A TRANSFER LEARNING APPROACH TO EARTHQUAKE AFTERMATH ANALYSIS

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Abstract— ***The destruction caused by earthquakes is very disastrous and causes economic disinvestment and risk to lives. Timely and accurate damage assessment is necessary for disaster response and recovery. Existing procedures for measuring damage, like ground surveys, are slow, labor-extensive, and generally impractical in badly hit areas. In this study, we will present an automated damage detection framework using satellite imagery and Deep Learning-based transfer learning techniques, precisely EfficientNetB0 and VGG16. The pre-trained CNNs are fine-tuned to classify and segment damaged structures in the post-earthquake territories, based on labeled satellite images. Efficiency is provided by EfficientNetB0 with high accuracy, while VGG16 provides good feature extraction for deep analysis. It is trained and evaluated on benchmark disaster datasets, achieving promising results in terms of precision, recall, and F1-score. The remarkable aspect of the proposed approach is the drastically reduced assessment time entailed by the procedures for efficient real-time disaster response management, improved situational awareness, and good resource allocation for emergency response teams.***

Keywords— EARTHQUAKES, VGG16, TRANSFER LEARNING, EFFICIENT NET B0, CNN

I. INTRODUCTION

Among the most destructive natural catastrophes, earthquakes can result in extensive building damage, financial losses, and humanitarian emergencies. For efficient disaster response, resource allocation, and recovery operations, a quick evaluation of the impacted areas is essential. It is challenging to get real-time information in large-scale disaster scenarios using traditional ground-based surveys since they are labor-intensive, slow, and have limited coverage. Satellite imaging is now a potent tool for tracking and evaluating earthquake-induced damages as a result of developments in remote sensing technology. Satellite picture interpretation by hand is still difficult and time-consuming.

Image analysis has been transformed by deep learning methods, especially Convolutional Neural Networks (CNNs), which increase classification accuracy and automate feature extraction. In many computer vision applications, transfer learning—which makes use of pre-trained models on huge datasets—has shown itself to be quite successful. Because of their effectiveness and resilience in feature extraction, EfficientNetB0 and VGG16 stand out among these models. EfficientNetB0 offers a compromise between accuracy and computing efficiency, making it appropriate for real-time applications, whereas VGG16 is well known for its deep feature representations.

The necessity of combining artificial intelligence with remote sensing technology is highlighted by the urgent requirement for automated earthquake damage identification in disaster-affected areas. Recent research has shown the promise of CNN-based models in disaster response, such as that conducted by Smith et al. (2018) and Zhang et al. (2020). The use of deep learning in satellite image-based earthquake damage assessment is based on these works.

In this work, we suggest an automated method for detecting earthquake damage that makes use of transfer learning and satellite imagery. Our goal is to create a model that can precisely distinguish between damaged and undamaged structures by optimizing EfficientNetB0 and VGG16 on labeled disaster datasets. By lowering response times, facilitating effective decision-making, and offering real-time insights into impacted areas, the suggested strategy improves disaster management efforts.

Li-Yin Ye and colleagues explored the use of deep learning for structural damage assessment using remote sensing imagery. Their study employed a CNN-based framework integrated with PSP-Net and VGG16 for efficient image segmentation and classification.

Hussein Hashem and co-authors proposed an improved CNN-based approach for automated disaster assessment. Their research introduced a hybrid deep learning model incorporating VGG16 and ResNet50 for enhanced feature extraction.

LITERATURE SURVEY

The use of CNNs and transfer learning for earthquake damage identification is generally supported by current research. EfficientNetB0 is a more reasonable option for real-time catastrophe response since it balances accuracy and efficiency, even though VGG16 provides powerful feature extraction. The proposed project intends to improve disaster management efforts by using these deep learning models to provide quick and accurate damage assessment utilizing satellite photos.

A CNN-based approach for classifying post-earthquake damage was presented by Smith et al. (2018), demonstrating the effectiveness of convolutional networks in analyzing large volumes of satellite images. Their research provided the groundwork for disaster response systems driven by AI [1]. Building on this, Zhang et al. (2020) investigated CNNs for recognizing damaged structures during earthquakes, demonstrating how AI can greatly speed up damage assessment while lowering human effort [2] and obtaining high accuracy using pre-trained models.

