Automatic Detection of Natural Disasters Using Faster R-CNN with ResNet50 Backbone

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***Abstract*—Natural disasters pose significant threats to human life and infrastructure. Timely detection and assessment of these events are crucial for effective disaster management. This study proposes an automatic detection system for natural disasters using aerial imagery. Accurate and timely detection of natural disasters is critical for minimizing their impact and supporting emergency response efforts. This study presents a comparative analysis of deep learning architectures for natural disaster detection using satellite and aerial imagery. Four models were evaluated as baseline CNN, ResNet50, Faster-CNN, and Faster R-CNN with a ResNet50 backbone using standard classification metrics. The results demonstrate that deeper and more sophisticated models significantly enhance detection performance. While the baseline CNN achieved modest results with 85.3% accuracy, integrating residual learning in ResNet50 improved accuracy to 92.7%. Region-based models further boosted performance, with Faster-CNN and Faster R-CNN attaining 95.1% and 97.1% accuracy, respectively. The superior performance of the Faster R-CNN with ResNet50 highlights its robustness and suitability for real-time disaster monitoring, offering a scalable and reliable solution for operational deployment in disaster management systems.**

Keywords—Natural disasters detection; satellite imagery; convolutional neural networks (CNN); transformers; deep learning; ResNet50; proactive monitoring; faster R-CNN; disaster prevention; computer vision

I. Introduction

Natural disasters are becoming more frequent and severe, underlining the urgent need for enhanced detection and management strategies. Traditional approaches often depend on manual analysis of aerial images, a process that can be both time-consuming and prone to human error. However, recent advancements in deep learning have opened new avenues for automating this task. Natural disasters (NDs), which include volcanic eruptions, earthquakes, landslides, floods, tsunamis, hurricanes, tornadoes, droughts, wildfires, and severe temperatures, pose enormous dangers to human life and infrastructure [1,2]. Throughout history, these events have caused widespread devastation and substantial loss of life. From earthquakes and volcanic eruptions to hurricanes, floods, and wildfires, natural disasters have profoundly affected both populations and the environment. Among the deadliest recorded were the 1931 China floods, triggered by intense rainfall and river overflows, which inundated over 50,000 square miles and claimed an estimated 3.7 million lives. Other significant natural disasters in history include the 1883 eruption of Krakatoa in Indonesia, which caused over 36,000 deaths and generated a massive tsunami that damaged coastal communities across the region [3]. The 1985 Mexico City earthquake, with a magnitude of 8.0, caused extensive damage to the city's infrastructure, resulting in more than 10,000 fatalities and leaving over 100,000 people homeless [4]. In recent years, natural disasters have continued to profoundly impact communities worldwide [5, 6]. For example, the 2011 Tohoku earthquake and tsunami in Japan claimed over 15,000 lives and severely damaged the country's infrastructure. In 2017, Hurricane Maria devastated Puerto Rico, causing widespread destruction and leaving most of the island without power for months [7]. Many communities face long-term struggles to rebuild their lives after such events, as the consequences of natural disasters can last for years or even decades, including the loss of homes and infrastructure, displacement of populations, and destruction of ecosystems.

Climate change has intensified the frequency and severity of these catastrophes, making it increasingly critical to develop strategies to mitigate their impacts [8]. In summary, natural disasters have historically caused tremendous harm to both communities and the environment. While technological advancements and improvements in disaster preparedness such as early flood detection systems, predictive analytics, machine learning, remote sensing, geographical information systems (GIS), satellite navigation, drone technology, cloud computing, enhanced communication and information sharing, resilient infrastructure, and early warning systems [9–12] have helped lessen their effects, natural disasters continue to pose serious challenges globally. Therefore, sustained investment in disaster preparedness and response remains essential to minimizing the impact on human lives, infrastructure, and ecosystems.

Fortunately, technological progress has greatly enhanced our ability to predict, respond to, and recover from these catastrophic events [13]. Technologies like remote sensing, radar, and satellite imaging provide diverse tools for monitoring the Earth's surface and atmosphere from a distance. Advances in these fields now allow for real-time tracking of natural disasters such as volcanic eruptions, wildfires, and landslides. By analyzing data collected through remote sensing systems, we can improve our understanding of the scale and intensity of these events, which supports the development of effective evacuation plans and recovery efforts. Leveraging this information is a key strategy for strengthening disaster preparedness. Additionally, technologies such as the Internet of Things (IoT), smartphones, and social media play a crucial role in the rapid collection and dissemination of information during natural disasters [14–21]. IoT devices, such as weather monitoring instruments and seismic sensors, provide real-time data that help emergency responders make quick, well-informed decisions. Likewise, smartphones and social media platforms serve as effective channels for alerting people in affected areas, delivering vital updates on evacuation routes, shelter availability, and other essential resources.

This study aims to thoroughly investigate how various technologies contribute to natural disaster management. It explores the roles of Remote Sensing, Radar, Satellite Imaging, Autonomous Robots and Drones, IoT, Smartphones, and social media in responding to events like earthquakes, volcanic eruptions, landslides, and tsunamis. These technologies have been key in safeguarding lives, enabling coordinated rescue operations, and reducing damage to infrastructure.

The structure of this study is as follows: Section II presents background information on natural disasters and their environmental impact. Section III offers a comprehensive description of the dataset utilized. Section IV outlines the methodology and the proposed model. Section V discusses the evaluation results, and finally, Section VI provides the conclusion.

II. Background

In recent years, the integration of satellite imagery with machine learning (ML) and deep learning methods has seen widespread use in various disaster management applications.

a) Earthquakes and volcanic eruptions: Earthquakes are among the most severe natural disasters, triggered by the sudden movement of tectonic plates beneath the Earth's surface, resulting in ground shaking and displacement [22]. These seismic events can cause extensive damage to infrastructure such as buildings, roads, and homes, and often lead to significant loss of life. The intensity of an earthquake is measured on the Richter Scale, which ranges from 1 to 10, with higher values indicating stronger quakes. According to the United States Geological Survey (USGS), approximately 20,000 earthquakes occur globally each year, with around 16 reaching a magnitude of 7.0 or above [23]. Earthquakes can also initiate secondary disasters such as landslides, tsunamis, and volcanic eruptions, increasing their overall impact (USGS, 2021) [24].

