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Scalable Approach to Create Annotated Disaster Image Database Supporting AI Driven Damage Assessment

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Abstract

This work proposes an AI-driven system for enhancing hurricane damage estimation through the use of deep learning models for precise identification and Classification of damaged building components. The system incorporates high-resolution aerial and satellite images to create an annotated database to enhance data analysis and processing. A CNN-based approach detects and classifies structural damage with the ability to distinguish between minor and major impact categories. The system employs geospatial data for precise localization and real-time alarm systems to aid emergency response teams. Through damage evaluation automation, this work aims to accelerate disaster response, reduce human effort, and improve recovery planning.

INTRODUCTION

The heightened frequency and intensity of hurricanes underscore the need for rapid and accurate damage assessments to guide disaster response operations. Manual surveys are time-consuming, labor-intensive, and subject to inconsistencies, and stifle vital recovery measures. To overcome these shortcomings, this research suggests an artificial intelligence-enabled framework using deep learning methods for effective damage assessment, several orders of magnitude faster and more accurate than traditional approaches.

The foundation of the suggested solution is a well-curated, tagged image repository for enhancing the detection and classification of structural damage with high granularity.

Employing high-resolution aerial and satellite imagery and training artificial intelligence models to recognize the impacted building elements with high accuracy, the system can effectively detect damaged building elements. The large dataset allows for effective data management, streamlines model training procedures, and ensures smooth deployment in real-world disaster situations. The outcome is an adaptable and scalable tool that helps responders optimize resource utilization and serve communities more effectively.

Our objective is to incorporate superior AI-based damage assessment techniques in disaster management systems, thus enabling faster recovery and enhancing future hurricane resilience.

By leveraging the power of automation and real-time analytical capacity, this research seeks to equip emergency response teams, reduce economic losses, and improve climate adaptability.

LITERATURE SURVEY

1. Alzughaibi, Ahmed A., et al. [4]"Post-disaster structural health monitoring system using personal mobile phones." 2019 IEEE Topical Conference on Wireless Sensors and Sensor Networks (WiSNet). IEEE, 2019. In this study, the application of mobile phones for post-disaster structural health monitoring is examined, as a means of being low-cost. Through smart phone sensors and AI models, the system provides real-time structural damage detection. However, the quality of sensors can affect the accuracy of assessment and real-world implementation may have some challenges in terms of standardization and scalability.

2. Bhuyan, Kushanav, et al.[6] "Mapping and characterizing buildings for flood exposure analysis using open-source data and artificial intelligence." Natural Hazards 119.2 (2023):805-835. the article depicts an AI-based approach to mapping flood-prone buildings by utilizing open-source geospatial data. It enhances the characterization of buildings through the use of deep learning models to improve flood risk assessment. Nonetheless, the open-source data might be inconsistent in resolution and coverage, and hence it could pose certain issues in accuracy of predictions.

3. Bloice, Marcus D.,Peter M. Roth, and Andreas Holzinger."Biomedical image augmentation using Augmentor."Bioinformatics 35.21 [3](2019): 4522-4524. The authors present Augmentor, an image augmentation tool that aims to improve biomedical datasets for deep learning applications. The authors show the benefits of augmentation in generalizing models but argue that too many transformations introduce artifacts that confuse AI models.

4. Rahnemoonfar, Maryam, Tashnim Chowdhury, and Robin Murphy. [5]"Rescue Net: A high-resolution UAV semantic segmentation dataset for natural disaster damage assessment." Scientific Data 10.1 (2023): 913. This paper presents Rescue Net, a UAV-captured dataset for disaster damage assessment using semantic segmentation techniques. While the dataset improves AI model training, challenges such as varying lighting conditions and occlusions in aerial imagery limit performance.

5. Rashedi Nia, Karoon. "Automatic Building Damage Assessment Using Deep Learning and Ground-Level Image Data." 2017. [2] The research specifies an automatic assessment scheme for damage via deep learning on images taken on the ground. Although it showed a very accurate result, the approach is incompetent in finding minor damages of the structure and cannot clearly separate between preexisting and disaster-induced defects.