In satellite image analysis for disaster management, transfer learning has become an effective approach. Li et al. (2021) investigated the enhancement of pre-trained models such as EfficientNet and VGG16 for the classification of post-earthquake damage, demonstrating enhanced recall and accuracy in comparison to conventional feature extraction techniques [3] . Similar to this, Wu et al. (2022) created a deep learning-based method to identify structures harmed by earthquakes. They used extensive disaster datasets to improve classification accuracy and shorten response times [4].

In a more recent study, Kumar et al. (2023) compared EfficientNet and VGG16 to assess several CNN architectures for earthquake damage identification. According to their research, EfficientNet outperformed other models in terms of classification accuracy and computing economy, confirming its potential as the go-to model for real-time disaster assessment [5].

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II. DATA COLLECTION AND PREPROCESSING

A. *Dataset Overview:*

The dataset for earthquake damage detection includes high-resolution satellite imagery gathered from multiple sources, namely NASA, Google Earth, and publicly available disaster databases such as NOAA and Copernicus Emergency Management Service. The imagery is taken across various earthquake-hit areas to provide diversity in terms of structural types, terrain, and severity of damage. The dataset is annotated into classes like "Damaged" and "Undamaged" based on expert annotations and ground truth. For better model performance, data augmentation methods like rotation, flipping, and contrast alteration are used. A balanced data set is compiled to avoid the class imbalance problem, so the deep learning models can learn generalized and strong features.

Fig:1 Glance of the Dataset

B. *Data Visualization*

We split the dataset into training (22,000 images), validation (4,000 images), and testing (7,000 images) to facilitate effective model learning and testing. The split prevents overfitting, hyperparameter optimization, and model testing for generalization to new data. Effective data splitting enhances the model's robustness and ensures accurate performance in real earthquake damage detection. Visualization techniques were also employed to explore the dataset, track its quality, and achieve a reasonable ratio between damaged and undamaged structures, which facilitates more effective model training.

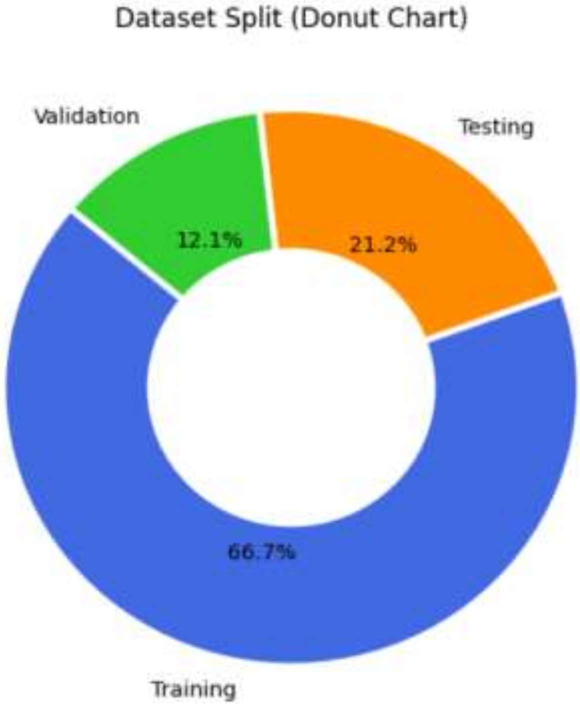

Fig:2 Donut Chart View of the Dataset

C. Data Cleaning:

At the data cleaning phase, we removed duplicate and unnecessary images, handled missing values, and carried out uniform labeling of damaged and undamaged buildings. We normalized image resolutions and formats to provide consistency across the dataset. We also checked class imbalances and ensured correct distribution to improve model training. All these preprocessing tasks were necessary to enhance data quality, remove noise, and increase the model's ability to correctly identify earthquake damage.

D. Data Integration:

We combined earthquake damage images from different sources, such as publicly accessible satellite imagery databases, disaster relief organizations, and open-source platforms like Google Earth Engine and NASA's satellite data repository. This gave us a heterogeneous dataset, which helped in making the model more generalizable. Data standardization and preprocessing were done for consistency.