Volcanic eruptions represent another dangerous type of natural disaster. These occur when magma from beneath the Earth's surface rises and is expelled, often due to tectonic activity. Eruptions can result in pyroclastic flows, ash falls, and lava flows, all of which can cause widespread destruction and loss of life. The Volcanic Explosivity Index (VEI) is used to quantify the magnitude of an eruption, considering the volume of ash, lava, and other materials released during the event (USGS, 2021) [25]. The consequences of natural disasters such as earthquakes and volcanic eruptions often extend far beyond their initial impact. Earthquakes can reshape landscapes, redirect rivers and streams, and thereby alter ecosystems and wildlife habitats. Similarly, volcanic eruptions that release significant quantities of ash and gases into the atmosphere can influence global weather patterns and air quality [26].

Vulnerable communities exposed to risks from earthquakes, quarry blasts, and volcanic activity can significantly reduce their vulnerability through proactive planning and mitigation strategies [27, 28]. The loss of lives and property can be minimized when individuals and authorities establish well-structured emergency plans, including evacuation routes, in advance. Furthermore, governments play a crucial role by enforcing resilient building codes and investing in infrastructure that is capable of withstanding seismic and volcanic events.

Public education is also a vital component in reducing disaster impact. It provides people with accurate knowledge and preparedness about resources, such as how to respond during an earthquake or volcanic eruption empowers communities to act swiftly and effectively in times of crisis. Raising awareness and building local capacity helps ensure a more resilient response to future natural disasters.

Ultimately, earthquakes and volcanic eruptions are devastating events with the potential to cause long-lasting harm to both human populations and the environment. Mitigating their effects requires a combination of infrastructure investment, disaster planning, and community education. In alignment with these goals, this research centers on enhancing the performance of neural networks for detecting natural disasters, particularly under constraints like limited labeled datasets and low-power hardware environments. The optimized Faster R-CNN model developed through this work is tailored for real-time implementation on lightweight platforms such as smartphones, satellites, and high-altitude weather balloons, making it a scalable and cost-effective solution for broad disaster monitoring and response.

b) Landslides and tsunamis: Landslides and tsunamis are among the most devastating natural disasters, capable of causing significant destruction and loss of life. Landslides typically occur due to the instability of soil and rock on slopes, often triggered by factors such as intense rainfall or seismic activity. The severity of a landslide is measured using the Landslide Hazard Scale, which considers its potential to damage infrastructure and endanger lives. Beyond their immediate destruction, landslides can have long-term environmental consequences, such as altering watercourse paths and destroying habitats.

Tsunamis, on the other hand, are massive ocean waves usually triggered by underwater earthquakes or other subsurface disturbances. These waves can cause widespread flooding and infrastructural devastation, especially in coastal regions. Their severity is measured by the Tsunami Magnitude Scale, which assesses their destructive potential based on wave height. Due to their ability to affect vast oceanic regions, tsunamis are particularly dangerous, illustrated by the 2004 Indian Ocean tsunami, which claimed over 200,000 lives across multiple countries [29]. Preparedness strategies can greatly reduce the impact of these disasters, as shown in Fig. 2. These include enforcing resilient construction standards, developing detailed emergency and evacuation plans, and implementing monitoring systems for early warning. Educating at-risk communities on recognizing early signs of landslides or tsunamis and how to respond appropriately is also crucial.

Technological solutions such as early warning systems have proven effective in reducing disaster impact [30–34]. Governments and organizations can further mitigate landslide risks through reforestation and improved land management, while coastal engineering solutions like seawalls and breakwaters help shield populations from tsunamis.

As illustrated in Fig. 1, the findings from related studies categorize the impact of various natural disasters across four critical domains: infrastructure damage, loss of life, environmental impact, and potential to trigger secondary disasters. Earthquakes and tsunamis score the highest in infrastructure damage and fatalities, both rated at 5, highlighting their extreme destructive capabilities. Volcanic eruptions follow with slightly lower but still severe impacts on infrastructure and human life, and they are rated highest for environmental damage with a score of 5 attributable to lava flows, ash dispersion, and toxic emissions. Landslides rank comparatively lower across all categories, particularly in their ability to cause secondary disasters, where they score 2.

Previous studies on disaster severity scales consistently highlight the varying degrees of impact that different natural disasters impose on communities and environments. Research emphasizes that earthquakes and tsunamis rank among the most severe disasters. Volcanic eruptions, while sometimes less destructive to build environments, are noted for their significant environmental impacts, including long-term effects on air quality and ecosystems. Landslides typically score lower on severity scales, as their effects tend to be more localized and less likely to trigger widespread secondary disasters. These findings highlight the need for disaster-specific risk assessments and preparedness strategies.

Table I provides a summary of methodologies, datasets, strengths, limitations, and findings related to earthquake, volcanic, landslide, and tsunami studies.

Their methodology includes reviewing impact metrics such as the Richter Scale and Volcanic Explosivity Index. The organization also emphasizes disaster preparedness through policy recommendations that include education, resilient infrastructure, and evacuation planning. Although the studies are largely descriptive and lack predictive modeling or modern machine learning integration, they highlight the importance of early warning systems and community resilience in reducing disaster impact.

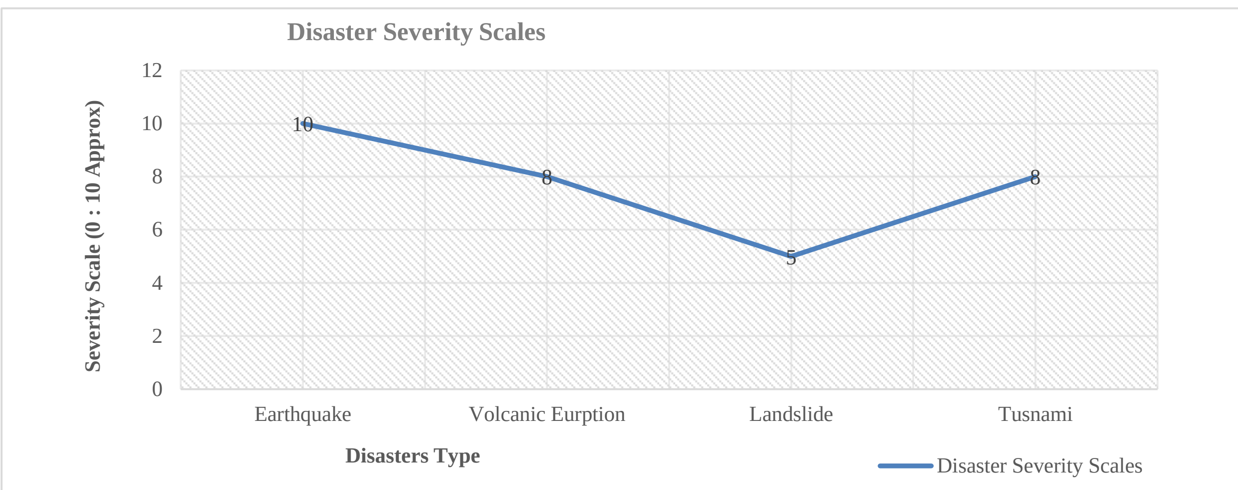

Fig. 1. Disaster severity scales.

