areas. The areas of maximal change can be determined by calculating the relative change between features taken from snapshots of data captured both before and after a disaster.

2.1 Bi-Temporal Satellite Images

Automatic building change detection (BCD) from aerial images is an important research area in the field of remote sensing **[7]** because the results are required for a variety of applications such as monitoring urbanization, identifying unauthorized or illegal structures, detecting changes in land use, updating digital maps, and route planning. BCD is used to evaluate the state of damaged structures following earthquakes and other natural disasters, aiding with rescue operations and rehabilitation plans. There are more and more distant sensing images that need to be processed as remote sensing technology advance. Due to the labor- and time-intensive nature of manual processing, which mostly relies on human interpretation, unsupervised algorithms are required to perform BCD in the absence of ground truth. Numerous BCD systems and techniques have been built for organizing remote sensing data, and more current techniques are always being developed.

The identification and monitoring of structures using remotely sensed photography is extremely valuable for tracking urbanization. Numerous techniques have been developed for the automatic detection of changes based on bi-temporal or multi-temporal remote sensing images. They range from pixel-oriented to object-oriented, from spectral-characteristics-based to artificial intelligence-based, and from pixel-oriented to object-oriented. BCD typically involves two main processes: building change generation (BCG) and segmentation of the building change map. The major part of BCD, BCG, which seeks to highlight changes in the buildings, has a direct impact on accuracy. In low- or medium-resolution photos, these approaches have been shown to be able to detect abrupt changes. In order to extract building areas, bi-temporal aerial photos are first combined using semantic segmentation based on a deep convolutional neural network to capture change information.

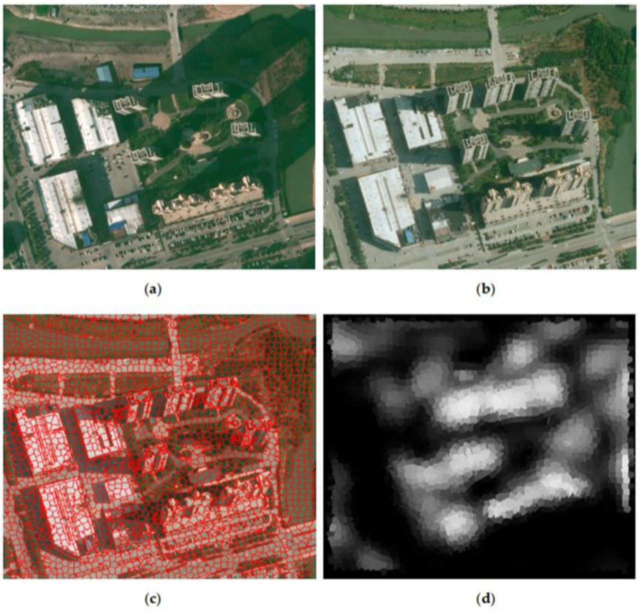

Fig - 2: Bi-temporal images, the corresponding image-object, and change confidence map. (a) The RGB aerial image at time t1, (b) the RGB aerial image at time t2, (c) superposition of the bi-temporal image-object and the RGB aerial image at time t2, and (d) the change map.

3. DEEP LEARNING FOR DISASTER IDENTIFICATION

Deep learning can be used to extract high-level semantic features from multi-temporal images **[2]**, such as spectrum, space, and texture, to create a nonlinear relationship between the attributes of ground objects in multi-temporal photos. Deep learning-based distant change detection models are distinct from conventional remote change detection algorithms. It can recognize data characteristics, reducing the dependency on labor-intensive human work during feature extraction in remote sensing photos. It not only increases the remote image change detection's accuracy but also provides a brand-new automatic and intelligent processing approach to meet the application's actual needs. In this study, changes in bi-temporal satellite images are detected using a feature change detection model based on VGG-19, and the results are then analyzed to determine the percentage likelihood that a disaster would occur. Humanitarian groups need to act quickly and effectively when a natural disaster occurs. Accurate knowledge of the calamity will be essential to providing an efficient rescue. Rich and trustworthy information is provided by satellite images to aid professional decision-making. Develop a deep learning workflow to assist assistance workers in time-limited emergencies in order to help identify disasters despite the lack of data. Assessing the applicability of learning-based transfer convolutional neural networks (CNNs) in supporting building damage assessment in an emergency context it is very important to identify the type of disaster that has occurred between earthquake and hurricanes.

