Earthquake Damage Assessment

A Report Submitted
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Bachelor of Technology
in
Computer Science & Engineering

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UNDERTAKING

I declare that the work presented in this report titled " Earthquake Damage Assessment" submitted to the Graphic Era Hill University, Dehradun is my original work.
I have not plagiarized or submitted the same work for the award of any other degree. In case this undertaking is found incorrect, I accept that my degree may be unconditionally withdrawn.

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CERTIFICATE

Certified that the work contained in the report titled
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Preface

As part of our B.Tech. curriculum, I had to make a report on the fascinating domain of assessing the damage caused by natural disasters using advanced tools like Convolutional Neural Networks (CNN) and image classification using BigTransfer (BiT). The project is aimed at assessing the damage caused by natural disasters like earthquake using deep learning.

In this report, I have explain how I did it. I talk about using convolutional neural networks (CNN) to figure out the patterns in what the computer sees and then classify them into categories based on the severity of the damage. This helps the computer identify and categorize the severity of the damage with high accuracy.

Overall, this project was a great learning experience that allowed me to apply theoretical concepts to real-world scenarios, giving us practical skills and knowledge that will be useful in the future.

Acknowledgements

It is my immense pleasure to thank the giants on whose shoulders I stand. First, I would like to thank my supervisor, Dr. Amit Gupta Sir for giving me much-needed support and guidance throughout our project duration. His advice, encouragement, and criticism were the primary sources of inspiration and innovation for me. Lastly, I would like to thank the panel members for providing me with their valuable time in evaluating this project and giving me valuable insights. I would also like to thank my family and friends for giving us help when we needed it.I would also like to thank the computer science department for giving ME the facilities and resources to work on our project.

Contents

0.1 Abstract

In today's technologically advanced world, technology plays a pivotal role in simplifying people's lives. One area where deep learning shines is in damage assessment caused by natural disasters.

Deep learning, a sophisticated form of machine learning based on intricate artifi- cial neural networks (ANNs), is commonly employed to accurately identify damages using data from images. In our study, we propose a model based on convolutional neural network (CCN) architectures to detect damages caused during earthquakes. By utilizing an extensive image dataset that encompasses a broad spectrum, I have constructed a robust statistical model.

Keywords: Deep Learning, CCN.

Chapter 1

Introduction

Introduction In this mini-project, I have proposed an innovative approach to damage severity assessment system using Convolutional Neural Networks (CNN) and Image Classification Using big-transfer (BiT) networks. Motivated by the growing demand for accurate and efficient techniques in computer vision, my goal is to develop a robust system that can accurately identify and classify severity of damages from images. By leveraging the power of deep learning, I hope to revolutionize human- computer interaction and enable advancements in the field. In this report, I will present our novel methodology, experimental results, and comparative analysis and will highlight the potential impact of my proposed approach on the field of assessment of severity of damage.

1.1 Rapid Damage Assessment

Within the first 48 to 72 hours of a disaster, humanitarian organizations carry out rapid damage assessments, which are seen to be essential to many disaster management efforts. In order to conduct emergency rescue and relief efforts, first responders can better comprehend the impacted areas and the amount of the damage by assess- ing the severity of damage. Humanitarian groups also select priority locations for in-depth assessments in order to provide long-term relief and rehabilitation for the impacted community, depending on the findings of their first damage assessment.

Conventional methods for conducting rapid damage assessments, however, necessitate sending specialists to the disaster-affected area to carry out field assessments. These methods involve taking images of the destroyed infrastructure, speaking with locals, and gathering pertinent information from other trustworthy sources. The professionals conduct evaluation and interpretation of the collected information prior to composing a report intended for planners and decision-makers. A couple of the difficulties faced by field assessment specialists include scarce human resources and unfavorable living conditions in the catastrophe location. The collection of data, the evaluation of the damage, and eventually the rescue efforts might all be delayed by such issues. Social media posts that include images can provide vital information about humanitarian relief efforts. The analysis of visual data provided on Twitter following the Nepal earthquake in real time was the main focus of this study.

1.2 NeuralNetwork

Neural Networks are made up of layer-organized, networked neurons or nodes. An input signal is received by each neuron, which then applies an activation function to process the signal and generate an output signal. In order for neural networks to execute tasks like pattern recognition, regression, and classification, they must first be trained with data in order for them to identify patterns and relationships.

