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DETECTION OF POST - EARTHQUAKE DAMAGE SEVERITY FROM SATELLITE IMAGES USING VGG19

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ABSTRACT

Effective assessment of building damage following earthquakes is crucial for prompt emergency response and allocation of resources. In this study, we propose an integrated approach that combines high-resolution building inventory data, earthquake ground shaking intensity maps, and post-event InSAR imagery analysis aided by recent advances in machine learning algorithms. Our methodology involves the utilization of ensemble models in a machine learning framework to classify the damage state of buildings affected by earthquakes. We leverage post event very high-resolution remote sensing imagery to identify collapsed buildings, with a particular focus on the potential of Convolutional Neural Networks (CNNs) in extracting deep features for this purpose. We compare the performance of CNN features with texture features using the Random Forest classifier. Additionally, we employ VGG19, a pre-trained deep learning model, to gain insights into the defining characteristics of images in terms of shape, color, and structure. The results of our approach are visualized through color-coded satellite images, where completely damaged buildings are represented in red, partially collapsed buildings in blue, and basically intact buildings in green. Regions marked in red denote areas requiring urgent assistance and support. The integration of remote sensing data, machine learning algorithms, and visual representations enhances the effectiveness of earthquake damage assessment and aids in facilitating timely and targeted emergency response efforts.

Keywords:

Remote sensing data, Ground shaking intensity maps, Color-coded satellite images, Emergency response.

INTRODUCTION

When earthquakes strike, it's really important to quickly figure out how much damage buildings have suffered so that rescue teams can help people effectively. This is where satellites come in handy. Satellites use different techniques like SAR, LiDAR, and optical imaging to take detailedpictures of areas affected by the earthquake from space. These methods are good because they cover large areas, give accurate results, and don't need lots of people on the ground to work. For example, SAR can see changes on the ground, LiDAR measures how tall buildings are, and optical images show what damaged buildings look like. By using all these methods together, we can tell exactly how much damage buildings have after an earthquake.

One way scientists figure out building damage is by using something called object-based image analysis (OBIA). They take the satellite images and divide them into smaller parts, then use computer programs to figure out if each part is damaged or not. OBIA is helpful because it's fast and accurate, looking at things like color, texture, and shape to decide if something is damaged. It's better than just looking atone dot at a time because it looks at the whole picture. For example, OBIA was used to find damaged buildings after the earthquake in Bam, Iran in 2004.

But scientists are also trying out new ways to find building damage, like using deep learning with CNNs. These are computer programs that learn from lots of pictures and can quickly tell if something is damaged or not. There are different types of CNNs, like GoogleNet and VGG, which aregood at recognizing things in pictures. But we're still learning how well they work for finding earthquake damage. For example, a SqueezeNet was used to find collapsed buildings after the earthquake in Haiti in 2010whichshows that this technology might be really helpful in responding to disasters.

LITERATURE SURVEY

Remote sensing technology has emerged as a critical tool for rapid and accurate identification of earthquake-damaged buildings, aiming to mitigate the ecological and environmental destruction wrought by seismic events. Earthquakes not only result in heavy casualties and economic losses but also trigger secondary disasters such as environmental pollution and solid waste accumulation. The challenges posed by such large-scale natural disasters are compounded by obstacles to ground transportation and communication, hindering immediate on-site assessments. Consequently, leveraging remote sensing technology becomes imperative for efficient extraction and monitoring of earthquake damage information.

Traditionally, earthquake-damaged building extraction methods have predominantly focused on single-temporal detection technologies due to the difficulty in obtaining pre-earthquake images of the same area. These methods primarily fall into two categories: pixel-based detections and object-oriented detections. Pixel-based classification methods, while simple, often fail to fully exploit the rich spatial information available in high-resolution seismic images, leading to misclassification of ground objects and reduced accuracy. Object-oriented detection methods, on the other hand, offer a more promising approach by segmenting images into meaningful homogeneous regions and then classifying each region based on a combination of spectral, shape, texture, semantic, and topological information.

