iJRASET
International Journal For Research in
Applied Science and Engineering Technology

# INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

**Volume:** 13 **Issue:** VIII **Month of publication:** August 2025

**DOI:** https://doi.org/10.22214/ijraset.2025.73939

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
*ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538*
*Volume 13 Issue VIII Aug 2025- Available at www.ijraset.com*

# Smart Classification of Damaged Buildings through Remote Sensing

V Ankitha[1], Dr. V Uma Rani[2], Dr. Sunitha Vanamala[3]
[1]*Post Graduate Student, MCA, Department of Information Technology, Jawaharlal Nehru Technological University, Hyderabad, India*
[2]*Professor and Head of Dept., Department of Information Technology, Jawaharlal Nehru Technological University, Hyderabad, India*
[3]*Lecturer, Department of Computer Science, TSWRDCW, Warangal, Telangana, India*

***Abstract: This study proposes a framework for semi-automated assessment of building damage caused by earthquakes using remote sensing imagerydatasets, combined with advanced machine learning techniques. The framework uses high-resolution post-event InSAR images. A machine learning approach is employed to classify the damage states of buildings in earthquake-affected areas. Multi-class damage classification are performed for earthquake events. The binary classification successfully identified over fifty percent of damaged buildings in previous studies. The multi-class damage classification using InSAR data represents a relatively novel application, and the case studies presented highlight one of the first such efforts to leverage InSAR imagery for building-level damage assessment using CNN model.***
***Keywords: Earthquake damage assessment, Remote sensing, InSAR, Machine learning, Building classification, Multi-class classification, Binary classification, Post-disaster analysis, Structural damage detection, Disaster management***

## I. INTRODUCTION

Buildings are vital components of human settlements, yet they are highly vulnerable to natural disasters, especially earthquakes. Past events such as the 2008 Sichuan, 2010 Chile, 2010 Haiti, and 2015 Nepal earthquakes caused widespread structural failures, highlighting the urgent need for rapid and reliable post-disaster damage assessment. Accurate building damage information is crucial for guiding emergency response, rescue operations, and recovery planning. However, traditional ground surveys are time-consuming and often impractical in inaccessible or hazardous regions, which has motivated the use of satellite-based assessment techniques.

Remote sensing technologies, including Synthetic Aperture Radar (SAR), LiDAR, and high-resolution optical imagery, provide large-scale and cost-effective solutions for monitoring disaster-affected areas. SAR is particularly effective in detecting surface changes, while optical and LiDAR data support the identification of damaged structures through spatial and height variations. Previous studies have applied methods such as Object-Based Image Analysis (OBIA) and machine learning classifiers, including Random Forest and Support Vector Machines (SVM), to enhance post-earthquake damage detection. Although effective, these approaches often require manual intervention, making them less efficient for rapid assessments.

In recent years, deep learning models, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for automatic feature extraction and image classification. CNN architectures like VGG, GoogleNet, and AlexNet have demonstrated superior performance in image recognition tasks and are increasingly being explored for seismic damage detection. Despite these advances, the application of CNNs in post-earthquake building damage classification remains relatively limited, with only a few case studies demonstrating their potential. This research addresses this gap by leveraging CNN-based models for automated earthquake-induced building damage classification, aiming to improve accuracy, scalability, and speed in disaster response systems.

### *A. Objective*

The primary objective of this research is to develop an automated and accurate framework for earthquake building damage assessment using remote sensing data and machine learning techniques. The goal is to:

*1)* Utilize remote sensing technologies such as Synthetic Aperture Radar (SAR) for large-scale post-disaster assessment.
*2)* Detect surface-level changes using SAR backscatter coefficients and intensity correlations.
*3)* Apply deep learning methods, specifically Convolutional Neural Networks (CNNs), for automated feature extraction and classification of building damage levels.

*4)* Provide a scalable and efficient framework capable of supporting rapid emergency response and recovery operations.

This research aims to bridge the gap between traditional remote sensing methods and modern deep learning approaches, enabling faster and more reliable earthquake damage detection.

## II. LITERATURE SURVEY

Lili Wang et al. [1] conducted a comprehensive review of 242 studies on building damage detection using deep learning models and remote sensing datasets. Their work emphasized the role of remote sensing in post-disaster assessment and categorized existing models into single-temporal and bitemporal approaches. While single-temporal methods, which use only post-event images with convolutional neural networks (CNNs), have shown promising results, the study highlighted significant challenges such as the scarcity of publicly available training datasets and limited accuracy in multi-class classification tasks. Although the review establishes the effectiveness of CNNs, the lack of large, diverse datasets restricts scalability and limits the precision of classification into multiple damage categories.

Zhonghua Hong et al. [2] proposed a novel convolutional neural network called Earthquake Building Damage Classification Net (EBDC-Net) for post-disaster building damage detection using aerial imagery. Unlike many earlier methods that classified buildings only as “intact” or “damaged,” this framework addressed the need for multi-level classification of damage severity. EBDC-Net integrates a feature extraction encoder for capturing semantic information and a classification module that combines global and contextual features to improve accuracy. Evaluated on UAV-based post-earthquake datasets, the approach achieved good accuracy. Despite its success, the model’s performance decreases as the number of damage categories increases, pointing to the difficulty of accurately distinguishing subtle variations in building damage.