1.2.1 Convolutional Neural Network

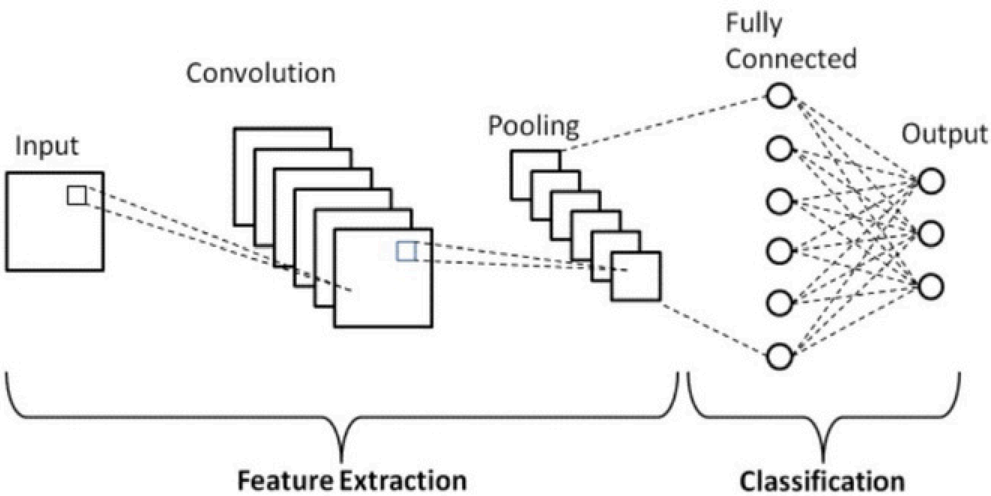
Convolutional Neural Network is what CNN stands for. It is a kind of artificial neural network that is frequently applied to computer vision and image recognition tasks. Animal visual processing processes, particularly the human visual cortex, serve as an inspiration for CNNs.

- Convulational layers: These layers are made up of filters, sometimes known as kernels, which glide over the input image and carry out convolution-like operations. Certain aspects of the image, including edges, textures, or forms, are extracted by each filter. To create a collection of feature maps, various filters are used to capture various facets of the input image.

- Pooling Layers: Pooling layers reduce the dimensionality of the feature maps by downsampling them after convolution. The two most popular pooling techniques, max pooling and average pooling, retrieve the most important characteristics from each feature map region.

- Activation Function: The output of convolutional and pooling layers is subjected to non-linear activation functions such as ReLU (Rectified Linear Unit). By adding non-linearity to the network, these functions let it to recognize intricate correlations and patterns in the input data.

- Fully Connected Layers: After being flattened, the output from the pooling and convolutional layers is routed through one or more fully connected layers. By teaching themselves to map the retrieved features to particular output classes, these layers carry out categorization.



CNN : Convolutional Neural Network

1.2.2 Image Classification using BigTransfer (BiT)

BigTransfer, or BiT, is a cutting-edge approach to transfer learning for image classification. When training deep neural networks for vision, transfer of pre-trained representations reduces hyperparameter tuning effort and increases sampling efficiency. BiT reexamine the traditional method of fine-tuning the model on a target task after pre-training on big supervised datasets. the significance of increasing the architectural capacity as the amount of pre-training data increases and selecting normalizing layers suitably. Given below is the explanation of how BiT works:

- State-of-the-Art Transfer Learning:: By fine-tuning on certain target tasks and pre-training on huge supervised datasets, BiT makes use of transfer learning. This method simplifies hyperparameter adjustment for deep neural network training in image classification and greatly improves sampling efficiency.

- Normalization Layer Selection: 2. BiT emphasizes the importance of appropriately choosing normalization layers during pre-training. This optimization ensures better performance and stability across different datasets and tasks.

- Architecture Scaling: BiT dynamically scales the architecture capacity based on the amount of pre-training data available. This scalability ensures optimal utilization of resources and improves the adaptability of the model to diverse datasets and tasks.

- Accessibility:BiT provides pre-trained models and code implementations in TensorFlow 2, Jax, and PyTorch. This accessibility empowers researchers and practitioners to achieve state-of-the-art performance on their specific tasks, even with limited labeled data per class.