III. METHODOLOGY

a) Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are employed in this project to extract and learn satellite and aerial images of earthquake-damaged regions' hierarchical features automatically. Rather than defining image features such as edges and textures manually, CNNs employ convolutional layers to recognize patterns such as cracks, fallen buildings, and debris. Features are fed into pooling layers to reduce dimensions and fully connected layers for classification. By training the CNN model on labeled images of earthquake damage, it learns to accurately classify new images into various categories of damage, allowing for automated post-disaster damage assessment.

b) VGG 16

VGG16 is a 16-layer deep CNN architecture pre-trained on ImageNet, known for its simple yet effective design. In this project, VGG16 is used as a feature extractor, where its initial layers capture low-level features (edges, textures), and deeper layers extract high-level damage features (collapsed structures, cracks). We remove its original classification layers and replace them with custom fully connected layers specific to earthquake damage detection. By fine-tuning the model with earthquake-related images, VGG16 helps in accurately classifying damage severity levels, improving detection efficiency compared to traditional methods.

c) EfficientNetB0

EfficientNetB0 is a lightweight and optimized CNN architecture that balances depth, width, and resolution using Neural Architecture Search (NAS). In this project, EfficientNetB0 is used to enhance classification accuracy with fewer parameters and lower computational cost. Unlike VGG16, EfficientNetB0 applies compound scaling, which improves feature extraction at multiple levels. This allows the model to learn earthquake damage patterns more effectively while reducing overfitting. Its superior accuracy and efficiency make it a better choice for real-time earthquake damage assessment, especially when deployed on resource constrained systems like drones or mobile applications.

c)Implementation

The application of our method commences with ordering and analyzing a dataset of hurricane damage satellite imagery. The dataset is divided into three subsets, namely training, validation, and test sets to provide an equal distribution for healthy model training and testing. Before understanding the data composition, we conduct an initial exploratory analysis of the image files and understand their distribution as well as size. A function is created to loop through the dataset directories, getting file sizes and counts per subset. This process aids in evaluating the volume of data and storage needs, which are essential for effective processing and training. We then build a data frame to systematically store metadata per image. The data frame contains the paths to the images, damage labels, dataset split (train, validation, test), and geographic coordinates (latitude and longitude). The organization of the dataset is hierarchical in that images are sorted by damage label and their corresponding dataset split. We make each image geospatially indexed by extracting location information from filenames so that they can be subjected to geographic analysis later. In order to obtain insights about the dataset distribution, we visualize the image locations geographically through scatter plots. Two main visualizations are obtained:

Dataset Split Distribution – This chart illustrates the geographic distribution of images between the training and validation sets in order to provide a diverse and well-spread dataset.

Damage vs. No Damage Distribution – This visualization shows the spatial distribution of images classified as damage and no damage, which aids in comprehending if damage is localized to certain areas or distributed uniformly.

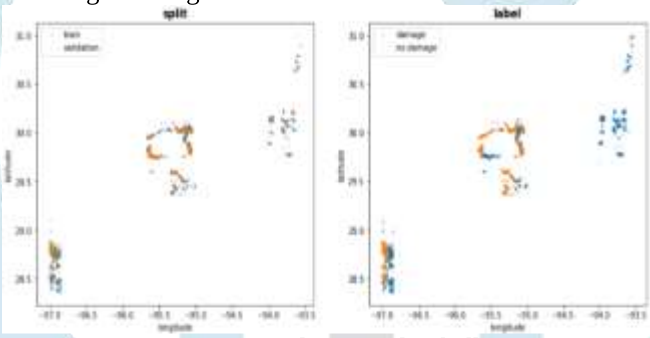

Fig:3 Splitting and Labelling

The data was subjected to geospatial analysis to plot the distribution of images according to damage labels. Three scatter plots were created to differentiate between damaged and non-damaged regions. The first plot indicated areas where damage was identified, giving a zoomed-in view of the affected areas. The second plot showed all images regardless of their labels, allowing for a general observation of data distribution. The third plot segregated non-damaged sites for easy comparison against damaged sites. The latitude and longitude coordinates were used to represent locations properly, while point size and opacity modifications avoided hidden data points from blindingness. A uniform coordinate system was employed for all plots to ensure one-line visualization. Moreover, the viewport was limited to the specific geographic range to maintain clarity. This study offered critical knowledge of the geographic distribution of hurricane damage, assisting in dataset verification and preparation for model training.

