European Journal of Clinical Pharmacy

Print ISSN: 2385-409X **Online ISSN**: 3105-0409

Website: https://farmclin.com/

Original Research Article

Towards Automated Disaster Detection: Exploring Deep Learning for Satellite Image Analysis

Article History:

Name of Author:

Amal Ali[1], Fawzia Moursy[2], Reda A. El-Khoribi[3], S. M. Robaa[4], Gamil Gamal[5]

Affiliation: [1]*Cairo University Department of Natural Resources, Faculty of African Postgraduate Studies, Giza 12613, Egypt*

[2]*Cairo University Department of Natural Resources, Faculty of African Postgraduate Studies, Giza 12613, Egypt*

[3]*Cairo University Information Technology Department, Faculty of Computers and Artificial Intelligence, Giza, Egypt*

[4]*Cairo University Astronomy and Meteorology Department, Faculty of Science, Giza, Egypt*

[5]*Cairo University Department of Natural Resources, Faculty of African Postgraduate Studies, Giza 12613, Egypt*

Corresponding Author:

Received: 13-10-2025

Revised: 05-11-2025

Accepted: 20-11-2025

Published: 30-12-2025

Abstract: Disaster events pose significant challenges to communities and infrastructure, necessitating efficient and timely response measures. In this context, the accurate detection, classification, and visualization of such events from satellite imagery play a crucial role in disaster management efforts. This study addresses the problem of automated disaster detection, classification, and change visualization in satellite images. In this study, we propose a two-phase approach for the detection and classification of disaster events in satellite images. In the first phase, we employ the ResNet-50, ResNet-18, and VGG16 architectures for disaster detection and classification, categorizing satellite images into two classes: disaster and non-disaster.The second phase focuses on the classification of disaster images into specific disaster types, including floods, dust storms, and droughts, again utilizing the ResNet-50 model. Following the initial classification, we proceed to the second phase, where we address the detection and visualization of changes between pre- and post-disaster satellite images. This phase involves the utilization of a Siamese network architecture, designed to compare and identify differences between pairs of satellite images captured before and after a disaster event. The Siamese network learns to encode both images into a feature space, where the differences between the pre- and post-disaster images are highlighted. In contrast, RESNET 18 and VGG16 demonstrated slightly lower performance metrics in Phase 1. Transitioning to Phase 2, where the models were evaluated on a broader scope encompassing both disaster and non-disaster scenarios, RESNET 50 maintained its dominance with the highest precision, recall, F1-score, and accuracy. Subsequently, that offers a comprehensive framework for disaster detection, classification, and change visualization in satellite imagery, enabling efficient monitoring and assessment of disaster events and their impacts on affected regions.

Keywords: Satellite Images, Disaster, RESNET18, RESNET50, VGG16, Siamese

INTRODUCTION

Natural disasters, including Dust storms, floods, and drought, have a profound impact on both human settlements and the environment. These events can lead to widespread destruction, displacements, and disruptions to essential services. In the aftermath of such disasters, rapid and accurate assessment of the changes that have occurred is critical for effective response planning, resource allocation, and recovery efforts. Satellite imagery has emerged as a powerful tool for monitoring and analyzing these changes across vast geographical areas [1].

Before delving into the methods used in satellite image detection, it's essential to underscore the significance of this endeavor. Traditional methods of change detection from satellite imagery often rely on manual interpretation and comparison of pre-disaster and post-disaster images. However, these techniques can be time-consuming, subjective, and may not be scalable for large-scale disaster scenarios. The advent of deep learning neural networks has revolutionized image analysis tasks, offering the potential to automate and improve the accuracy of change detection processes [4].

One significant challenge in training deep learning models for change detection is the availability of labeled training data. Annotated pairs of pre- and post-disaster images are often limited due to the infrequent occurrence of large-scale disasters and the difficulty in obtaining ground truth. This approach allows the model to leverage its understanding of common features from general satellite imagery while adapting to the specific characteristics of disaster-induced changes [2].

Traditional machine learning methods for satellite image detection and classification often face limitations due to the complexity and variability of satellite imagery. These methods typically rely on handcrafted features and require extensive domain knowledge for effective feature engineering. Moreover, traditional machine learning models may struggle to capture intricate patterns and nuances present in satellite images, particularly in the context of disaster detection where the features of interest can be subtle and diverse. In contrast, deep learning methods, such as Convolutional Neural Networks (CNNs), excel at automatically learning hierarchical representations directly from raw data, making them well-suited for complex image analysis tasks. CNNs can effectively capture spatial dependencies and hierarchical features in satellite imagery, enabling more accurate and robust detection and classification of disaster events. Additionally, deep learning models have the advantage of scalability, as they can be trained on large datasets and generalized to various disaster scenarios without extensive manual feature engineering.