4. CHANGE DETECTION

4.1 Implementation of AI based Change Detection for Disaster Identification

Images captured at two-time intervals must be overlaid in order for the comparison between corresponding places to make sense. The latter aims to eliminate atmospheric attenuation distortion caused by absorption and scattering in the atmosphere as well as radiance or reflectance differences brought on by the digitalization process of sensors, which reduces false alarms brought on by these radiation errors in change detection **[4]**. A substantial, top-notch training set that can aid algorithms in comprehending particular patterns or series of outcomes is necessary in order to construct the AI model. Bi-temporal images are labelled or annotated in certain ways to help the AI model quickly pick up on the traits of the altered objects. Below Figure 1, represents an annotated example for building change detection, which is composed of two remote sensing images captured at two different time intervals and a corresponding ground truth labelled with building changes at the pixel level. The AI model can be trained in a supervised manner using the data from the real world. A training set for AI model training and a test set for accuracy assessment throughout the training process can typically be created from the training set after it has been generated. Iteratively and alternatively, the testing and training operations are carried out. Bi-temporal pre- and post-disaster images consisting of buildings is supplied to change detection algorithm. Change maps can be produced more intelligently and automatically for useful applications by utilizing a trained AI model. Additionally, this can support the generalization potential and resilience of the model, which is a crucial component in assessing the viability of the change detection method based on AI and it predicts the percent probability of occurrence of disaster and identify the type of disaster.

4.2 Conventional and AI based Change Detection methods

Data acquisition is the first step in both the traditional change detection flow and the AI-based change detection flow, with the goal of obtaining the change detection map for various applications **[3]**. While AI-based systems normally require an additional training set creation process and an AI model training process for change detection, traditional approaches typically involve two phases after data preparation, including a homogenization process and a change detection process. AI techniques are the mainstays of AI-based methodologies. Artificial intelligence (AI) techniques, often known as machine intelligence, can improve performance in a variety of data-processing jobs. It can be described as a system's capacity to accurately understand external input, learn from that data, and use that learning to accomplish particular tasks and goals through adaptable changes.

4.3 Deep Learning based Change Detection methods

For an accurate understanding of land surface changes using Earth observation data, change detection (CD) is a crucial tool. It is also crucial for spotting linkages between social and environmental events in geoscience. To produce a precise change map, a supervised deep learning (DL)-based change detection method was suggested. The use of DL to tackle the CD problem with multitemporal remote sensing imageries is growing in popularity because of its excellent performance and tremendous potential in the fields of pattern recognition and nonlinear problem modelling **[5]**. Convolutional neural networks (CNN) in particular are used in deep learning (DL) algorithms to monitor environmental change and classify it into change and no change classes. There have been significant advancements in change detection, as shown by the systematic analysis and widely deployed networks in DL, but there are still numerous obstacles in CD because of a lack of training data, prior knowledge, image complexity, etc. However, even if these difficulties are overcome, there are still many fundamental problems in RS datasets that have not yet been addressed, such as heterogeneous data, multiresolution images, and global information of high-resolution and large-scale images. This is because of changing requirements and diverse data. Therefore, it is strongly advised that future research concentrate more on these difficulties.

4.4 Building Change Detection methods

New applications for resolving geospatial problems in metropolitan areas have been developed as a result of the accessibility of high-resolution satellite imagery. Due to its wide range of applications, such as city modelling, map updating, and urban monitoring, building detection from remote sensing images has been an important area of research. An image must be manually processed, which takes a lot of time and effort. As a result, techniques have been created that need little or no human effort. Building detection has improved recently thanks to several automatic and semi-automated techniques **[6]**.

In general, there are two aspects to the building detection process using satellite images: object and threshold-based. Segments are generated and given features by the object-based approach (shape, spectral, and height). To identify buildings, the threshold-based method creates a normalized difference vegetation index (NDVI) and digital surface model (DSM).