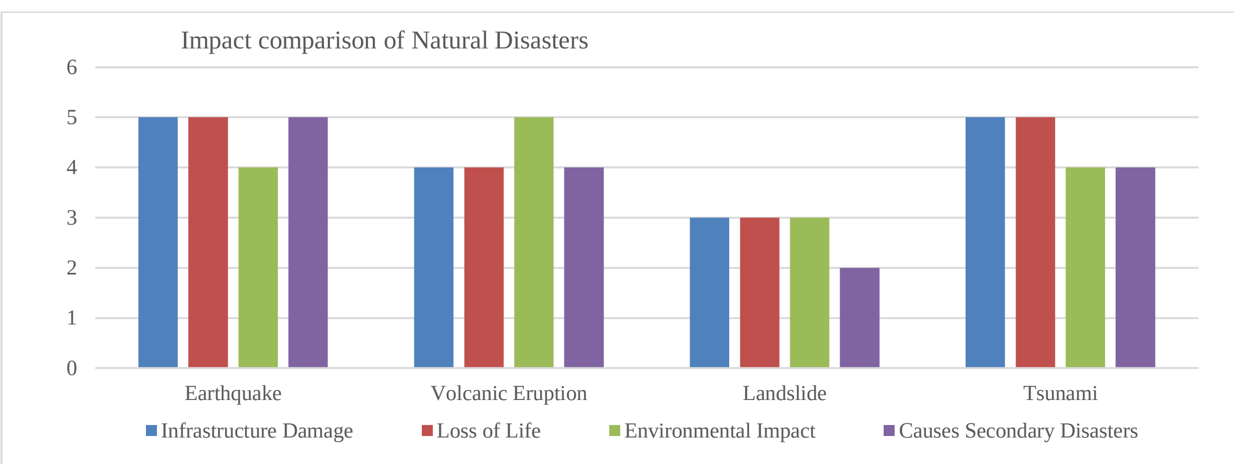

Fig. 2. Impact comparison of natural disasters.

TABLE I SUMMARY OF REVIEWED LITERATURE ON NATURAL DISASTERS INCLUDING METHODOLOGIES, DATASETS USED, STRENGTHS, LIMITATIONS, AND KEY FINDINGS (ADAPTED FROM USGS SOURCES [22–34])

Authors	Methodology	Dataset Used	Strengths	Limitations	Results
USGS [22-26]	Review and statistical analysis of natural disaster events including earthquakes and volcanic eruptions	USGS earthquake and volcano datasets	Covers a wide range of disaster types and global data; provides detailed impact metrics (e.g., Richter, VEI)	Primarily descriptive; lacks predictive modeling or real-time response components	About 20,000 earthquakes/year; 16 with magnitude ≥7.0; volcanoes cause atmospheric impact and secondary disasters
USGS [27-28]	Policy recommendations and preventive strategies for earthquake and volcanic events	Preparedness guidelines, infrastructure resilience studies	Emphasizes disaster risk reduction through education and infrastructure	Limited in terms of implementation analysis or specific case studies	Recommendations for community preparedness, evacuation plans, and resilient construction
USGS [29-34]	Descriptive analysis and historical review of landslides and tsunamis	Historical tsunami data (e.g., 2004 Indian Ocean event), Landslide Hazard Scale	Combines geological triggers with societal impact; includes early warning systems	Descriptive in nature, lacks integration with modern ML-based forecasting systems	Landslides disrupt habitats and waterways; tsunamis cause mass casualties and international devastation

III. DATASET

The dataset employed in this study is composed of satellite images capturing the aftermath of landslides and floods across selected regions in Japan and Thailand. The images were carefully selected to encompass a wide range of environmental and urban settings, enhancing the model's ability to generalize effectively. This dataset forms the foundation for training and evaluating the proposed deep learning model aimed at accurately classifying and identifying disaster-affected areas. In total, approximately 10,000 images were compiled, with an equal distribution between landslide, earthquake and flood scenarios to ensure a balanced learning dataset.

A. Data Collection

The images were acquired through publicly accessible geospatial platforms, primarily Google Earth, which offers high-resolution satellite images of global terrain. The selection process involved identifying locations in Japan and Thailand historically affected by floods, Earthquakes and landslides, followed by extracting relevant imagery from these regions. Care was taken to exclude poor-quality or ambiguous images to maintain the reliability of the dataset. This manual curation ensured that the resulting image collection was both representative and robust for the purposes of training a convolutional neural network (CNN) for disaster classification.

B. Annotations

To prepare the dataset for supervised learning, each image was annotated with bounding boxes highlighting the regions impacted by either landslides or floods. These annotations were carefully reviewed to ensure precision in identifying disaster-affected zones. Each bounding box was labeled with a corresponding class identifier, such as "landslide" or "flood", enabling the model to learn category-specific features. The annotations were stored in JSON format, which ensures compatibility with common deep learning frameworks and streamlines their integration into the training and evaluation pipeline.

IV. METHODOLOGY

A. Data Processing

Data processing plays a foundational role in the success of any deep learning pipeline, especially when dealing with image-based tasks such as Natural Disasters detection. The process begins with normalization, a critical step that involves scaling the raw pixel intensity values of each image to a standardized range typically [0, 1]. This transformation ensures uniformity across all input data, mitigating the effects of varying image brightness or contrast that could otherwise bias the learning process. Normalization also improves the stability and speed of training by helping the optimizer navigate the loss landscape more effectively.

Following normalization, the dataset undergoes a systematic splitting procedure to facilitate robust model training and evaluation. Using stratified sampling, the dataset is divided into three distinct subsets: 70% of the images are assigned to the training set, 15% to the validation set, and the remaining 15% to the testing set. Stratification ensures that the class distribution (i.e., Flood, Earthquakes and Landslide images) remains consistent across all subsets, which is essential for obtaining an unbiased performance evaluation and preventing skewed learning outcomes.

To further prepare the images for ingestion into the deep learning model, a series of image processing techniques are applied to enhance both the quality and diversity of the dataset. First, all images are resized to a fixed dimension of 224×224 pixels, which aligns with the input layer requirements of architectures of ResNet50 and ConvNeXt-Small. This uniform resizing ensures that the model receives input in a consistent shape, reducing computational complexity and memory overhead while preserving key spatial information.