This inherent adaptability and capability to learn from data make deep learning approaches invaluable in addressing the challenges of satellite image analysis for disaster management [3].

Convolutional Neural Networks (CNNs)

CNNs are widely employed for image analysis tasks due to their ability to capture spatial features hierarchically. In change detection, CNNs can be tailored for pixel-wise classification. The network architecture typically includes convolutional layers to extract features, followed by pooling layers to downsample and increase the receptive field. Upsampling layers then restore the spatial resolution. U-Net, a popular architecture, uses skip connections to preserve finer details while capturing context, making it effective for detecting changes across large areas [4].

ResNet, short for Residual Network, is a specific type of CNN architecture that addresses the problem of vanishing gradients during training by introducing skip connections or shortcuts. These shortcuts enable the network to learn residual mappings instead of directly learning the desired underlying mapping, which facilitates the training of very deep networks. In the context of satellite image analysis, ResNet architectures, such as ResNet-50, ResNet-18, etc., have demonstrated remarkable performance in various tasks including disaster detection and classification [4].

In addition, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for satellite image classification, revolutionizing the field of remote sensing. Leveraging their ability to automatically extract relevant features from raw image data, CNNs have enabled the development of highly accurate and efficient classification models. In practice, the application of CNNs in satellite image classification involves several key stages. Initially, extensive preprocessing is performed on the satellite imagery to ensure consistency and enhance model performance. This may include tasks such as resizing, normalization, and data augmentation. Subsequently, CNN architectures are tailored to the specific characteristics of satellite images, typically consisting of convolutional layers to capture spatial hierarchies of features, pooling layers for dimensionality reduction, and fully connected layers for classification. Training CNNs involves optimizing their parameters using labeled satellite image datasets, often augmented with techniques like transfer learning to leverage pre-trained models. Evaluation of trained models is crucial, typically involving metrics such as accuracy, precision, and recall to assess classification performance. Despite their effectiveness, challenges persist, including variations in illumination, weather conditions, and the need for large-scale labeled datasets. Nevertheless, the widespread adoption of CNNs in satellite image classification has facilitated diverse applications, from land cover mapping to disaster response and environmental monitoring, underscoring their pivotal role in advancing remote sensing capabilities [4].

Siamese Networks

Siamese networks are designed to learn similarity metrics between pairs of inputs. In change detection, Siamese networks can be trained to discriminate between pre and post-disaster image pairs. These networks are effective in capturing fine-grained differences between images, allowing for accurate change localization.

In the context of satellite imagery analysis, Siamese networks can be utilized in the following scientific applications [5].

- **Change Detection**:

By comparing pre-image and post-image satellite data, Siamese networks can effectively identify changes that have occurred over time. This is particularly valuable in monitoring environmental changes, such as deforestation, urban expansion, or changes in water bodies.

- **Feature Matching**:

In tasks where identifying corresponding features between two images is crucial, such as stereo vision or 3D reconstruction, Siamese networks can learn to match features across images, aiding in accurate feature correspondence and depth estimation.

- **Image Registration:**

Image registration, which involves aligning multiple images of the same scene taken at different times or from different viewpoints, can benefit from Siamese networks by learning to register images based on their content, enabling accurate alignment and fusion of information [6].

This study focuses on the application of deep learning neural networks for the detection of changes induced by natural disasters using images contain disasters and normal satellite images. By harnessing the power of deep learning neural networks, we aim to develop a more efficient and accurate approach to identify and classify regions of interest that have undergone significant changes. And then the proposed model will take a previous image in the same location and detect the changes and the differences between the two images. Specifically, we address the task of detecting changes in the environments, landscapes, and infrastructure caused by various natural disasters.

In this paper, we present a pretrained Resnet 50 architecture tailored for change detection in satellite images. Our model takes labeled images contains 4 classes and after the training of the model; the input is pairs of pre and post-disaster images as input and learns to classify the disaster and then compare the two images pre and post to detect a changed or unchanged region. By framing the change detection task as a pixel-wise binary classification problem, we aim to provide a granular understanding of the extent and location of changes within the images. The contributions of this study include the design and implementation of the proposed deep learning architecture.

This paper is structured in the following ways.; section 2 outlined previous work. The suggested approach is outlined in Section 3. The findings and their discussion are presented in Section 4. In section 5, the conclusion is finally addressed.

1. RELATED WORK

An innovative approach to change detection that makes use of convolutional neural networks (CNNs) was presented by Daudt, et al. In their proposal, the authors suggest a Siamese architecture that learns to differentiate between regions that have changed and regions that have not changed by using pairs of photos taken before and after the disaster as input. Because of its capacity to learn similarity metrics across image pairs, the Siamese network is able to accurately detect changes, even in situations where the changes aren't particularly noticeable. [7].