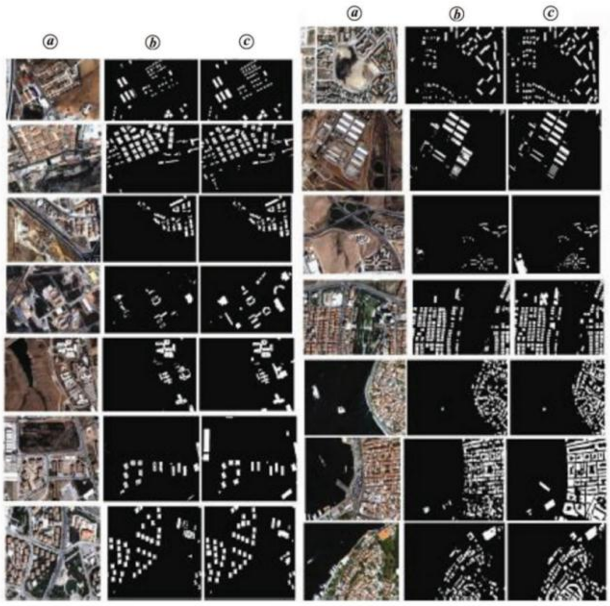

Fig - 3: Building detection from VHR multispectral images has been made possible via a cognitive-based automated method. Results of cognitive-based methods where (a) indicates input images; (b) output images and

(c) reference images.

5. WORK RELATED TO DISASTER IDENTIFICATION USING MACHINE LEARNING AND DEEP LEARNING

Disaster managers and responders rely on timely and accurate information about the disaster situations during sudden natural disasters in order to develop effective disaster management strategies and make swift response decisions.

In a study performed by Xiao Chen, et al. **[8]** automates the process of using satellite imagery to locate damaged structures and to categorize the severity of the damage. The Unet model, which holds image data in the form of compressed data, is used to extract features from the images. Building location and damage classification are automated using a learning technique built on top of satellite photos.

The difficulty in determining the boundaries of computationally expensive objects is due to the substantial amount of data.

Carlos Gonzalez, et al. **[9]**, proposes the portability and acceleration of the inferences process on a deep convolution neural network model to detect rapid earthquake damage on very high resolution (VHR) remote sensing data using the Intel OpenVINO toolkit. Experimental results demonstrate that the optimised model offers good accuracy for damage identification with a notable increase in execution speed on CPU+GPU. The network cannot be trained more quickly using OpenVINO, and it is not always simple to retrain the models using specific data.

Pei-Jun Lee, et al. **[10]** presents a system of combining deep learning and image transform algorithms to detect landslide location in satellite images. To identify whether satellite photos of landslides are present, a convolution neural network is deployed. The Hue - Bi-dimensional Empirical Mode Decomposition (H-BEMD) transformation algorithm is suggested in order to accurately identify landslides under various illumination situations from classed landslide photos. To determine the algorithm that is most appropriate for real-time implementation, the four networks' performances are assessed and contrasted in terms of accuracy and real-time performance. A large dataset is needed for the classification strategy, which reduces the generalizability of the model.

Diyana Kinaneva, et al. **[11]**, propose a platform that uses Unmanned Aerial Vehicles (UAVs), which constantly patrol over potentially threatened by fire areas. The UAVs have on-board computing capabilities and make use of the capabilities of artificial intelligence (AI). Early forest fire detection is accomplished by using both fixed-wing and rotary-wing UAVs. It's possible that the UAVs can't efficiently cover every area. Disasters that might strike in unexpected places wouldn't be detected by the system. A large dataset is needed for the classification strategy.

Shaheen Khatoon, et al. **[12]**, proposed a disaster taxonomy for emergency response and utilized the same taxonomy with an emergency response pipeline and deep learning-based image classification to automate the decision-making process for emergency response. In order to evaluate disaster-related images and determine the types of disasters, algorithms like VGG-16 and You Only Look Once (YOLO) are utilized. CNN-based classification and object detection, models are used to classify incoming images into the disaster or non-disaster types. An information fusion module that combines the two-level labelled images and maps them to a specific response category inferred by the taxonomy. Images on social media might not always be reliable; they might be made up. It can be challenging to obtain pictures that adequately depict every aspect of a disaster-affected country.