6. Ro, Sun Ho, and Jie Gong. "Scalable approach to create annotated disaster image database supporting AI-driven damage assessment."[1] Natural Hazards 2024, 1-20. In this study, an annotated large-scale image database is built in order to support the development of AI-based damage evaluation systems in post-disaster structural elements. The addition of the database may improve model accuracy, but its annotation requires manual efforts by human experts in ensuring accuracy.

7. Zhu, Xiaoyu, Junwei Liang, and Alexander Hauptmann. "MsNet: A multi-level instance segmentation network for natural disaster damage assessment in aerial videos."Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (2021). The study presents Ms Net, a multi-level instance segmentation network to determine disaster damage from aerial video content. Although it enhances the performance of damage classification, it fails with occlusions, scale changes, and poor video inputs.

PROBLEM STATEMENT

Traditional disaster damage assessment is slow, subjective, and inefficient. The lack of high-quality, annotated image datasets limits AI-driven evaluation, hindering rapid and accurate structural analysis for emergency response.

METHODOLOGY

This study outlines a scalable framework for developing an AI-driven disaster image database, focusing on data collection, annotation, model development, training, deployment, and continuous improvement to enhance damage assessment accuracy.

A. Data Collection:

1. Dataset Compilation: Collect disaster images from satellites, drones, and ground sources to ensure standardized resolution, lighting, and metadata to ensure consistency.
2. Temporal Collection: Capture images before, during, and after the disaster to include a comprehensive dataset for event analysis.

B. Data Annotation:

1. Damage Classification: Specify damage intensity grades and structural elements (roof collapse, building collapse).
2. Automated Pre-annotation & Quality Control:
Apply pre-trained AI models for the initial annotation and manual verification to achieve high accuracy.

C. Framework and Model Development:

1. Cloud Architecture: Design a cloud-based architecture to store images, process, and retrieve in scalable fashion.
2. Preprocessing Pipeline: Standardize images by

removing noise, segmentation, and feature extraction to increase model performance.

D. Training:

1. Augmentation and Optimization:
Apply data augmentation techniques for improving generalization, and tune up hyper parameters for high accuracy.

2. Performance Evaluation: Evaluate model accuracy by precision, recall, F1 score, and the IoU metrics.

E. Training:

1. Real-Time Analysis & Integration: Deploy the model on a cloud environment for real-time disaster analysis and integrate with the emergency response systems.

2. Field Testing & Feedback: Test the system's performance in actual disaster scenarios and gather user feedback for improvement.

F. Continuous Improvement:

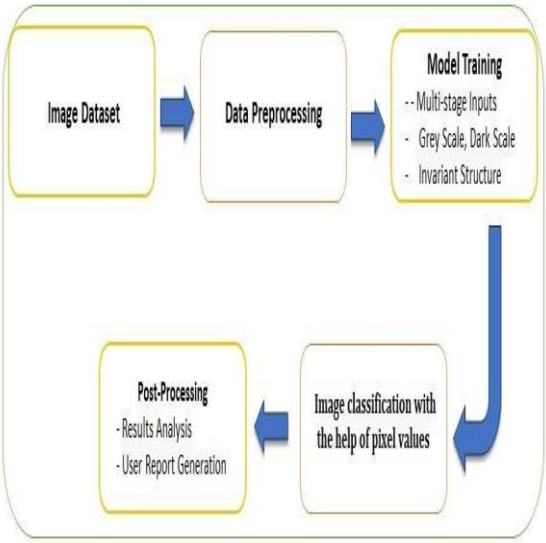
1. Pipeline for Updates: Update the database, retrain models, and incorporate the latest AI advancements.

2. Adaptation to New Technologies: Regularly incorporate new AI models, datasets, and real-time monitoring capabilities.

G. Documentation and Knowledge Sharing:

1. Comprehensive Documentation: Maintain records of data sources, annotation methods, and model training parameters for reproducibility.