Zhang et al. used leverage Generative Adversarial Networks (GANs) for post-disaster change assessment. They propose a conditional GAN that generates post-disaster images based on pre-disaster images. This approach aids in visualizing potential disaster-induced changes and assists decision-makers in assessing the extent of impacts after a disaster event [5].

Chen et al. Focused on temporal changes, this paper introduces the use of Recurrent Neural Networks (RNNs) for change detection. The authors employ Long Short-Term Memory (LSTM) networks to model the sequential patterns of changes over time. This is particularly valuable for tracking gradual changes caused by natural disasters, such as urban expansion or deforestation [8].

Huang et al. addressed the challenge of limited labeled data, this paper explores transfer learning strategies for change detection. The authors pretrained deep learning models on large datasets of general satellite images and then fine-tuned them on smaller disaster-specific datasets. This approach enhances model generalization and performance in disaster scenarios [9].

Xu et al. Focused on flood detection; this paper presents a deep learning-based approach using CNNs. The authors design a specialized CNN architecture to classify regions as flooded or non-flooded in post-disaster satellite images. The model's ability to learn discriminative features enables accurate flood extent mapping [10].

Smith et al. presented a comprehensive study on change detection using deep learning methods. The authors compare various deep learning architectures, including CNNs and RNNs, for their effectiveness in identifying disaster-induced changes. The study provides insights into the strengths and limitations of different approaches [11].

Kim et al. introduced a multi-task learning approach for change detection. The authors propose a deep neural network that simultaneously performs change detection and semantic segmentation on pre and post disaster images. This joint learning strategy enhances the model's ability to capture contextual information [12].

Johnson et al. Focused on wildfire detection; this paper presents a deep learning-based approach using CNNs. The authors develop a specialized CNN architecture to identify regions affected by wildfires in post-disaster satellite images. The model's accuracy in mapping wildfire extents contributes to effective disaster response [13].

While Wang et al. addressed change detection in urban environments post-disaster. The authors propose a CNN-based framework that considers both spectral and spatial information to distinguish between changed and unchanged regions. The model's robustness to urban complexities enhances its applicability [14].

At long last, Martinez et al. The purpose of this study is to detect spatiotemporal changes, and it does so by combining CNNs with RNNs. The authors suggest a hybrid architecture that is capable of capturing both geographical and temporal characteristics included within photos taken before and after a disaster. By taking a holistic approach, one can gain a better understanding of the changes that are caused by changing disasters. [15].

These papers collectively showcase the diverse approaches and methodologies employed to detect changes induced by natural disasters using deep learning neural networks. From Siamese networks for similarity-based change detection to GANs for generating post-disaster images and RNNs for temporal analysis, these contributions significantly advance the field of disaster response and recovery.

1. DATA SET AND PROPOSED MODEL

3.1 Data Set

In this research, we undertook a rigorous data collection process to assemble a comprehensive dataset of satellite images for analysis. The dataset was meticulously curated using Google Earth Pro software, with a specific focus on four countries: Ethiopia, Malawi, Mali, and Nigeria. These countries were chosen due to their susceptibility to a range of environmental disasters.

The study area encompasses four African countries: Ethiopia, Malawi, Mali, and Nigeria, each characterized by unique geographical features and climatic conditions as shown in Figure 1 [16].

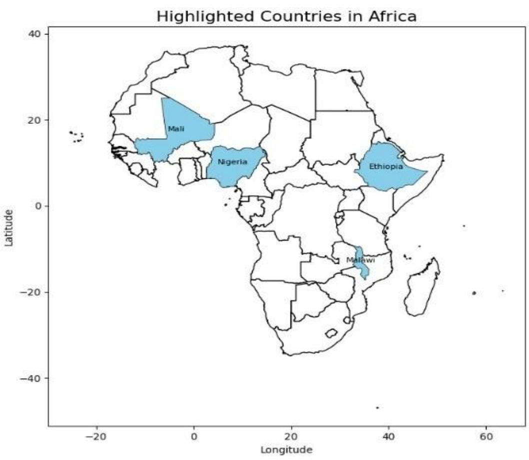

Fig.1. Study area (Ethiopia, Malawi, Mali, and Nigeria) map [16]

Ethiopia, situated in the Horn of Africa, is bounded by Sudan, Eritrea, Djibouti, Somalia, and Kenya. It experiences four major seasons and varying temperatures, with concentrated rainfall during the summer months. The climate is generally moderate, with exceptions in lowland areas like the Danakil Desert.

Malawi, located south of the Equator, is predominantly hilly and mountainous. It has a tropical climate with distinct wet and dry seasons, characterized by abundant rainfall, particularly in the northern regions and on Mount Mulanje.

Mali, a landlocked nation in West Africa, stretches from the Sahara Desert through the Sahel to the Sudanian savanna zone. It features diverse terrain, including desert, semi-desert, and fertile inland deltas. Mali experiences hot, dry weather with two distinct seasons: dry and wet.