Next, noise reduction is performed using Gaussian filtering, a technique that smooths out high-frequency noise that may be present due to atmospheric distortions, sensor limitations, or compression artifacts in the satellite imagery. By applying a Gaussian kernel, subtle variations in pixel values are averaged in a way that retains important edges and features while suppressing random noise, thereby improving feature extraction in the early convolutional layers of the model.

To combat overfitting and improve the model's generalization to unseen data, data augmentation techniques are extensively employed. These include random rotations, horizontal and vertical flips, and color jittering, each of which introduces controlled variability into the training data without altering its semantic content. For instance, rotating an image by a few degrees or flipping it horizontally simulates different orientations of wildfires captured by satellites, making the model invariant to spatial transformations. Similarly, jittering the color channels mimics variations in lighting conditions and image sensors, thereby improving robustness.

Lastly, image enhancement is applied using histogram equalization, a method that redistributes the intensity values in an image to span a wider range of contrasts. This process makes subtle features more visually prominent, such as smoke patterns, vegetation boundaries, or burn scars, which might otherwise be indistinguishable in low-contrast areas. Enhanced contrast not only benefits visual interpretation but also improves the sensitivity of the model to faint or ambiguous features that are crucial for early wildfire detection.

Taken together, this comprehensive data and image preprocessing strategy ensures that the input images fed into the deep learning model are clean, balanced, diverse, and information-rich. It significantly enhances the model’s ability to learn meaningful patterns, generalize real-world conditions, and make reliable predictions in operational wildfire monitoring systems. Fig. 3 shows the data processing flowchart.

B. Model Architecture

The proposed model for object detection in Natural disaster imagery leverages the power of Faster R-CNN, a state-of-the-art deep learning framework designed for efficient and accurate object localization and classification. Faster R-CNN integrates two key components: a Region Proposal Network (RPN) and a Fast R-CNN detection network.

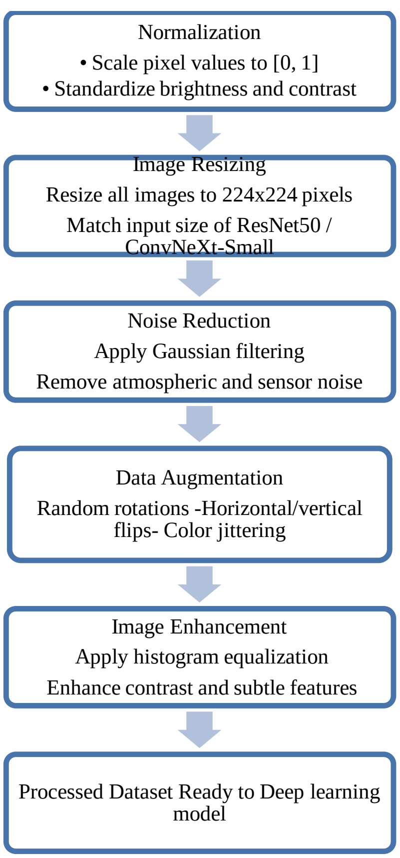

Fig. 3. Data processing.

1) Backbone ResNet50 as feature extractor. ResNet50, a deep convolutional neural network with 50 layers, has become a foundational architecture in image recognition and computer vision due to its innovative residual learning approach. A major challenge when training very deep networks is the vanishing gradient problem, where gradients diminish as they are propagated backward through numerous layers during training [35]. ResNet50 addresses this issue by incorporating skip connections, or residual connections, which allow gradients to flow more freely by bypassing one or more layers. These connections enable the network to learn identity mappings, helping the optimization process converge more quickly and reliably despite the increased network depth. With its 50 layers, ResNet50 effectively captures hierarchical representations of input images, learning simple features such as edges and textures in the initial layers and progressively more complex, abstract patterns like shapes, objects, and spatial relationships in the deeper layers. This capability is particularly advantageous for satellite image analysis, where features can vary significantly in scale, rotation, texture, and context. Whether distinguishing collapsed buildings, flooded areas, or wildfire scars, ResNet50’s rich and multiscale feature representations allow for more accurate identification of disaster-affected regions. In this system, ResNet50 acts as the feature extraction backbone of the detection pipeline, converting raw satellite imagery into a feature map that encodes spatial and contextual information crucial for downstream object detection.

2) Region proposal network. The Region Proposal Network (RPN) scans the image to generate potential regions of interest (ROIs) that are likely to contain objects. Meanwhile, the Relationship Proposal Network (Rel-PN) is a deep learning architecture designed to improve scene understanding by effectively detecting meaningful relationships between objects within an image [36,37]. The process starts with an input image that is passed through a Backbone Convolutional Neural Network (CNN) to extract detailed feature maps. These feature maps are then analyzed by the RPN, which proposes candidate regions in the image that are likely to contain objects.

Instead of examining all possible object pairs (which grow quadratically), the Rel-PN intelligently selects only the most promising object pairs that are likely to be involved in a relationship. This selection is based on learned spatial and contextual cues. These relevant object pairs are then passed to a Relationship Classifier, which determines the specific type of interaction or relationship between them such as "person riding horse" or "dog next to man” [38].

3) Fast R-CNN detection network. The Fast R-CNN component refines the proposed regions by classifying them and adjusting their bounding boxes. Fast R-CNN is a deep learning architecture designed for efficient and precise object detection in images. The process begins with an input image that passes through multiple convolutional layers to extract feature maps. These feature maps are then processed by the Region of Interest (RoI) Pooling layer, which selects regions likely to contain objects [39]. The selected regions are further passed through fully connected layers to produce high-level features. Finally, the network generates two outputs: a classification output that predicts the object classes, and a bounding box regression output that fine-tunes the coordinates of the bounding boxes around the detected objects.

This architecture greatly enhances both the speed and accuracy of object detection by sharing convolutional computations and utilizing RoI pooling to focus on relevant image regions. Its unified design supports end-to-end training and significantly speeds up the detection process compared to earlier two-stage detectors.

At the core of this architecture lies the ResNet50 backbone, a deep convolutional neural network renowned for its powerful feature extraction. ResNet50 employs residual learning through skip connections, allowing gradients to bypass one or more layers during backpropagation. This approach addresses the vanishing gradient problem, enabling effective training of very deep networks. Consequently, ResNet50 excels at learning rich, hierarchical visual representations, which are essential for accurately detecting wildfire-related features in satellite or aerial imagery.

The training procedure was meticulously crafted to maximize the model's performance on the prepared dataset. The network was trained over 10 epochs using stochastic gradient descent (SGD) with a momentum term to speed up convergence and minimize oscillations. A learning rate of 0.005 was set to regulate the step size during weight updates, while a weight decay of 0.0005 served as a regularization method to prevent overfitting. These training parameters collectively helped develop a highly effective detection model, capable of accurately identifying fire-prone areas within complex visual scenes.