Krishna KantSingha, et al. **[13]**, proposed a novel neuro fuzzy classifier Hybrid Kohonen Fuzzy C-Means-r (HKFCM-r). The classifier is a combination of the FCM-r clustering method and the Kohonen Clustering Network (KCN). The input and output layers make up the sole two layers of the HKFCM-r network architecture, which is comparable to a straightforward KCN network. The hybridization results in a more efficient, less complex and faster classifier for classifying satellite images. To evaluate the effectiveness of the method, the error matrix was computed. One of the two clustering methods, KCN, uses an artificial termination strategy and is sequential. The KCN may have a sluggish convergence rate and may not always be able to handle complexity well.

Soma Shiraishi, et al. **[14]**, proposes an automatic disaster detection system by implementing one of the advance deep learning techniques, convolutional neural network (CNN), to analysis satellite images. By establishing an automatic disaster detection system, the data given here could help with advancements in efficiently detecting natural disasters. The training data set for each disaster consists of 30000–40000 patches, and each patch is automatically trained in CNN to identify the immediate geographic area of the event. The proposed system needs a lot of data since optical pictures from disaster-affected areas will have a variety of features that are particularly challenging to cover in the training set.

Ying Liua, et al. **[15]**, propose a deep learning-based landslide recognition method for optical remote sensing images. In order to capture more distinct features hidden in landslide image. A specific wavelet transformation is proposed to be utilized as the pre-processing technique in order to capture more different features buried in landslide images. Pre-processing and classification model training landslide feature representation comprising two phases of the suggested landslide recognition approach. Support vector machine (SVM) and artificial neural network (ANN) are used as the counterparts to show how well our suggested model performs. Wave transforms are quite sophisticated and demand a lot of computing power. A lot of data is needed for the auto encoder used for denoising and feature extraction.

Keiller Nogueira, et al. **[16]**, proposed a Relation network designed for taking into account the relationship between pairs of objects during training. Two neural networks, f and g, that have jointly learned parameters make up an RN. Neural networks are employed and trained for classification in runs 1, 2, 3, and 4, with a flooding event serving as the positive class. In those runs, the test set was ranked from highest to lowest according to the classification score to produce the final ranking. A large dataset is required for the classification method. A dataset, no matter how huge, won't be able to effectively cover all the variables of a disaster impacted area, which decreases the generalizability of the model for use cases like disaster identification.

6. METHODOLOGY AND EXPERIMENT

In this paper, we propose a 2phase network for disaster identification and classification. The first network is a deep learning-based change detection **[17]** framework that analyses bi-temporal satellite images of urban areas mainly containing building as the topographical features to generate a change map. The generated change map is further analyzed to compute the percentage probability of occurrence of disaster. If a disaster is predicted to have occurred by the first network, the second network then tries to identify the type of disaster between hurricane and wildfire.

6.1 Change Map Generation

For change map generation, a feature extractor **[18]** is implemented using a pre-trained VGG-19 model **[19]**. Bi-temporal satellite images, i.e., images at two consecutive time intervals are used as input this network. Image at time interval T1 and time interval T2 are given as input to the feature extractor model one after the other to generate two feature maps. The two generated feature maps are compared to generate a change map. For this comparison, a mathematical function termed Reduced Sum of Squares (RSS) **[20]** is used. This method is used to identify any discrepancies in the two generated feature maps. The RSS method outputs a change map. We then use Otsu thresholding method **[21]** to analyze the change map to identify an optimal threshold value of pixels. If a pixel value in the change map is an above the identified threshold, the pixel is represented in white in the displayed change map and if the change map pixel value is below the identified threshold, it is represented in black. The black region in the change map represents unchanged areas in the bi-temporal images and the white pixels represent the changed areas in the bi- temporal images.

6.2 Change Map Analysis

In the generated change map, the number of black pixels i.e., the pixels representing no change and the number of white pixels i.e., pixels representing change are computed. The percent probability of occurrence of disaster is then calculated as percent of white pixels i.e., pixels representing change present in the change map.