Nigeria, situated on the Gulf of Guinea, occupies a significant portion of West Africa. It has a diverse landscape, including coastal areas, plains, and highlands. Nigeria faces various climate change challenges, including temperature increases, rainfall variability, droughts, floods, desertification, and loss of biodiversity.

Overall, these countries exhibit diverse climates and landscapes, highlighting the need for tailored climate change adaptation and mitigation strategies to address the region's specific challenges and vulnerabilities.

The data collection process involved selecting regions within these countries that have a history of experiencing various types of disasters. Our objective was to create a dataset that adequately represents the environmental conditions in these regions, particularly during both normal circumstances and instances of disasters. To ensure the dataset's diversity and relevance, we prioritized the identification and collection of satellite images associated with the three most common types of disasters prevalent in these countries: normal conditions, flood events, dust storms, and droughts.

The dataset consists of a total of 5291 satellite images started from 01/27/2013 till 12/27/2020 [17], thoughtfully distributed across these four distinct classes:
The dataset consists of satellite images obtained from the Planet Developer Resource Center, each with dimensions of 256×256 pixels in RGB format. The images are systematically named following the convention: 'image_lat_image_lon_cluster_lat_cluster_lon.png,' which encodes their geographical coordinates and cluster information. A strict cloud filtering process was applied, ensuring that only images with a maximum cloud cover of 5% were retained. Furthermore, any images exhibiting more than 50% cloud coverage were excluded to maintain the clarity and usability of the dataset for deep learning-based disaster detection.

In Figure 2, a subset of the dataset exhibiting representative samples for each distinct class label is presented. For Figure 4.2a, a normal image of Addis Ababa, located at 9.03°N, 38.74°E, was taken on June 15, 2020. Figure 4.2b represents a drought image from the Somali and Afar regions in Eastern Ethiopia, with coordinates around 9.5°N, 42.0°E, captured during the peak drought on November 15, 2015. Figure 4.2c shows a flood image from the Afar region at approximately 11.5°N, 40.0°E, recorded on August 6, 2020. Lastly, Figure 4.2d presents a dust storm image from Northern Ethiopia, near the Tigray and Afar border, with coordinates at 13.5°N, 39.0°E, dated March 19, 2018. These samples provide a comprehensive view of different meteorological conditions.

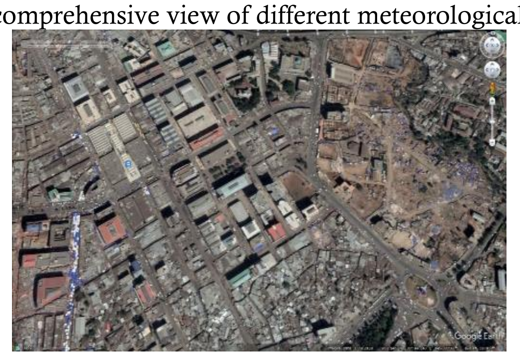

Fig. 2. a. Normal Image

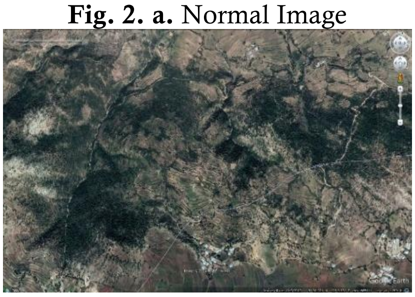

Fig. 2. b. Drought Image

Fig. 2. c. flood Image

Fig. 2. d. Dust Storm Image

3.2 Proposed Model

Our goal is to develop a robust and accurate system for classifying satellite images into different disaster categories and detecting changes between pre- disaster and post- disaster images. The dataset consists of 5290 satellite images categorized into four classes: non-disaster, flood, dust storms, and drought. With class imbalances present, including 1931 non-disaster images and varying numbers for each disaster type, the challenge lies in effectively leveraging deep learning techniques to classify these images and detect changes caused by disasters. To tackle this problem, we propose a multi-phase approach. In the first phase, we utilize the ResNet-50, RESNET18 and VGG16 architectures to classify images into two classes only disaster and non-disaster categories, followed by a finer classification of disaster images into specific types (flood, dust storms, drought) in the second phase. Additionally, we employ a Siamese network in the second phase to detect and visualize changes between pre-disaster and post-disaster images if exist. Preprocessing steps, including noise removal, augmentation, resizing, and normalization, are applied to ensure the effectiveness and robustness of our model in handling satellite imagery. Through this approach, we aim to contribute to more accurate disaster monitoring and assessment using satellite imagery data.