However, traditional object-oriented classification methods suffer from limitations such as inaccurate spatial relations between objects and segments, leading to imprecise extraction results. Moreover, these methods often require a large number of parameters to be manually specified, introducing subjectivity and reducing classification accuracy. To address these challenges, researchers have emphasized the importance of representative object features in seismic image information extraction.

Various feature-based building extraction methods have been proposed, focusing on spectral features, normalized difference vegetation index (NDVI), modified normalized difference water index (MNDWI), texture features, and mathematical morphology. Mathematical morphology, in particular, shows promise in exploring building features by extracting characteristics of intact and collapsedbuildings using different shaped structuring elements.

Recent advancements in morphological methods for building detection have yielded promising results. Zhang proposed a straightforward building detection method based on filtering vegetation at significantly smaller scales. Vu integrated LiDAR data within a multi-scale morphological space to conduct building detection via clustering methods. Chen enhanced progressivemorphological filtering by incorporating a region-growing algorithm based on RANSAC. Huang introduced a novel morphological building index (MBI) for automatic building extraction.

Despite these advancements, previous studies have predominantly focused on the extraction of intact buildings, neglecting the critical aspect of identifying collapsed buildings. This limitation renders existing methods unsuitable for seismic damage information extraction, highlighting the need for innovative approaches tailored specifically for this purpose.

In conclusion, remote sensing technology holds immense potential for facilitating rapid and accurate identification of earthquake-damaged buildings. While traditional method have made significant strides in leveraging spectral, shape, texture, and mathematical morphology-based features, there remains a pressing need for novel approachesthat address the challenges associated with accurately extracting seismic damage information, particularly the identification of collapsed buildings. By advancing the state-of-the-art in feature-based extraction methods and overcoming the limitations of traditional object-oriented classification techniques, researchers can contribute to more effective disaster response and mitigation strategies, ultimately minimizing the ecological and environmental impact of seismic events.

EXISTING SYSTEM:

The existing system utilizes pre and post-event very high-resolution remote sensing imagery to identify collapsed buildings. Convolutional Neural Networks (CNNs) is used to extract deep features for identifying collapsed buildings from the imagery data. In addition, a random forest classifier is utilized to compare the texture features and CNN features for classification purposes. The results indicate that the CNN feature with the random forest method achieves an Overall Accuracy of 87.6%. However, the existing system faces several challenges.

Drawbacks:

- Classification of Images with different positions isdifficult.
- Needs high resolution images.
- Large datasets are required, training takes longer time

PROPOSED METHOD

- VGG19 (Visual Geometry Group) is an advanced CNN algorithm used in the proposed system.

- From Post - earthquake satellite images, Output displays completely damaged buildings in red, partially collapsed buildings in blue, and intact buildings in green.

- The visual representation of color-coded satellite images will enhance the effectiveness of emergencyresponse.

Advantages

- Precision in damage assessment.
- Advance Machine learning Integration.
- Effective communication through visualization.

METHODOLOGY

Data Collection:
Obtain pre and post-event satellite imagery of the area affected by the 2010 Haiti earthquake.

Feature Extraction:
Extract texture features from the satellite images, such as patterns and variations in pixel intensity, to represent building characteristics.

Image Preprocessing:
Prepare the satellite images for analysis by removing noise, correcting distortions, and enhancing features.

Convolutional Neural Network (CNN) Training:
Train a CNN model using the pre- and post-event satellite images to learn features relevant to distinguishing collapsed and non-collapsed buildings.

Model Evaluation:
Evaluate the performance of the CNN model in distinguishing collapsed and non-collapsed buildings using a validation dataset.