Chapter 2

Related Work

Several studies have underscored the importance of imagery in disaster response, utilizing various sources such as aerial and satellite photos. For instance, Turker and San (2004) analyzed post-seismic aerial photos to assess infrastructure damage following the Izmit earthquake in Turkey. Plank (2014) discussed Synthetic Aperture Radar (SAR) techniques for damage assessment, comparing them with optical sensors. Conversely, Fernandez Galarreta et al. (2015) and Attari et al. (2017) emphasized the value of Unmanned Aerial Vehicle (UAV) photos in damage assessment, while Ofli et al. (2016) highlighted the drawbacks of satellite photography.
Researchers have also explored social media image analysis for disaster response, as seen in the work of Daly and Thom (2016) and Mouzannar et al. (2018). Daly and Thom (2016) examined photos from social media to identify regions affected by fires using geotagged data, while Mouzannar et al. (2018) focused on damage detection, categorizing harm to people and the environment.

Traditional methods like SAR techniques and satellite image processing have been utilized in past research for damage assessment, but they can be time-consuming and rely on costly data sources. Hence, there's a growing interest in utilizing non-traditional sources like social media for quick damage assessment. Our work, inspired by Nguyen et al. (2017), employs an image processing pipeline to leverage Twitter photos for real-time damage evaluation, integrating human-in-the-loop and deep learning techniques to streamline the process.

Chapter 3

Methodology and Results Analysis

3.1 DataSetCollection

This study uses the social media dataset . The dataset includes images of Nepal Earthquake Disaster dataset. The dataset included images with three different types of class information:

(i) severe damage
(ii) mild damage
(iii) little or no damage.

Fig. 2 : Overview of sample data image

3.2 Preprocess the Dataset

The photos will then be resized to (128 * 128 * 3), where 3 denotes the RGB component of the image and (128 * 128) denotes its height and breadth. By dividing each pixel value by 255, the image pixel values in the range 0–1 are normalized. Following the necessary preprocessing, the photos are sent straight into the pretrained models' input in order to extract the relevent characteristics.

3.3 Implementing the Model

Using CNN

Once the CNN architecture is established, the model undergoes training using the Adam optimizer with categorical cross-entropy loss. The training dataset, comprising processed images and their associated labels, is utilized to iteratively update the model weights across multiple epochs.

To manage computational complexity and prevent overfitting, certain convolu- tional layers are followed by max-pooling layers, which reduce spatial dimensions of feature maps. Dropout layers are strategically placed after some convolutional and max-pooling layers to randomly drop a fraction of input units during training. A flattening layer converts the output of convolutional layers into a one-dimensional vector, preparing it for input to fully connected layers.

Fully connected dense layers, located at the end of the network, perform classification based on extracted features. These layers incorporate ReLU activation functions and dropout regularization. The final layer, comprising three neurons with softmax activation, generates class probabilities for the multi-class classifica- tion task.

Through iterative refinement and optimization, the CNN model achieves high accuracy in distinguishing disasters.

Using BiT

BigTransfer, or BiT, is a cutting-edge transfer learning technique for classify- ing images. When training deep neural networks for vision, transfer of pretrained representations increases sampling efficiency and simplifies hyperparameter tweak- ing. BiT reexamine the traditional method of fine-tuning the model on a target task after pre-training on big supervised datasets. the significance of increasing the architectural capacity as the quantity of pre-training data increases and selecting normalizing layers suitably.

In this report, we present a TensorFlow-based implementation for creating a dataset and applying transfer learning using the Big Transfer (BiT) model for image classification tasks. The primary objective is to demonstrate a streamlined approach for dataset creation, image preprocessing, and model integration using TensorFlow and TensorFlow Hub.

For transfer learning, we utilize the Big Transfer (BiT) model, which is a state-of-the-art pre-trained image classification model available through TensorFlow Hub.

We instantiate the BiT model using hub.KerasLayer() with the provided module URL, moduleurl.Thispre $- trainedmodelissettobenon - trainable(trainable = False), ensuringthatthepre - trainedweightsarefrozenduringfine - tuning.$

Model Integration: We define an input layer with shape (224, 224, 3) to match the input dimensions required by the BiT model. The output from the BiT model is obtained by passing the input layer through the BiT model, and then, we add a dense output layer with softmax activation to classify images into three categories. This output layer is responsible for making predictions based on the features extracted by the BiT model.