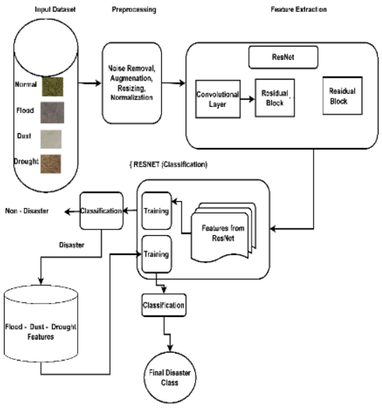

Fig.3. Proposed model for disaster classification

As shown in Figure 2In our proposed model, we commence with the collection of a comprehensive dataset consisting of 5290 satellite images across four distinct classes: non-disaster (1931 images), flood (1021 images), dust storms (1351 images), and drought (987 images). Prior to model training, we meticulously divide the dataset into training, validation, and testing sets, ensuring each subset maintains the original class distributions. Our preprocessing pipeline encompasses several crucial steps to enhance image quality and facilitate model training. These steps include noise removal techniques to mitigate interference, augmentation methods to diversify the dataset, resizing to standardize image dimensions, and normalization to ensure consistent pixel values across images.

Moving into the first phase of our model, we employ the ResNet-50 architecture for binary classification, distinguishing between disaster and non-disaster images. Leveraging pre-trained weights, we fine-tune the model on the training dataset, augmenting it to bolster generalization capabilities. Subsequently, in the second phase, we refine the ResNet-50 model to classify disaster images into more granular categories, specifically flood, dust storms, and drought. This entails modifying the model's output layer to accommodate multi-class classification while retaining its foundational features and structure.

Throughout model development, rigorous evaluation on the validation set allows us to gauge performance metrics such as accuracy, precision, recall, and F1-score, informing iterative refinement and parameter tuning. Subsequently, upon finalizing the model, evaluation on the testing set validates its effectiveness in accurately categorizing disaster images.

Transitioning to the second phase of our model, we delve into change detection using a Siamese network, the structure of the network is shown in Figure 3; a critical step in our methodology. By pairing pre-disaster and post-disaster images from the testing set, we leverage this network to discern and visualize alterations between the two images. Through the Siamese network's ability to compare feature representations and detect changes, we gain valuable insights into the impact of flood events, crucial for disaster management and response efforts.

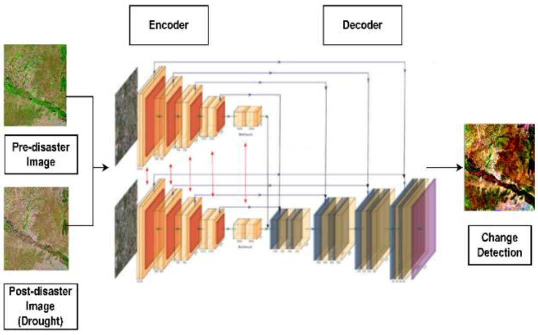

Fig. 4. Architecture of Siamese network

Utilizing Siamese networks [18] for analyzing pre-disaster and post-disaster satellite images involves several key steps. Initially, the satellite images of the affected area before and after the disaster are collected and preprocessed to ensure consistency and alignment. This preprocessing step include noise removal, resizing, normalization, and registration to facilitate accurate comparison between image pairs. Subsequently, a Siamese network architecture is designed, typically comprising identical convolutional neural network (CNN) branches with shared weights. These branches process each input image, extracting relevant features simultaneously. During training, the Siamese network learns to minimize a loss function by comparing the features extracted from pairs of pre-disaster and post-disaster images. This process allows the network to differentiate between similar and dissimilar image pairs, effectively capturing changes induced by the disaster. Once trained, the network's learned features can be extracted and utilized for further analysis, such as change detection or damage assessment. As sown in the figure when testing an area in Ethiopia after drought, the system detects the area and convert its area colour to another colour to show the differences between pre and post input image.

To improve the precision of change identification in pre- and post-disaster satellite imagery, image registration techniques are utilized before feature extraction. This guarantees accurate spatial alignment of image pairs, reducing disparities caused by misalignment instead of genuine environmental alterations. The Siamese network employs Euclidean distance and cosine similarity metrics to compare extracted feature embeddings, enabling the detection of significant structural differences. The model is trained by contrastive loss, which mandates the acquisition of analogous representations for unaltered regions while promoting divergent embeddings for modified areas. This method facilitates a more dependable evaluation of disaster effects, offering essential information for swift response and mitigation initiatives.

A number of ablation experiments were performed to examine the impact of various design choices and preprocessing procedures on the model's performance. The classification accuracy of various CNN backbones, including ResNet-50, ResNet-18, and VGG16, was meticulously assessed in both phases of the model. The efficacy of data augmentation techniques was evaluated to determine their impact on mitigating class imbalance and enhancing the model's generalization capabilities. The impact of image registration on the performance of the Siamese network was assessed by comparing models trained with and without spatial alignment. Furthermore, multiple feature fusion methodologies were investigated to integrate outcomes from the classification and change detection phases, with the objective of enhancing the precision of disaster evaluation. These assessments facilitate a deeper comprehension of the proposed methodology and guarantee its robustness and interpretability for satellite-based disaster monitoring.