Algorithm I: Faster R-CNN with ResNet50 Algorithm for Natural Disasters Detection

```
Input: Image I
Output: List of detected objects with class labels and bounding boxes
# Step 1: Preprocessing
I_preprocessed = Preprocess(I)   # resize, normalize, augment (rotation, flip, jitter)

# Step 2: Feature Extraction using ResNet50
Feature_Map = ResNet50_Backbone(I_preprocessed)
# Step 3: Region Proposal Network (RPN)
Anchors = GenerateAnchors(Feature_Map)
Objectness_Scores, BBox_Offsets = RPN(Feature_Map, Anchors)
# Step 4: Proposal Selection
Proposals = ApplyBoundingBoxRegression(Anchors, BBox_Offsets)
Proposals = FilterLowScores(Proposals, Objectness_Scores, threshold)
Proposals = NonMaximumSuppression(Proposals, iou_threshold)

# Step 5: RoI Pooling
Fixed_Size_Features = []
For each Proposal in Proposals:
   RoI_Feature = RoIAlign(Feature_Map, Proposal)
   Fixed_Size_Features.append(RoI_Feature)

# Step 6: Fast R-CNN Head
Class_Scores, Final_BBox_Offsets = FastRCNN(Fixed_Size_Features)
# Step 7: Bounding Box Refinement
Final_BBoxes = ApplyBoundingBoxRegression(Proposals, Final_BBox_Offsets)

# Step 8: Final Classification & Suppression
For each box in Final_BBoxes:
   if max(Class_Scores) > class_threshold:
      Keep box with label = argmax(Class_Scores)
   else:
      Discard box
Final_Detections = NonMaximumSuppression(Final_BBoxes, iou_threshold)
Return Final_Detections
```

In this pipeline, the Faster R-CNN algorithm (Algorithm I) functions as a two-stage object detection framework that combines high-accuracy classification with precise localization. Initially, input images are fed into a deep convolutional backbone ResNet50, which extracts hierarchical feature maps. These feature maps are then processed by the Region Proposal Network (RPN), which generates candidate object regions by assessing anchor boxes based on their objectiveness scores and refining their positions. The top proposals are further refined through Region of Interest (RoI) pooling and passed to the Fast R-CNN module, which classifies each region and adjusts its bounding box coordinates. During training, the model simultaneously optimizes classification loss (using cross-entropy) and localization loss (using Smooth L1), employing stochastic gradient descent (SGD) with momentum and weight decay for parameter updates. This architecture strikes an effective balance between speed and accuracy, making it well-suited for detecting complex patterns in high-resolution images, such as those captured by satellites. Fig. 4 presents the block diagram of proposed Faster R-CNN.

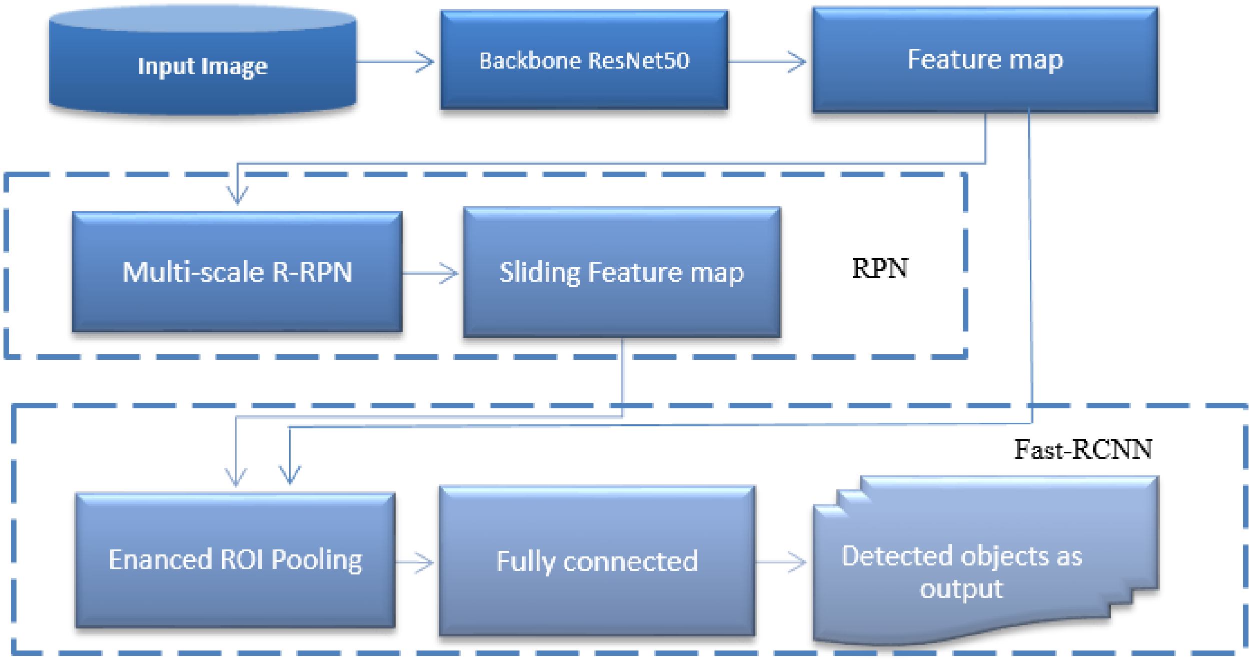

Fig. 4. Block diagram of proposed Faster R-CNN.

C. Training Phase: Loss Computation and Optimization

During the training phase of a two-stage object detection model like Faster R-CNN, the network learns to classify objects and accurately localize them within images. This is accomplished through a multi-task loss function that combines classification loss and localization loss. The model parameters are then optimized using backpropagation with Stochastic Gradient Descent (SGD), incorporating momentum and weight decay.

Classification Loss measures how closely the predicted class probabilities align with the true labels. Specifically, Cross-Entropy Loss is employed, with Softmax Cross-Entropy used for multi-class classification tasks. Given a predicted probability distribution p and the ground truth class c, the classification loss is:

Where, $$L_{cls}=-\log(p_c) \quad (1)$$

p_c is the predicted probability for the correct class c.