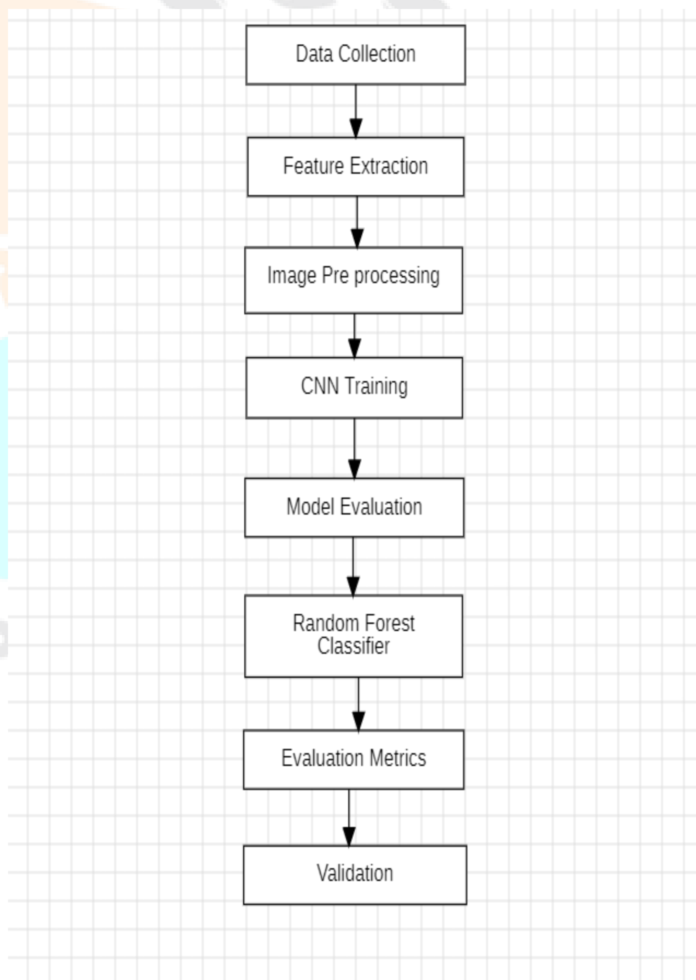
Random Forest Classifier:
Train a random forest classifier using the features extracted from the satellite images texture features and features learned by the CNN).

Model Comparison:
Assessing Performance: CNN Model vs Random Forest Classifier in Differentiating Collapsed and Non-collapsed Buildings.

Integration:
Combine the learned features from the CNN model with the random forest classifier to improve classification accuracy.

Evaluation Metrics:
Calculate evaluation metrics such as overall accuracy, kappa coefficient, and confusion matrix to assess the performance of the models.

Validation:
Validate the models using additional datasets or cross-validation techniques to ensure robustness andgeneralizability.



MODULE DESCRIPTION

Data Collection:

The earthquake dataset utilized in this project was sourced from Kaggle, comprising three categories: high damage, moderate damage, and no damage. Each category consists of 50 images, with pixel values serving as input and labels as output for training.

Pre-processing:

Pre-processing is crucial for enhancing image quality and improving visualization. Steps involved include background elimination, removal of non-essential blood supplies, imageenhancement, and noise removal. These procedures ensure that the subsequent phases of the methodology yield accurate results by addressing issues that may impede visualization.

Train-Test Split and Model Fitting:

The dataset is divided into training and testing sets to evaluatemodel performance on unseen data and assess its generalization capability. Model fitting involves training the selected algorithms on the training data.

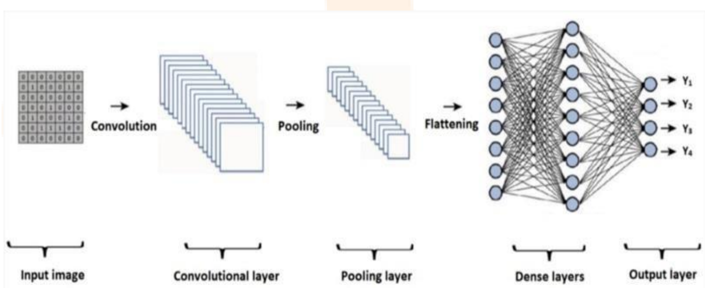
Model Evaluation and Predictions:

In the final step, the model's performance is evaluated on the testing data using scoring metrics, with the accuracy score being the chosen evaluation metric. The process involves creating a model instance, fitting the training data, makingpredictions on the testing data, and calculating the accuracy score. This evaluation is conducted for various classification algorithms, with the corresponding test accuracy scores summarized for each algorithm.