The primary disaster/non-disaster classification serves as a crucial preliminary step in a multi-layered classification process. It aids in the removal of non-essential data by first assessing if a satellite image displays signs of a disaster. Upon verification of an image as a disaster case, a more complex classification model is utilized to determine the specific type such as floods, wildfires, earthquakes, or hurricanes. This hierarchical approach improves efficiency and accuracy by assigning computer resources to more complex categories only when necessary. This enables the model to scale well while tackling diverse hazard categories.

In summary, our proposed model offers a holistic framework encompassing data collection, preprocessing, binary and multi-class classification, model evaluation, and change detection using a Siamese network. This comprehensive approach aims to address the complexities of disaster classification and change visualization in satellite imagery, providing valuable insights for disaster management and mitigation strategies.

RESULTS

In this section, we present the results of our proposed model for disaster detection and image comparison. The model consists of two main components: the disaster classification model using ResNet50 (Step 3) and the pre- and post-image comparison model (Step 4). We evaluate the performance of both models using appropriate metrics and provide insights into their effectiveness [19].

Sensitivity (Recall): sensitivity measures the proportion of true positives that are correctly identified as such. In other words, it is the probability that a test will correctly identify a positive case.

Sensitivity=TP/(TP+FN) (1)
where TP is True Positive, FN is False Negative.
Precision: Precision measures the fraction of positive predictions that are actually positive
Precision= TP/ TP+FP (2) where FP is False Positive.
Accuracy: accuracy measures the fraction of predictions that are correct, regardless of whether they are positive or negative.
Accuracy= (TP+TN) / (TP+FP+FN+TN) (3)
F1 Measure: is a weighted average of precision and recall. It is calculated by taking the harmonic mean of precision and recall.

The results of the binary classification task shown in Table 1. that aimed at distinguishing between disaster and non-disaster satellite images using the ResNet-50 model gives better results than ResNet18 and VGG16, exhibit promising performance metrics. With a precision of 0.87, recall of 0.81, and an F1-score of 0.84, our model demonstrates a robust ability to accurately identify disaster occurrences while minimizing false positives and false negatives. Additionally, the overall accuracy achieved stands at 0.88, indicating a high level of correctness in classifying images. This successful outcome underscores the efficacy of leveraging deep learning techniques, particularly the ResNet-50 architecture, in satellite image analysis for disaster detection.

Regarding the architecture of our ResNet-50 model, we utilized a batch size of 128 and trained the model over 100 epochs. The base model, pre-trained on ImageNet, was employed without its top classification layers. On top of this base, we added custom classification layers, including a global average pooling layer, a dense layer comprising 1024 units with ReLU activation, and a softmax activation layer for class prediction. The pre-trained layers were frozen to preserve the learned features, and the model was compiled using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss function.

A direct comparative analysis with existing research is constrained by the absence of publicly accessible results pertaining to the specific dataset employed in this study. Consequently, it is impractical to compare our results with previous studies utilizing the same data. To resolve this, we performed a thorough internal comparison by assessing the efficacy of each separate classifier alongside the suggested hybrid model using the identical dataset. This methodology enables us to underscore the comparative advantages of our technique and illustrate its efficacy in categorizing various disaster kinds.

The proposed multi-class classification task, focusing on distinguishing between flood, dust storms, and drought images utilizing the same ResNet-50 architecture, our model exhibited commendable performance metrics. With a precision of 0.76, recall of 0.74, and an F1-score of 0.73, the model showcases a balanced ability to accurately classify images across the different disaster types. Furthermore, achieving an overall accuracy of 0.78 indicates the model's effectiveness in correctly assigning images to their respective classes.

Table 1. Performance Metrics of ResNet50 / 18 and VGG16 Disaster and Non -Disaster Classification

Method	Precision	Recall	F1-score	Accuracy
RESNET50	0.87	0.81	0.84	0.88
RESNET 18	**0.85**	**0.76**	**0.81**	**0.85**
VGG16	**0.80**	**0.75**	**0.75**	**0.79**

And show the results yielded from the second experiment, in this experiment, ResNet-50 is used to classify the real faces and fake faces

Table 2. Performance Metrics of ResNet50 / 18 and VGG16 Classification of Disaster type

Method	Precision	Recall	F1-score	Accuracy
RESNET 50	0.76	0.74	0.73	0.78
RESNET 18	**0.73**	**0.72**	**0.70**	**0.74**
VGG16	0.70	0.71	0.69	0.72