Localization Loss L_{loc} measures how precisely the predicted bounding boxes align with the ground truth boxes. Typically, $Smooth_{L1}$ Loss is used for this purpose, as it is less sensitive to outliers compared to the standard L2 loss. For each coordinate x of the bounding box, the $Smooth_{L1}$ loss is defined as follows:

$$Smooth_{L1}(x) = \begin{cases} 0.5|x| & < 1 \\ |x| - 0.5 & otherwise \end{cases}$$

Therefore, the overall localization loss between the predicted bounding box t and the ground truth t* is defined as:

$$L_{loc}= \sum_{i\in\{x,y,w,h\}} SmoothL1(t_i-t_i^*) \quad (2)$$

The total loss function is then:

$$L_{Total}=L_{cls}+\lambda\cdot L_{loc} \quad (3)$$

where, λ is a balancing factor (usually set to 1), adjusting the relative importance of classification and localization.

D. Backpropagation and Optimization

After calculating the loss, the gradients of the loss with respect to the model's parameters are determined through backpropagation. The optimizer used is Stochastic Gradient Descent (SGD) with Momentum, a technique that enhances gradient descent by speeding up convergence, particularly in situations involving high curvature or noisy gradients. The weight update rule is:

$$Vt+1=\mu vt-\eta\cdot\nabla L \quad (4)$$

$$\theta t+1= \theta t +Vt+1 \quad (5)$$

Here, θ represents the model weights, Vt denotes the velocity (momentum term), μ is the momentum coefficient set to 0.9, and η is the learning rate, which is 0.005. ∇L represents the gradient of the loss with respect to the parameters. Weight decay helps reduce overfitting by discouraging large weight values. It alters the parameter update rule as follows:

$$\theta_{t+1}=\theta_t+V_{t+1}-\eta\cdot\lambda_w\cdot\theta_t \quad (6)$$

where, λ_w is the weight decay factor (0.0005).

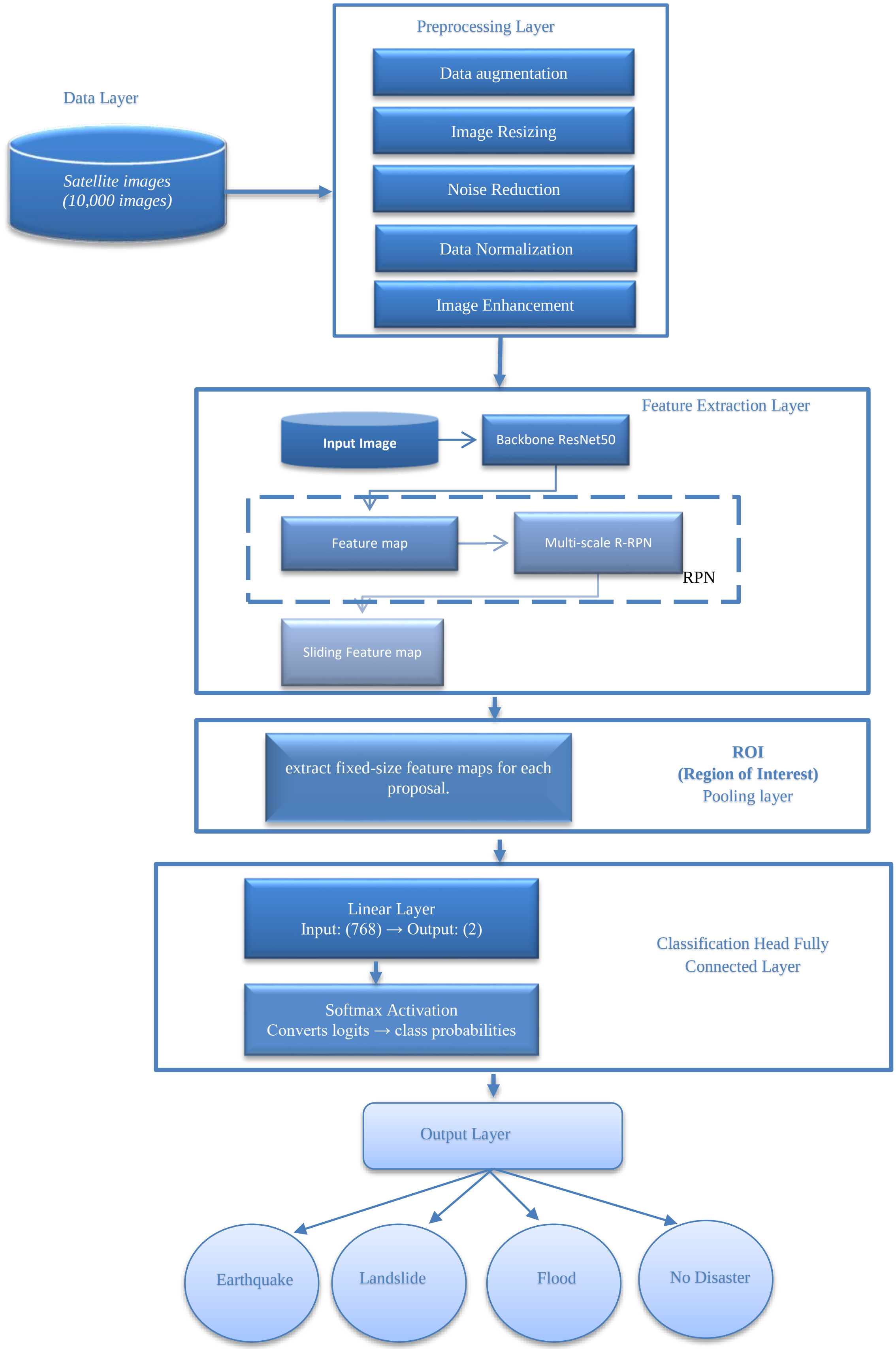

Fig. 5. Proposed model.

V. Results

The performance of the proposed Natural Disasters detection models (Fig. 5) was comprehensively evaluated using standard classification metrics accuracy, precision, recall, and F1-score across four different architectures: CNN, ResNet50, Faster-CNN, and Faster R-CNN with a ResNet50 backbone (see Fig. 6). The baseline CNN model attained an accuracy of 85.3%, with precision at 82.1%, recall at 78.5%, and an F1-score of 80.2%. Although this model served as a reasonable starting point, it exhibited limitations in generalization, likely due to its shallow depth and limited feature extraction capabilities. Significant improvement was achieved with ResNet50, which utilizes residual connections to facilitate learning in deeper networks. This model reached 92.7% accuracy, 90.4% precision, 89.3% recall, and an F1-score of 89.8%, demonstrating its superior ability to capture complex patterns in wildfire imagery. Further gains were observed with the Faster-CNN model, which incorporates region-based object detection. It attained 95.1% accuracy, 94.0% precision, 92.8% recall, and an F1-score of 93.4%, highlighting the advantage of combining detection and classification techniques. The highest performance was achieved by the Faster R-CNN architecture with a ResNet50 backbone, delivering outstanding results with 97.1% accuracy, 95.8% precision, 96.2% recall, and a well-balanced F1-score of 96.0%.