ALGORITHM AND PROCESS

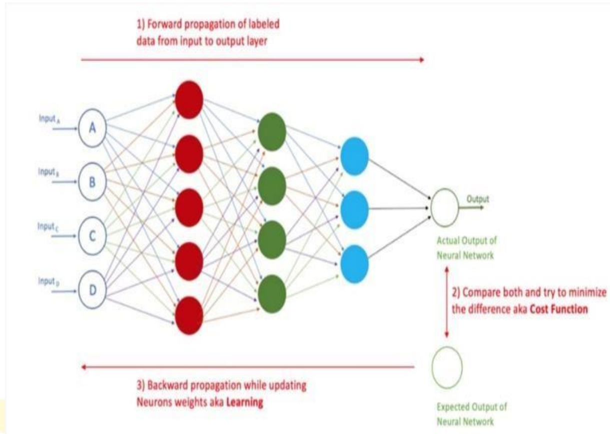
CNN Architecture:

CNN contain a combination of layers which transform an image into output the model can understand.



Process :

During forward and backward propagation, the neural network processes all training samples to adjust weights until optimal values are found. Only the most influential and predictive neurons are activated to make accurate predictions.



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VGG 19 Model :

Load your model: Get your VGG19 model ready.

Prepare your data: Ensure your dataset is ready, with images labeled as either having trees (target = 1) or not having trees (target = 0).

Extract and freeze VGG19's initial layers: Set up a function to extract and freeze the pre-trained layers of VGG19, which will allow it to utilize transfer learning.

Apply the function to your datasets: Use the function to extract features and labels from your training, validation, and test datasets.

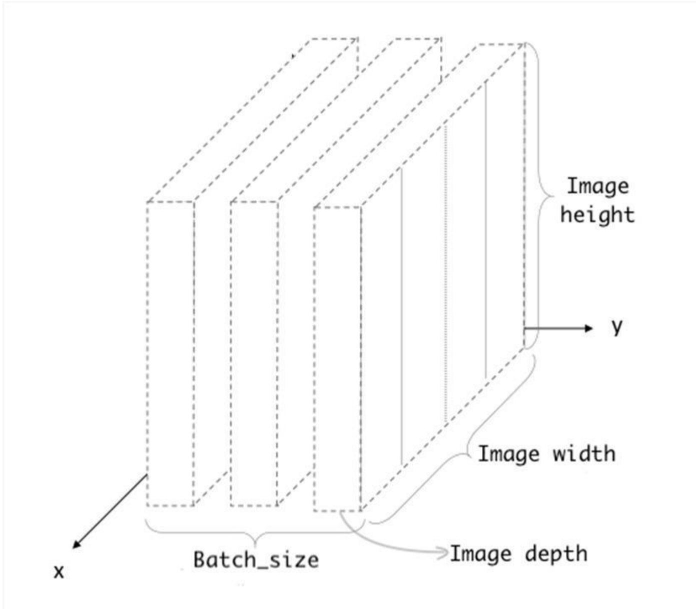
Format your data: Make sure your data is properly shaped tofit the model's requirements.

Save extracted features and labels: Store the extracted features and labels in a separate folder for easy access by the final classification layer.

Build the classification layer: Add a shallow neural network on top of the pre-trained VGG19 layers to create your image classifier.

Evaluate training performance: Print the training history, showing how accuracy increases and loss decreases with each epoch, demonstrating how well the model learns over time

Input :



Batch size:
This refers to how many images or examples are processed together during one training cycle. A larger batch size consumesmore memory.

Height & Width:
These are the dimensions of your image, representing its size inpixels.

Depth:
This indicates the number of color channels in the image. For colored images, this is typically 3 (for Red, Green, and Blue), while for black and white images, it's 1.

So, the input data for a model is structured as a 4D array, with the batch size indicating how many images are processed at once, and the height, width, and depth specifying the dimensions and color information of each image.