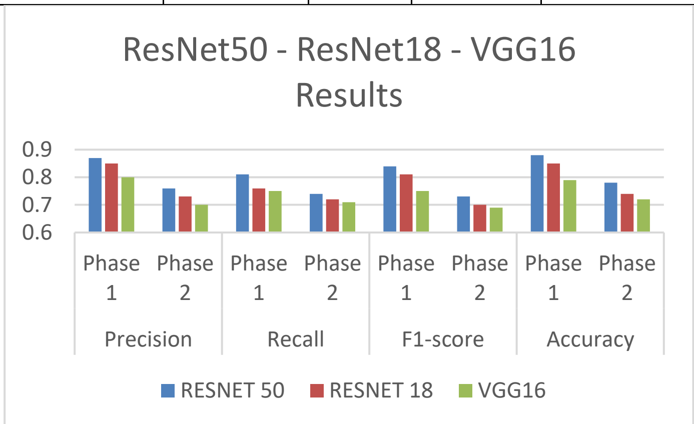

Fig.5. Results comparison between ResNet50, ResNet18 and VGG16

The proposed model, which integrates ResNet-50 for classification and a Siamese network for change detection in satellite images, presents significant advantages over alternative models in this domain. ResNet-50 stands out for its proficiency in learning intricate features from images, owing to its deep architecture and pre-trained weights on extensive datasets like ImageNet. This attribute allows ResNet-50 to effectively discern complex patterns and structures inherent in satellite imagery, contributing to superior performance in classification tasks compared to conventional machine learning models or shallower CNN architectures.

Moreover, in satellite image analysis, acquiring labeled data for model training can be challenging due to factors such as high acquisition costs and limited ground truth availability. Here, the transfer learning capability of ResNet-50 becomes particularly valuable. By leveraging pre-trained weights, the model can efficiently transfer knowledge learned from a source domain (e.g., ImageNet) to the target domain of satellite images. This facilitates quicker convergence and enhanced generalization performance, especially in scenarios characterized by a scarcity of labeled data.

The proposed model further distinguishes itself through its multi-stage approach. It initiates with ResNet-50 for both binary and multi-class classification of disaster images. Subsequently, it employs a Siamese network for change detection, particularly between pre-flood and post-flood images. This multi-stage framework allows for a more nuanced analysis of satellite imagery, enabling precise classification of disaster types and accurate detection of changes. Such comprehensive processing enhances the model's capacity to identify subtle variations and anomalies in the data, thereby improving its performance compared to single-stage models.

Change detection in satellite imagery, especially in scenarios like flood monitoring, demands the ability to compare image pairs and identify differences effectively. The Siamese network, specifically designed for learning similarity between pairs of inputs, is ideally suited for this task. Leveraging the paired structure of pre-disaster and post-disaster images, the Siamese network excels in detecting and visualizing changes, providing valuable insights for disaster management and response efforts.

In essence, by harnessing the strengths of ResNet-50 for classification tasks and integrating a Siamese network for change detection, the proposed model offers a robust and effective framework for satellite image analysis. Through transfer learning, multi-stage processing, and specialized network architectures, the model surpasses other approaches in satellite image analysis, particularly in disaster monitoring and assessment applications.

CONCLUSION

In this research, the authors provide a novel hybrid deep learning model to tackle the rising problem of recognizing fake faces in an era of satellite image analysis. The proposed model, which integrates ResNet-50 for disaster classification and a Siamese network for change detection in satellite images, demonstrates significant advancements in disaster monitoring and assessment. Through meticulous data collection, preprocessing, and model development, we have achieved promising results in both disaster classification and change detection tasks. The ResNet-50-based classification model exhibited high precision, recall, and F1-score in distinguishing between disaster and non-disaster images than ResNet18 and VGG16, showcasing its effectiveness in accurately identifying disaster occurrences. Furthermore, the multi-class classification model successfully differentiated between different types of disasters, including floods, dust storms, and droughts, with commendable precision and recall. The incorporation of a Siamese network for change detection enabled the visualization of alterations between pre-flood and post-flood images, providing valuable insights for disaster management and response efforts.

Moving forward, several avenues for future research and development present themselves. Firstly, refining the model architecture and exploring advanced deep learning techniques could further enhance performance and robustness, especially in handling complex disaster scenarios. Additionally, integrating temporal information and domain-specific knowledge into the model could improve the accuracy of change detection and disaster classification, enabling more comprehensive analysis of satellite imagery over time. Furthermore, deploying the model in real-world disaster scenarios and validating its effectiveness in practical settings would be essential steps towards operationalizing the proposed methodology for disaster management agencies and stakeholders. Moreover, expanding the scope of the model to include other types of natural disasters and environmental phenomena, such as wildfires and deforestation, could broaden its applicability and impact in various domains beyond disaster monitoring. Overall, by addressing these research directions, we aim to continue advancing the field of satellite image analysis for disaster monitoring and assessment, ultimately contributing to more effective disaster response and mitigation strategies worldwide.