Percent probability of occurrence of disaster = (No. Of white pixels / Total no. of pixels) * 100

6.3 Transfer Learning based Binary Classification

Transfer learning **[22]** is machine learning research problem wherein a model previously trained is reused on a similar but different dataset. The previously learnt knowledge such as weights and common features are reused in a similar use case. An Inception v3 **[23]** pre- trained model is used for binary classification with its last layer frozen. The model is given a single-temporal post disaster image as input and predicts the type of disaster between hurricane and wildfire as output.

6.4 Dataset and Pre-processing

The dataset selected is the xBD labeled dataset **[24].** The dataset is a collection of satellite images from before and after natural disasters. Almost all images contain buildings which are determined to be in one of 4 damage categories after the disaster -no damage, minor damage, major damage, or destroyed. The pre and post disaster images of each building are of virtually identical resolution and framed in a similar area in the image Each building also comes "pre-outlined" within its image. The csv files containing the labels indicate polygons in which each building in an image is contained, helping to locate individual buildings in each image. Data Pre-processing is applied to the images used for training Inception V3 model for identifying the type of disaster between hurricane and earthquake. Post disaster images are collected from pre and post disaster bi-temporal satellite images of hurricane and earthquake hit areas. The images are converted from BGR color format to Keras compatible RGB color format. The images are resized to 244 X 244 (input size of Inception V3 model). Class labels “hurricane and earthquake" are assigned to the corresponding images. Images are converted into Numpy array format and are normalized to the interval [0,1]. The dataset is built in to train and test set in the ratio 8:2. The categorical labels are encoded into binary digits of 0 and 1.

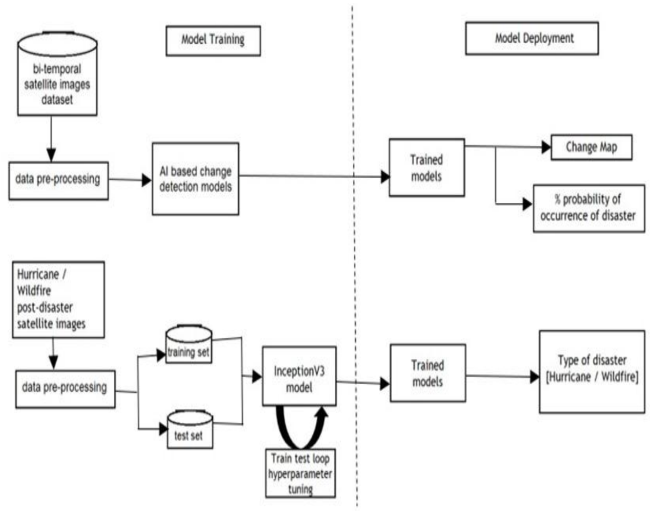

Fig - 4: Proposed System Architecture

The dataset is a collection of bi-temporal satellite images taken before and after natural disasters. Almost all images contain buildings that have been determined to be pre and post disaster images of the same building, with nearly identical resolution and framed in a similar area of the image. These images are pre-processed before being used to train the Inception V3 model to distinguish between hurricanes and earthquake. Pre and post disaster bi-temporal satellite images of hurricane and earthquake hit areas are used to create post disaster images. The images are given the class labels "Hurricane and Earthquake." For feature extraction, the VGG-19 model based on transfer learning is used.

The model extracts features from two bi-temporal satellite images. The two feature maps are compared using Reduced Sum of Squares (RSS) mathematical functions to generate a change map, where white pixels represent change and black pixels represent no change. A disaster's percentage occurrence is calculated as the percentage of white pixels in the change map. The transfer learning-based Inception V3 model is trained to distinguish between hurricane and earthquake disasters based on satellite images of disaster-affected areas. For identifying disaster between hurricane and earthquake, the VGG-19-based AI change detection model and the trained Inception V3 model are deployed. Figure 4 depicts pictorial representation of proposed system architecture. After uploading bi-temporal satellite images, the user receives a change map and a prediction of the percentage of disaster occurrence, and if a disaster occurs, the type of disaster is predicted between hurricane and earthquake.