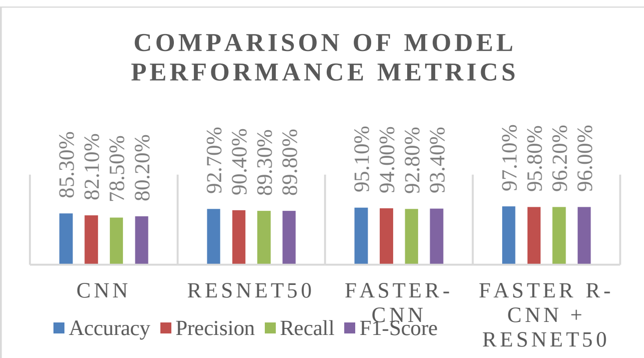

Fig. 6. Comparison of model performance metrics.

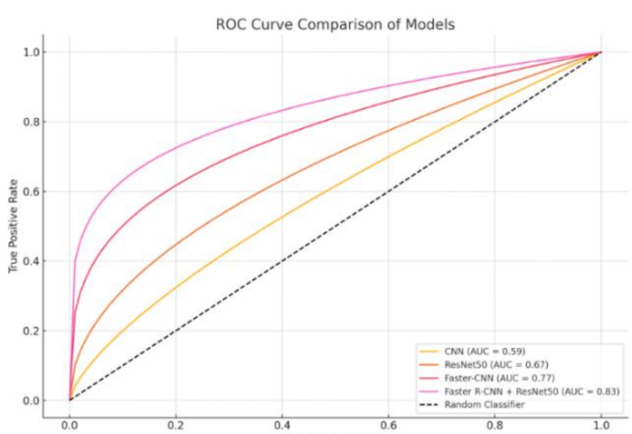

Fig. 7. ROC Curve comparison of models.

These metrics underscore the model's ability to detect Natural disasters regions with high reliability and minimal false predictions. ROC curve analysis further validated these findings. The AUC scores increased progressively across models, with CNN yielding the lowest AUC at 0.59, followed by ResNet50 at 0.67, Faster-CNN at 0.77, and the highest AUC of 0.83 achieved by the Faster R-CNN + ResNet50 model (see Fig. 7).

These results confirm the superior classification capability of the proposed framework, demonstrating robust performance and high discriminative power across all classes. This strong performance highlights the model's readiness for real-world deployment in early wildfire detection systems. Table II presents the proposed model results.

TABLE II Proposed Model Results

Model	Accuracy	Precision	Recall	F1-Score
CNN	85.3%	82.1%	78.5%	80.2%
ResNet50	92.7%	90.4%	89.3%	89.8%
Faster-CNN	95.1%	94.0%	92.8%	93.4%
Faster R-CNN + ResNet50	**97.1%**	**95.8%**	**96.2%**	**96.0%**

VI. Conclusion

This study systematically evaluated the effectiveness of deep learning architectures for natural disaster detection using remote sensing imagery. The baseline CNN, although functional, struggled with generalization due to its limited depth. Incorporating residual connections through ResNet50 significantly enhanced feature representation and classification performance. Further integration of region-based object detection in the Faster-CNN model yielded additional improvements. The highest-performing model, Faster R-CNN with a ResNet50 backbone, achieved exceptional accuracy, precision, recall, and F1-score, demonstrating its potential for real-time disaster detection. These results underscore the value of combining deep residual learning with object detection mechanisms for robust and scalable disaster response solutions. Future work may focus on expanding dataset diversity, incorporating multimodal data, and optimizing inference speed for deployment in real-time early warning systems. Future work will focus on expanding the dataset with additional disaster types and temporal satellite data to analyze changes over time. Moreover, integrating multi-spectral satellite data could further enhance feature discrimination, improving detection in low-visibility or cloud-covered scenarios.

References

[1] M.S. Abdalzaher, H.A. Elsayed, M.M. Fouda, M.M. Salim, Employing machine learning and iot for earthquake early warning system in smart cities, Energies 16 (1) (2023) 495.

[2] S.S. Moustafa, M.S. Abdalzaher, H. Abdelhafiez, Seismo-lineaments in Egypt: analysis and implications for active tectonic structures and earthquake magnitudes, Rem. Sens. 14 (23) (2022) 6151.

[3] S. Self, M.R. Rampino, The 1883 eruption of krakatau, Nature 294 (1981) 699–704.

[4] E. Rosenblueth, R. Meli, The 1985 Mexico earthquake, Concr. Int. 8 (5) (1986) 23–34.

[5] M. Elhadidy, M.S. Abdalzaher, H. Gaber, Up-to-date psha along the gulf of aqabadead sea transform fault, Soil Dynam. Earthq. Eng. 148 (2021) 106835.

[6] M.S. Abdalzaher, M. El-Hadidy, H. Gaber, A. Badawy, Seismic hazard maps of Egypt based on spatially smoothed seismicity model and recent seismotectonic models, J. Afr. Earth Sci. 170 (2020) 103894.

[7] M.S. Abdalzaher, M.S. Soliman, S.M. El-Hady, A. Benslimane, M. Elwekeil, A deep learning model for earthquake parameters observation in iot system-based earthquake early warning, IEEE Internet Things J. 9 (11) (2022) 8412–8424.

[8] R. Khurana, D. Mugabe, X.L. Etienne, Climate change, natural disasters, and institutional integrity, World Dev. 157 (2022) 105931.

[9] M.S. Abdalzaher, M. Sami Soliman, S.M. El-Hady, Seismic intensity estimation for earthquake early warning using optimized machine learning model, IEEE Trans. Geosci. Rem. Sens. 61 (2023), 1–1.

[10] M.M. Salim, H.A.E.A. Elsayed, M.S. Abdalzaher, A survey on essential challenges in relay-aided d2d communication for next-generation cellular networks, J. Netw. Comput. Appl. (2023) 103657 [Online]. Available: https://www.sciencedirect.co m/science/article/pii/S1084804523000760.

[11] M.M. Salim, H.A. Elsayed, M.A. Elaziz, M.M. Fouda, M.S. Abdalzaher, An optimal balanced energy harvesting algorithm for maximizing two-way relaying d2d communication data rate, IEEE Access 10 (2022), 114 178–114 191.

[12] M.M. Salim, H.A. Elsayed, M.S. Abdalzaher, M.M. Fouda, Rf energy harvesting dependency for power optimized two-way relaying d2d communication, in: 2022 IEEE International Conference on Internet of Things and Intelligence Systems (IoTaIS), 2022, pp. 297–303.