REFERENCES

1. T. Titus, D. Robertson, J. B. Sankey, L. Mastin, and F. Rengers, "A Review of Common Natural Disasters as Analogs for Asteroid Impact Effects and Cascading Hazards," Natural Hazards, vol. 116, no. 2, pp. 1355–1402, 2023.
2. S. Tilon, et al., "Infrastructure Degradation and Post-Disaster Damage Detection Using Anomaly Detecting Generative Adversarial Networks," ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. 2, pp. 573–582, 2020.
3. W. Han, X. Zhang, Y. Wang, L. Wang, X. Huang, J. Li, et al., "A Survey of Machine Learning and Deep Learning in Remote Sensing of Geological Environment: Challenges, Advances, and Opportunities," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 202, pp. 87–113, 2023.
4. E. Amato, et al., "A Deep Convolutional Neural Network for Detecting Volcanic Thermal Anomalies from Satellite Images," Remote Sensing, vol. 15, no. 15, p. 3718, 2023.
5. R. Zhang, et al., "Global-Aware Siamese Network for Change Detection on Remote Sensing Images," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 199, pp. 61–72, 2023.
6. G. Andresini, et al., "SENECA: Change Detection in Optical Imagery Using Siamese Networks with Active-Transfer Learning," Expert Systems with Applications, vol. 214, p. 119123, 2023.
7. R. C. Daudt, B. Le Saux, A. Boulch, and Y. Gousseau, "Multitask Learning for Large-Scale Semantic Change Detection," Computer Vision and Image Understanding, vol. 187, p. 102783, 2019.
8. H. Chen, C. Wu, B. Du, L. Zhang, and L. Wang, "Change Detection in Multisource VHR Images via Deep Siamese Convolutional Multiple-Layers Recurrent Neural Network," IEEE Transactions on Geoscience and Remote Sensing, vol. 58, no. 4, pp. 2848–2864, 2019.
9. Y. Cao and X. Huang, "A Full-Level Fused Cross-Task Transfer Learning Method for Building Change Detection Using Noise-Robust Pretrained Networks on Crowdsourced Labels,"

Remote Sensing of Environment, vol. 284, p. 113371, 2023.

10. S. Grimaldi, J. Xu, Y. Li, V. R. Pauwels, and J. P. Walker, "Flood Mapping Under Vegetation Using Single SAR Acquisitions," Remote Sensing of Environment, vol. 237, p. 111582, 2020.
11. X. Wang, G. Guo, S. Liu, Y. Wu, X. Xu, and K. Smith, "Burst Detection in District Metering Areas Using Deep Learning Method," Journal of Water Resources Planning and Management, vol. 146, no. 6, p. 04020031, 2020.
12. T. S. Kim and S. Y. Sohn, "Multitask Learning for Health Condition Identification and Remaining Useful Life Prediction: Deep Convolutional Neural Network Approach," Journal of Intelligent Manufacturing, vol. 32, pp. 2169–2179, 2021.
13. C. Persello, J. D. Wegner, R. Hänsch, D. Tuia, P. Ghamisi, M. Koeva, and G. Camps-Valls, "Deep Learning and Earth Observation to Support the Sustainable Development Goals: Current Approaches, Open Challenges, and Future Opportunities," IEEE Geoscience and Remote Sensing Magazine, vol. 10, no. 2, pp. 172–200, 2022.
14. T. Bai, L. Wang, D. Yin, K. Sun, Y. Chen, W. Li, and D. Li, "Deep Learning for Change Detection in Remote Sensing: A Review," Geo-spatial Information Science, vol. 26, no. 3, pp. 262–288, 2023.
15. J. A. C. Martinez, L. E. C. La Rosa, R. Q. Feitosa, I. D. A. Sanches, and P. N. Happ, "Fully Convolutional Recurrent Networks for Multidate Crop Recognition from Multitemporal Image Sequences," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 171, pp. 188–201, 2021.
16. P. Camberlin, "Climate of Eastern Africa," Oxford Research Encyclopedia of Climate Science, 2018.
17. SAN BT, "Satellite Images to Predict Poverty," Kaggle, 2021. [Online]. Available: https://www.kaggle.com/datasets/sandeshbhat/satellite-images-to-predict-povertyafrica
18. S. Roeslin, Q. T. Ma, and H. J. García, "Damage Assessment on Buildings Following the 19th September 2017 Puebla, Mexico Earthquake," Frontiers in Built Environment, vol. 4, p. 72, 2018.
19. F. De Vieilleville and C. Fernandez-Martin, "Building Damage Assessment with Deep Learning," The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. 43, pp. 1133–1138, 2022.