We have presented a comprehensive pipeline for dataset creation, image preprocessing, and transfer learning using TensorFlow and TensorFlow Hub. By leveraging pre-trained models like BiT, we can efficiently tackle image classification tasks with minimal effort in model training and achieve competitive performance.

3.4 Construct the Model

We will use t Conv2D layers to create our CNN architecture, with MaxPooling2D and Dropout layers coming next. Subsequently, the feature retrieved from these Conv2D layers is passed into a layer after being flattened using a Flatten layer. Lastly, the output of this layer is used by a Dense layer with softmax activation to forecast the degree of damage.

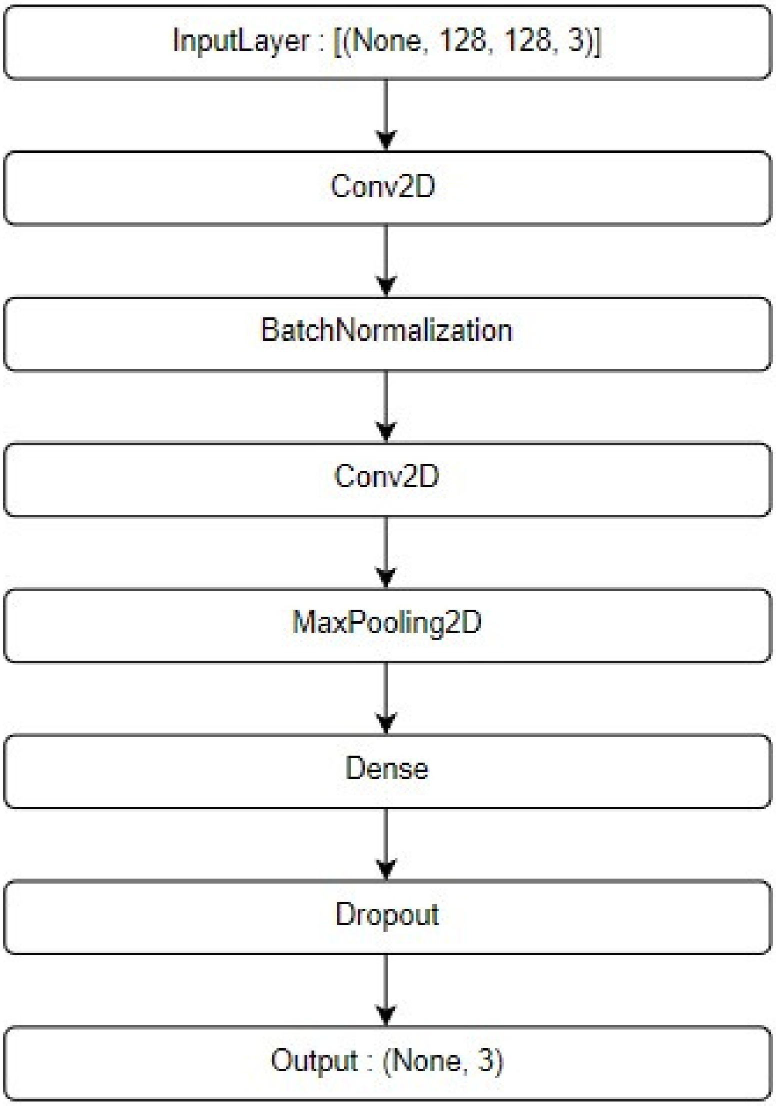


Fig. 3 : Model

3.5 Results

After training the CNN model the accuracy we get on training dataset is to be 96.68% and testing dataset is to be 82.28%. While using the BiT model , the ac- curacy we achieved on training dataset is 90.01% and on the testing dataset it is 84.48%.