RESULT AND ANALYSIS

Figure 1

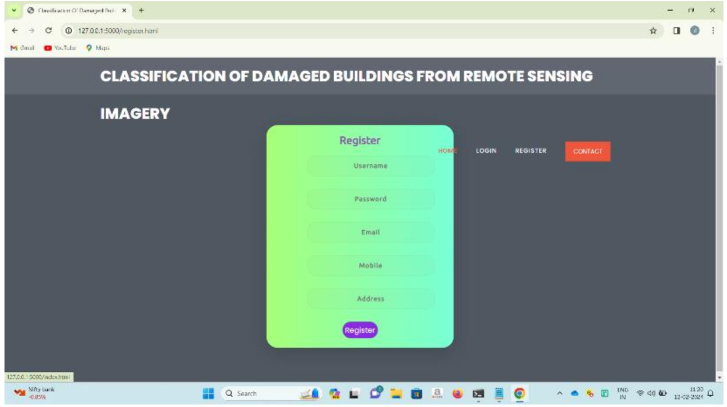


Figure 2

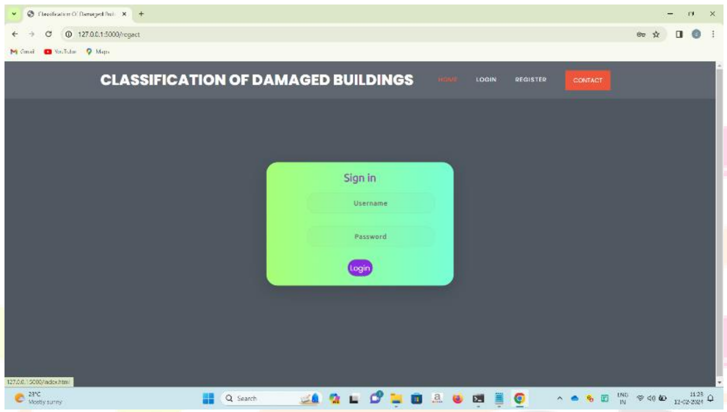


Figure 3

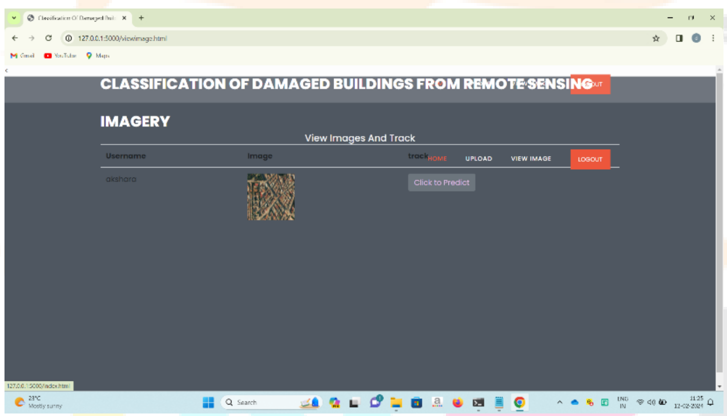
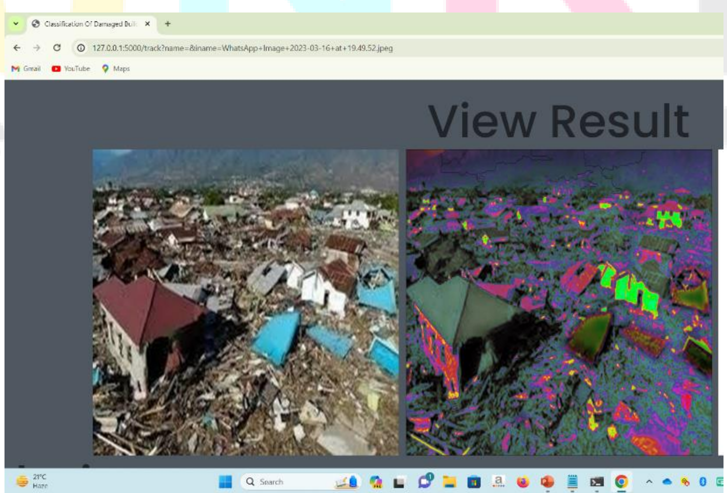