7. TESTING

TABLE -1: Test Cases for Bi-temporal Satellite Images

Test Cases for Bi-temporal Satellite Images				
Test #	Test data input	Expected result	Actual result	Pass or fail
1.	bi-temporal satellite image without damage	100% no damage	100% no damage	pass
2.	bi-temporal satellite image with mild damage	X% chances of occurrence of disaster	X% chances of occurrence of disaster	pass
3.	bi-temporal satellite image with moderate damage	Y% chances of occurrence of disaster	Y% chances of occurrence of disaster	pass
4.	bi-temporal satellite image with high damage	Z% chances of occurrence of disaster	Z% chances of occurrence of disaster	pass
5.	bi-temporal satellite image with complete damage	100% disaster occurred	100% disaster occurred	pass

8. RESULTS

It is possible to determine whether or not the disaster has occurred using the change map created after analysis of the uploaded images. The bi-temporal images' changed areas are represented by white pixels on the change map while their unchanged areas are represented by the black region in the change map. The number of black pixels, or pixels representing no change, and the number of white pixels, or pixels representing change, are computed for the generated change map. The percentage of white pixels, or pixels representing change in the change map, that are present is then used to calculate the percentage of a disaster occurring.

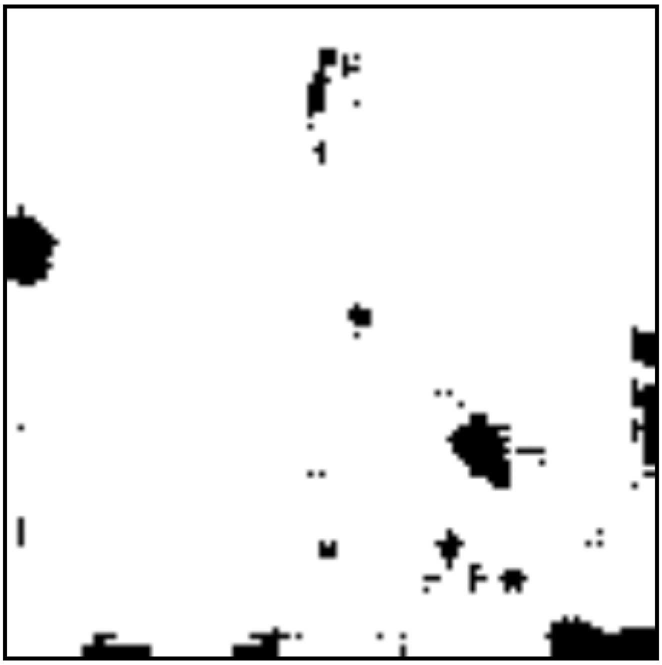

Fig - 5: Sample of Change Map generated

The above Figure 5 shows the change map created for the bi-temporal images used for testing. The percentage of disasters that occurred, estimated to be 97.397%, and the type of disaster, estimated to be "Wildfire," are also determined using the same change map.

9. CONCLUSION

The goal of this project is to develop a system that successfully recognizes disasters using bi-temporal satellite photos and offers relevant information such as the type of disaster and an analysis report. The proposed system intends to apply multiple change detection frameworks for disaster identification and to compare them in order to discover the best approach for the use case.

By the end of this project, the model will be capable of:

- Generating change map
- Predict the percent probability of occurrence of disaster
- Predict the type of disaster between hurricane and earthquake

Result

The results are displayed on the screen. It includes a change map, percent probability of occurrence of disaster and the type of disaster between hurricane and earthquake.

Performance Analysis

The change maps generated and percent probability of occurrence of disaster have over ninety percent accuracy as determined through manual evaluation. The accuracy of the InceptionV3 pre-trained model for predicting the type of disaster between earthquake and hurricane is 89%.

9.1 Application

- Utilized for rapid, timely and efficient disaster response.
- Enables operators and planners to organize better disaster response.
- Provides guidance to emergency responders to rescue victims.
- Yields information that is used to help expedite clean-up and rebuilding.
- Provides up-to-date information to emergency responders, government authorities, and concerned citizens, allowing them to effectively identify hazards.

9.2 Limitation

The proposed system model can predict the type of disaster between earthquake and hurricane only.

9.3 Future scope of the project

Extending the project's capabilities to predict more types of disasters like wildfire, tsunami, etc. Extending the project's capabilities to predict the extent of damage caused by disaster.

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