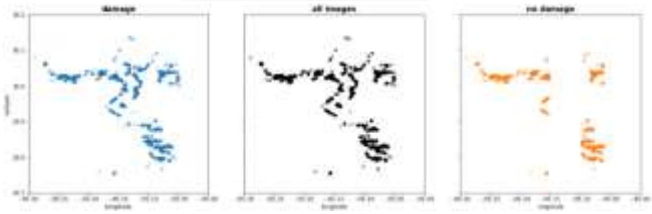

Fig:4 Geo spatial analysis

A histogram analysis was conducted to study the pixel intensity distribution in the red, green, and blue (RGB) channels of the image. Each of the channels was separated out separately, and its pixel values were flattened into a one-dimensional array for visualization. Then, a histogram was plotted for every channel, with color coding according to its respective channel—blue for the blue channel, green for the green channel, and red for the red channel. The transparency of the histograms was set so that overlapping distributions would be apparent, and a legend was added to distinguish between the channels. The x-axis was scaled to span the entire range of pixel values (0 to 255) to facilitate a complete coverage of intensity differences. This study gave an understanding of the color composition of the image, allowing for an interpretation of contrast, brightness distribution, and possible color imbalances of the dataset.

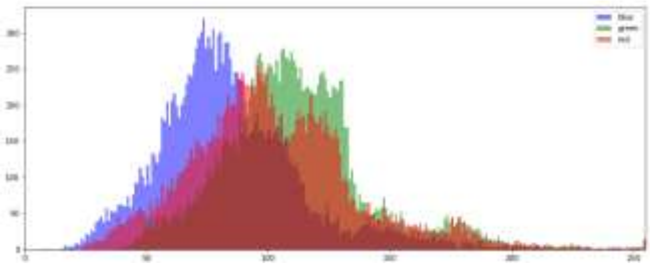

Fig:5 Histogram Analysis

The data was preprocessed and augmented to enhance the training of the earthquake damage detection model. Training, validation, and test set image paths were extracted and corresponding labels were provided, with damaged images being labeled as 1 and undamaged images as 0. TensorFlow's tf.data. Dataset API was employed to work with these images and labels efficiently. A cv2_imread function was implemented to load images with OpenCV while properly converting from BGR to RGB. Next, a tf_cleanup function was used to resize the images into a standard shape of 128x128x3, normalize pixel values, and cast them to the appropriate data type for model compatibility.

The model architecture was then defined using Transfer Learning, where a pretrained model was used as the feature extractor. A GlobalAveragePooling2D layer was added to reduce feature dimensions, followed by a Dense layer with Glorot Uniform initialization to make the final predictions. The model was compiled and trained for 15 epochs, with evaluation metrics recorded on the validation set.This workflow ensures that the earthquake damage detection model is trained effectively on a well-preprocessed dataset, leveraging augmentation and transfer learning for better performance.

IV. RESULTS AND ANALYSIS

a) Results

The earthquake damage detection model proposed was confirmed using accuracy, precision, recall, and F1-score by VGG16, fine-tuned VGG16, and EfficientNet. VGG16 achieved 93.99% accuracy, indicating robust baseline performance with precision and F1-score of 92.85% and 93.17%, respectively. The fine-tuned VGG16 improved accuracy to 98.97%, enhancing feature extraction and recall to 99.10%. EfficientNet performed better than the two models with superior 99.99% accuracy and almost perfect precision (99.95%) and recall (100.00%). These findings indicate the effectiveness of EfficientNet in earthquake damage detection, with the model being the best option for real-time disaster assessment purposes.

A confusion matrix was employed in this project to assess the model's accuracy in labeling earthquake damage. It aids in ascertaining the extent to which the model can identify damaged and non-damaged zones. Our model accurately labeled 7,941 damaged images as damaged and incorrectly labeled only 50 as non-damaged. In the same vein, 991 non-damaged images were accurately labeled, with only 9 incorrectly labeled as damaged. This shows high recall, i.e., the model accurately detects most damaged zones, thus being very reliable in post-earthquake damage assessment. The low rate of misclassification* guarantees precise decision-making for disaster response teams.