Below is the flowchart for the same

	Training accuracy	Test accuracy
CNN Model	96.68%	82.28%
BiT Model	90.01%	84.48%

Fig. 4.1 : Training and Test Result

	precision	recall	f1-score	support
0	0.84	0.85	0.84	1584
1	0.47	0.29	0.37	451
2	0.86	0.92	0.88	1784
accuracy			0.82	3819
macro avg	0.71	0.68	0.69	3819
weighted avg	0.82	0.83	0.80	3819

Fig. 4.2 : CNN Model Result

	precision	recall	f1-score	support
0	0.86	0.86	0.86	1584
1	0.48	0.29	0.36	451
2	0.86	0.95	0.90	1784
accuracy			0.84	3819
macro avg	0.71	0.67	0.68	3819
weighted avg	0.84	0.83	0.81	3819

Fig. 4.3 : BiT Model Result

3.5.1 Result Analysis

- **Accuracy:**

Accuracy measures how well a machine learning model can correctly predict or classify a given set of data.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision:**

Precision is the percentage of true positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall:**

Recall calculates the percentage of true positive predictions out of all actual positive cases in the data.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **Accuracy & Loss:**

Following are the loss and accuracy curves per epoch:

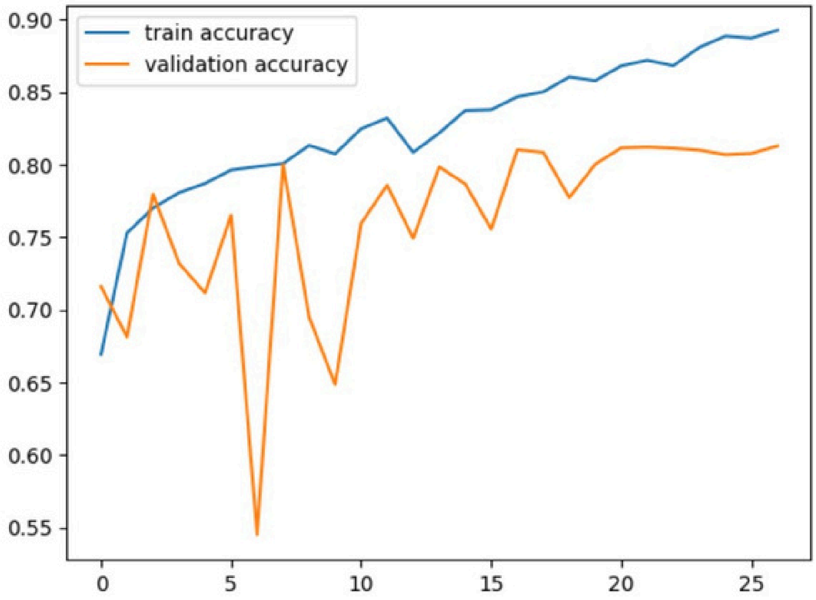


Fig. 5 : Accuracy Curve

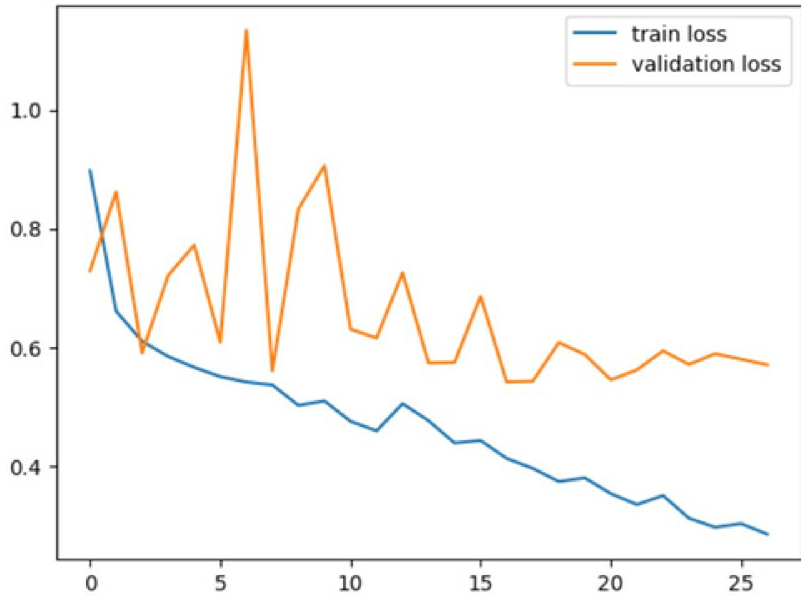


Fig. 6 : Loss Curve

Confusion Matrix:

Confusion Matrix: A confusion matrix is a machine learning tool that evaluates the performance of a classification model. The table displays the true positive, true negative, false positive, and false negative values for each class in the model. These values are used to compute metrics like as accuracy, precision, recall, and F1 scores. The confusion matrix for test data is as below:

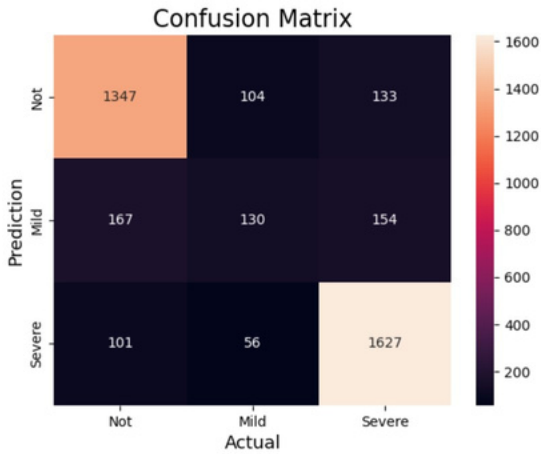


Fig. 7 : Confusion Matrix

Chapter 4

Conclusion and Future Work

4.1 Conclusion

Big data—produced by social media platforms, for example—supplants conventional, standard data sources like space and aerial-based remote sensing during emer- gencies by offering never-before-seen access to real-time, on-the-ground information. Resolution constraints make it particularly difficult to acquire data and information for metropolitan areas, on top of the inherent gaps in remote sensing data caused by platform or revisit restrictions or atmospheric interference. Prioritizing site visits for assessment is made possible by seeing possible damage at the block or street level. However, because of its scale, complexity, and, in the case of social media, hetero- geneity (diversity), using big data effectively is difficult. This study offers a novel approach to identifying environmental hazards from user-contributed data on social media. An estimate of the damage can be produced once the remote sensing data have been gathered and combined with contributing data. Social media platforms are useful for pinpointing ”hot spots” inside cities, although other sources offer more precise information at the street level (such as images). Contributed ground data offer a another source of information because revisit times and cloud cover can also limit the amount of data obtained via remote sensing.

In addition, we’ve found that using Google Colab as our main modeling software application has greatly expedited the procedure. By utilizing Google Colab's cloud-based infrastructure, we have been able to reduce storage limitations and develop and run sophisticated machine learning models without straining our local computing resources. Our codebase is accessible and portable thanks to the easy interface with Google Drive, which enables us to work together and refine our research from any place and on a variety of computer systems.

Essentially, our findings highlight how machine learning can be a game-changer when it comes to addressing practical problems like disaster damage assessment. Through pushing the limits of model architecture and utilizing cutting-edge software programs like Google Colab, we open up new avenues for precise, effective, and user- friendly approaches to comprehending and deciphering human behavior from visual data. This study has implications for a wide range of applications, from robotics and surveillance to healthcare and beyond.

4.2 Future work

Currently, our machine learning model has been trained to assess damage on social media images. However, we plan to expand our capabilities in the future by incorporating additional data sources and types of media for more comprehensive damage assessment. Specifically, we aim to:

Integration of Drone Shot Images: In the future, we intend to incorporate drone-shot images into our assessment framework. Drone imagery provides high- resolution, bird's eye views of disaster-affected areas, offering valuable insights into damage extent and severity. By leveraging this Visual Representation Learning. In Proceedings of the 34th additional data source, we aim to enhance the accuracy and granularity of our damage assessments.

Text-Based Damage Assessment: Beyond visual data, text data from so- cial media posts, news articles, and other sources can provide valuable context and information about the impact of disasters. We plan to develop natural language pro- cessing (NLP) algorithms to analyze text data and extract relevant insights related to damage assessmennt.

Video Data Analysis:: Video footage captured during and after disasters can offer dynamic insights into the evolving situation on the ground. We aim to develop machine learning models capable of analyzing video data to assess damage in real-time. By extracting relevant features and patterns from videos, we can augment our damage assessment capabilities and provide timely information to support response and recovery efforts.

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