2. Collaboration & Publication: Share findings through academic publications, government agencies, and AI research communities to enhance disaster response efforts.



SYSTEM ARCHITECTURE

Satellite Imagery Processing

1. Image Acquisition: This step involves collecting satellite imagery from both pre- and post-disaster situations. The images are paired according to their geographical locations (for instance, Pair A and Pair B).
2. Standardization: To ensure uniform processing, images are resized to 224 × 224 pixels. This standardization helps maintain consistency in lighting, resolution, and format.

Feature Extraction using ResNet-18

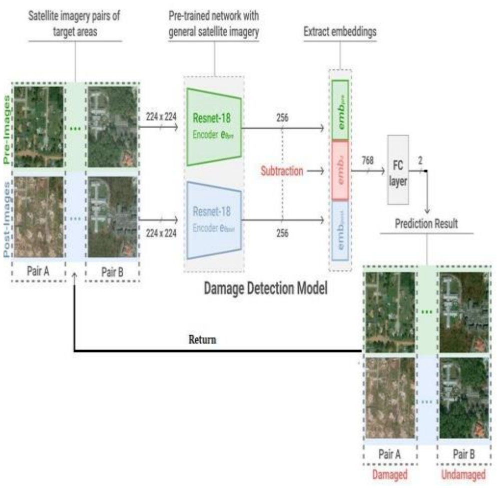
1. Pre-trained ResNet-18 Encoder: The process employs a ResNet-18 encoder that has been pre- trained on a wide range of satellite imagery. Two distinct ResNet-18 encoders are used to analyze pre- disaster and post-disaster images separately.
2. EmbeddingGeneration:.Eachimageisprocessed through the encoder, resulting in 256-dimensional embeddings. These embeddings effectively capture the structural and environmental characteristics before and after the disaster.

Damage Detection Model

1. Feature Subtraction: By subtracting the embeddings from the pre- and post-disaster images, we can emphasize the structural changes. The differences highlight damage indicators such as collapsed buildings, debris, or structural deformations.
2. Concatenation: There sulting difference embeddings are concatenated to create a 768-dimensional feature vector, which is then fed into a fully connected (FC) layer.
3. Classification Layer: The fully connected (FC) layer analyzes the feature vector to determine whether the region is classified as Damaged or Undamaged. The final output consists of two categories (binary classification).

Prediction and Output

1. Damage Classification: The system categorizes each pair of satellite images as"Damaged" (e.g., Pair A) or "Undamaged" (e.g., Pair B).
2. Visualization and Return::The resulting difference embeddings are concatenated to create a 768- dimensional feature vector, which is then fed into a fully connected (FC) layer.
3. Classification Layer: The results are visualized by mapping the damage levels onto the original satellite images. This output is then incorporated into disaster response frameworks to facilitate quick assessments and relief planning.



CONCLUSION

The development of this AI-driven disaster assessment framework is moving along smoothly. Key elements like data collection, annotation, and model training have been successfully put into action. The system allows for real-time analysis and integrates seamlessly with emergency response systems, providing quick and precise damage assessments using satellite, drone, and ground imagery. Ongoing improvements, such as feedback loops and adaptive learning, help to enhance the model's accuracy over time. This system greatly boosts the efficiency of disaster response by facilitating quicker decision-making, optimizing resource allocation, and aiding recovery efforts. Although there are still are as to refine in terms of scalability and automation, the project is making steady progress toward deployment.

FUTURESCOPE

The future potential of this AI-driven disaster assessment framework lies in its ability to evaluate a range of disasters, including floods, wildfires, and earthquakes, making it a flexible tool for quick and precise damage assessment. By incorporating real-time sensor data and 3D imaging, the clarity of insights will be significantly improved; while crowd sourced images from those affected will enhance coverage. Additionally, direct integration with emergency response systems will facilitate automated reporting and damage cost estimates, speeding up the distribution of aid. As the model advances through adaptive learning and climate trend analysis, it will be essential in disaster preparedness, promoting smarter and more resilient recovery strategies.

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