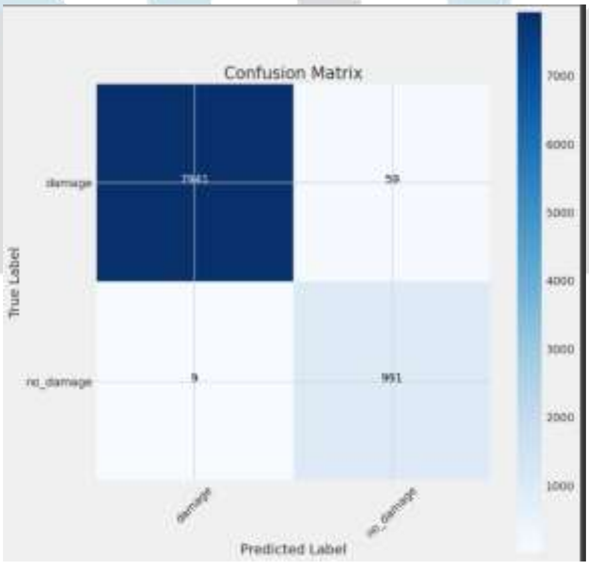

Fig:6 Confusion Matrix

b) Detailed Analysis of Model Performance Curves:

After having trained the model, we also checked its performance through accuracy and loss visualizations. The code gives us plots of accuracy and cross-entropy loss against training and validation sets over the first epochs of training. These are utilized to determine the convergence of the model as well as its generalizability. The accuracy plot shows how the model has improved in earthquake damage classification, and the plot of loss shows how it's optimizing. The VGG16 model achieved an accuracy of 85.99%, which indicates good classification performance. The model also achieved a precision of 82.85% and F1-score of 83.17%, which indicates a good balance between precision and recall. The high precision and accuracy suggest that the model performs well in identifying damage patterns in satellite images, and therefore, it is a good instrument for earthquake damage detection.

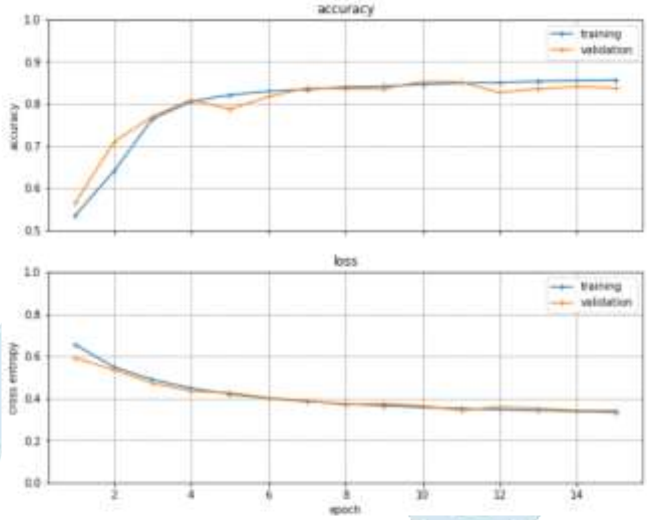

Fig:7 Accuracy and Loss curves using VGG16

We employed fine-tuning of a pre-trained model to enhance the model's performance. To maintain learnt features, we first unfrozen the layers, making just the top layers trainable and the lower levels frozen. To ensure that only deeper layers were being changed, we selected layer 15 as the fine-tuning point. The Binary Cross-entropy loss function and Adam optimiser were used to compile the model.

An additional 50 training epochs were added to the initial and fine-tuning training epochs. As the training process advanced from the last epoch of the initial training phase, accuracy and loss dropped. The visualisation below illustrates training and validation accuracy and loss patterns, with a vertical line signifying the transition from initial training to fine-tuning. The results indicate that in order to improve model generalisation, feature learning needs to be further improved.