Figure 4



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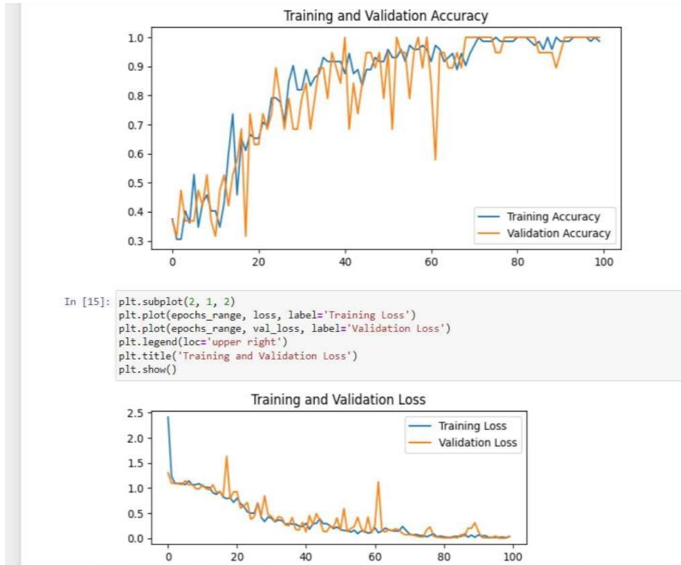

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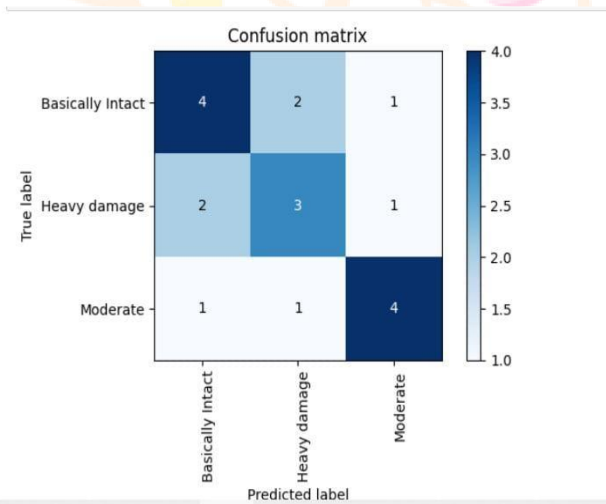

Figure 7

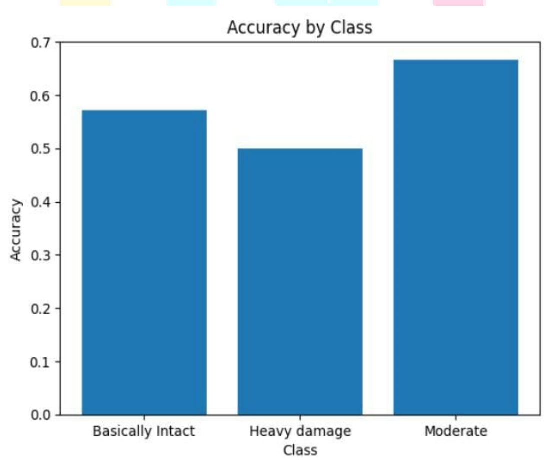

Figure 8

CONCLUSION

This is an integrated approach combining high-resolution building inventory data, earthquake ground shaking intensity maps, and post-event InSAR imagery analysis with advanced machine learning algorithms for effective earthquake damage assessment. By leveraging Convolutional Neural Networks (CNNs) to extract deep features from remote sensing imagery, we enhance the identification of collapsed buildings.

We compared CNN features with texture features using the Random Forest classifier and utilized the pre-trained VGG19 deep learning model for image characteristic analysis.

Our results, depicted through color-coded satellite images, clearly highlight completely damaged buildings in red, partially collapsed ones in blue, and intact buildings in green. Red-marked regions denote areas needing urgent assistance, aiding targeted emergency response. The integration of remote sensing data, machine learning algorithms, and visual representations enhances earthquake damage assessment efficacy. Providing timely information, our approach facilitates swift and efficient emergency responses, minimizing earthquake impact and saving lives in affected communities.

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