[13] M.S. Abdalzaher, H.A. Elsayed, Employing data communication networks for managing safer evacuation during earthquake disaster, Simulat. Model. Pract. Theor. 94 (2019) 379–394.

[14] M.S. Abdalzaher, K. Seddik, O. Muta, Using repeated game for maximizing high priority data trustworthiness in wireless sensor networks, in: 2017 IEEE Symposium on Computers and Communications (ISCC), 2017, pp. 552–557.

[15] M.S. Abdalzaher, O. Muta, A game-theoretic approach for enhancing security and data trustworthiness in iot applications, IEEE Internet Things J. 7 (11) (2020) 11250–11261.

[16] M.S. Abdalzaher, K. Seddik, O. Muta, Using stackelberg game to enhance cognitive radio sensor networks security, IET Commun. 11 (9) (2017) 1503–1511.

[17] M.S. Abdalzaher, K. Seddik, M. Elsabrouty, O. Muta, H. Furukawa, A. AbdelRahman, Game theory meets wireless sensor networks security requirements and threats mitigation: a survey, Sensors 16 (7) (2016) 1003.

[18] M.S. Abdalzaher, K. Seddik, O. Muta, An effective stackelberg game for highassurance of data trustworthiness in wsns, in: 2017 IEEE Symposium on Computers and Communications (ISCC), 2017, pp. 1257–1262.

[19] M.S. Abdalzaher, K. Seddik, O. Muta, A. Abdelrahman, Using stackelberg game to enhance node protection in wsns, in: 2016 13th IEEE Annual Consumer Communications & Networking Conference (CCNC), 2016, pp. 853–856. [20] M.S. Abdalzaher, O. Muta, K. Seddik, A. Abdel-Rahman,

[20] H. Furukawa, B-18-40 a simplified stackelberg game approach for securing data trustworthiness in wireless sensor networks, in: 2016 IEICE General Conference. Plus 0.5em Minus 0.4emIEICE, 2016, p. 538.

[21] M.S. Abdalzaher, O. Muta, Employing game theory and tdma protocol to enhance security and manage power consumption in wsns-based cognitive radio, IEEE Access 7 (2019), 132 923–132 936.

[22] S.A. Mahin, Lessons from damage to steel buildings during the northridge earthquake, Eng. Struct. 20 (4–6) (1998) 261–270.

[23] L. Highland, P.T. Bobrowsky, et al., The Landslide Handbook: a Guide to Understanding Landslides. Plus 0.5em Minus 0.4emUS Geological Survey Reston, 2008. VA, USA.

[24] C.M. Scheip, K.W. Wegmann, Hazmapper: a global open-source natural hazard mapping application in google earth engine, Nat. Hazards Earth Syst. Sci. 21 (5) (2021) 1495–1511.

[25] K.M. Cooper, K. Anderson, K. Cashman, M. Coombs, H. Dietterich, T. Fischer, B. Houghton, I. Johanson, K.J. Lynn, M. Manga, et al., Coordinating science during an eruption: lessons from the 2020–2021 k i lauea volcanic eruption,, Bull. Volcanol. 85 (5) (2023) 1–13.

[26] E. Ghamry, E.K. Mohamed, M.S. Abdalzaher, M. Elwekeil, D. Marchetti, A. De Santis, M. Hegy, A. Yoshikawa, A. Fathy, Integrating pre-earthquake signatures from different precursor tools, IEEE Access 9 (2021), 33 268–33 283.

[27] M.S. Abdalzaher, S.S.R. Moustafa, M. Abd-Elnaby, M. Elwekeil, Comparative performance assessments of machine-learning methods for artificial seismic sources discrimination, IEEE Access 9 (2021), 65 524–65 535.

[28] S.S.R. Moustafa, M.S. Abdalzaher, M.H. Yassien, T. Wang, M. Elwekeil, H.E.A. Hafiez, Development of an optimized regression model to predict blastdriven ground vibrations, IEEE Access 9 (2021), 31 826–31 841.

[29] G. Bankoff, J. Christensen, bordering on danger: an introduction, Nat. hazards and peoples Indian Ocean world: Bordering on danger (2016) 1–30.

[30] M.S. Abdalzaher, S.S.R. Moustafa, H.A. Hafiez, W.F. Ahmed, An optimized learning model augment analyst decisions for seismic source discrimination, IEEE Trans. Geosci. Rem. Sens. 60 (2022) 1–12.

[31] O. Hamdy, H. Gaber, M.S. Abdalzaher, M. Elhadidy, Identifying exposure of urban area to certain seismic hazard using machine learning and gis: a case study of greater cairo, Sustainability 14 (17) (2022) 10722.

[32] S.S.R. Moustafa, M.S. Abdalzaher, M. Naeem, M.M. Fouda, Seismic hazard and site suitability evaluation based on multicriteria decision analysis, IEEE Access 10 (2022) 69 511–569 530.

[33] M.S. Abdalzaher, H.A. Elsayed, M.M. Fouda, Employing remote sensing, data communication networks, ai, and optimization methodologies in seismology, IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 15 (2022) 9417–9438.

[34] S.S.R. Moustafa, M.S. Abdalzaher, F. Khan, M. Metwaly, E.A. Elawadi, N.S. Al-Arifi, A quantitative site-specific classification approach based on affinity propagation.

[35] Ali, R. R., Yaacob, N. M., Alqaryouti, M. H., Sadeq, A. E., Doheir, M., Iqtait, M., ... & Yaacob, S. S. (2025). Learning Architecture for Brain Tumor Classification Based on Deep Convolutional Neural Network: Classic and ResNet50. Diagnostics, 15(5), 624.

[36] Dong, R., Xia, J., Zhao, J., & Hong, L. (2025). CL-PSDD: Contrastive Learning for Adaptive Generalized Pavement Surface Distress Detection. IEEE Transactions on Intelligent Transportation Systems.

[37] Lin, H., Li, N., Yao, P., Dong, K., Guo, Y., Hong, D., ... & Wen, C. (2025). Generalization-Enhanced Few-Shot Object Detection in Remote Sensing. IEEE Transactions on Circuits and Systems for Video Technology.

[38] Zhang, J., Elhoseiny, M., Cohen, S., Chang, W., & Elgammal, A. (2017). Relationship proposal networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 5678-5686).

[39] He, Z., & He, Y. (2025). AS-Faster-RCNN: An Improved Object Detection Algorithm for Airport Scene Based on Faster R-CNN. IEEE Access.