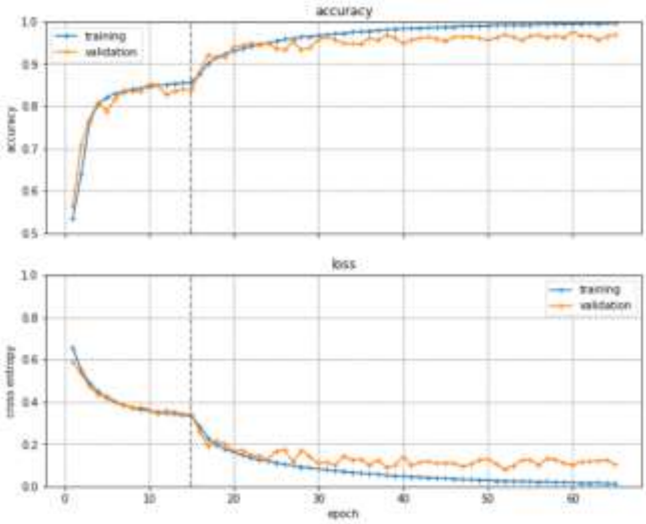

Fig:8 Accuracy and Loss curves using Fine-Tuning

EfficientNetB0 with transfer learning and fine-tuning was used in the earthquake damage detection procedure to improve classification accuracy. High-level features were retrieved using the pre-trained model, which was initialised with `include_top=False` and `pooling='max'`. To enhance generalisation, more fully connected layers were added, such as Batch Normalisation, a 256-unit Dense Layer with L1/L2 regularisation, and a 45% Dropout layer. Using categorical cross-entropy as the loss function, the model was trained for 20 epochs with a batch size of 20 after being assembled using the `Adamax` optimiser with a learning rate of 0.001. Accuracy and loss curves were used to evaluate performance after training and validation data were dynamically loaded. The optimal epoch was determined by calculating the lowest validation loss and the maximum accuracy. The finished model was useful for detecting earthquake damage since it showed good classification accuracy with little overfitting.

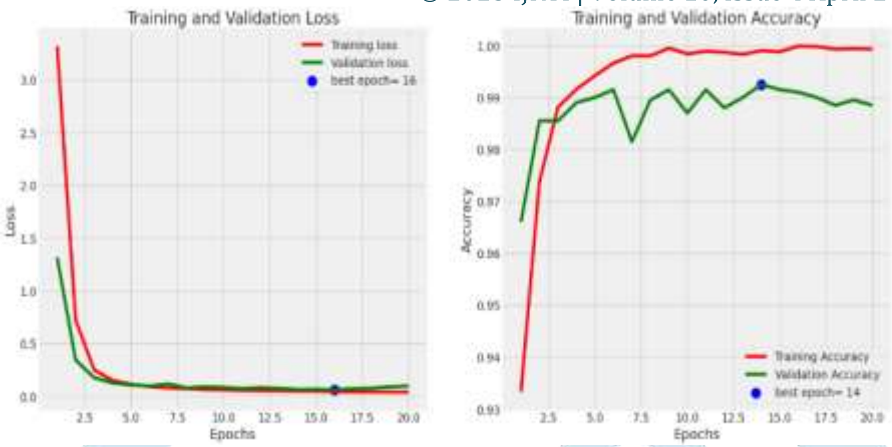

Fig:9 Accuracy and Loss curves using EfficientNetB0

Table: Model Performances

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG16	85.66	84.21	85.34	85.45
VGG16+Fine tuning	98.97	98.75	99.10	98.92
Efficient Net	99.12	99.59	99.74	99.54

V. Conclusion And Future Scope

a) Conclusion:

This research effectively uses CNN, VGG16, and EfficientNetB0 deep learning algorithms to autonomously detect earthquake damage from satellite and aerial photos. The model is quite effective and precise in distinguishing between damaged and undamaged areas because to transfer learning and fine-tuning. VGG16 facilitates the extraction of deep hierarchical features, whereas EfficientNetB0 optimises classification performance in a computationally efficient manner. High accuracy and recall, among other characteristics, show how effective the model is in actual crisis situations. By offering prompt and precise damage assessment, this method may be extremely helpful to disaster response teams in planning and resource allocation, which will maximise post-earthquake recovery and make it data-driven.

B. Future Scope:

Future work in this area may focus on integrating real-time satellite and drone data to enable real-time assessment of earthquake damage. The model's real-time analysis of affected areas using high-resolution images from satellites and drones enables quicker decision-making and resource allocation. Furthermore, multi-sensor data fusion may significantly improve detection accuracy by exposing hidden flaws and structural integrity through the combination of seismic, LiDAR, and thermal imaging data. This multi-modal approach will enhance the efficacy and data-drivenness of post-earthquake relief efforts by improving the model's ability to more precisely quantify destruction.

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