Sajitha et al. [3] advanced building damage classification by integrating machine learning models with high-resolution remote sensing imagery. Their study introduced an Enhanced U-Net (EU-Net), designed to capture complex visual signals and improve classification speed and precision. By employing Siamese U-Net architecture, the model simultaneously performed feature extraction and similarity measurement between pre- and post-event images. This design reduced inference time while enhancing predictive accuracy. Results showed that EU-Net outperformed traditional classification methods, making it more effective for real-time disaster management scenarios. However, the model’s reliance on carefully curated training data suggests limitations in adaptability when applied to broader or less-structured datasets.

## III. METHODOLOGY OF PROPOSED SYSTEM

### *A. Proposed System*

The proposed methodology incorporates the VGG19(Visual Geometry Group 19) architecture, a sophisticated convolutional neural network (CNN) model.VGG19 leverages pre-trained layers that offer a deep understanding of visual characteristics such as shape, colour and structural patterns, thereby enhancing image interpretation. The architecture comprises two convolutional layers, followed by 14 pooling layers, and culminates with three fully connected layers. By processing post-earthquake satellite imagery, the system visually categorizes building damage:completely destroyed structures are highlighted in red, partially damaged buildings appear in blue and undamaged or minimally affected structures are marked in green.

### *B. Dataset Description*

The dataset used in this study consists of high-resolution remote sensing images of buildings impacted by earthquakes. The primary goal of this dataset is to support the classification of structures into different levels of damage, thereby enabling accurate and rapid post-disaster assessment. The images are organized into three major categories:

- Intact Buildings: Structures that show no visible signs of damage and remain stable.
- Moderately Damaged Buildings: Buildings that have sustained partial damage but still maintain structural integrity.
- Heavily Damaged Buildings: Structures that are severely impaired or have collapsed completely.

This dataset is vital for training machine learning models to recognize varying damage levels and develop reliable classification systems for post-disaster assessments.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
*ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538*
*Volume 13 Issue VIII Aug 2025- Available at www.ijraset.com*

### *C. System Architecture*

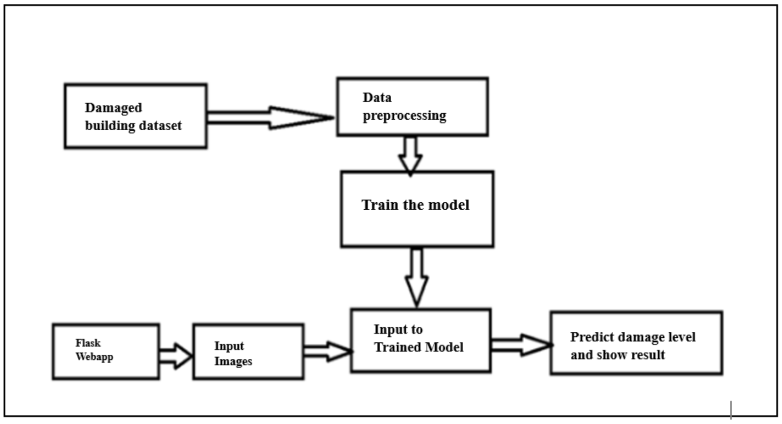



Figure-1: System Architecture of the Smart Classification of Damaged Buildings System

The system architecture for earthquake building damage classification is structured to ensure efficient processing, training, and deployment of the model. It begins with the damaged building dataset, which contains labeled images representing different levels of structural damage. This dataset undergoes data preprocessing, where images are cleaned, resized, and normalized to ensure uniformity and improve model performance.

The preprocessed data is then used to train the model, leveraging a deep learning architecture (VGG19) to learn hierarchical features from the input images. Once trained, the model becomes capable of distinguishing between intact, moderately damaged, and heavily damaged buildings.

For deployment, a Flask web application serves as the user interface. Users can upload input images of earthquake-affected regions, which are passed to the trained model. The model processes these inputs and predicts the building damage category. Finally, the results are displayed in a clear and interpretable format, showing the predicted damage level for each building.

This modular architecture ensures scalability, usability, and real-time applicability, making it suitable for disaster management and rapid response operations.

### *D. Methodology*

The proposed system adopts a structured, multi-stage methodology to classify earthquake building damage using deep learning and remote sensing imagery. Each phase ensures that the model is trained efficiently, produces reliable predictions, and can be deployed for real-time disaster response. The methodology consists of the following steps:

#### *1) Data Preprocessing:*

The damaged building dataset, containing intact, moderately damaged, and heavily damaged images, is first preprocessed. Images are resized to a fixed resolution, normalized for pixel intensity, and augmented through transformations such as rotation, flipping, and scaling to improve dataset diversity and reduce overfitting. This step ensures consistency and improves the robustness of the training process.

#### *2) Model Training:*

A pre-trained VGG19 architecture is employed for feature extraction and classification. Transfer learning is applied by fine-tuning the network on the earthquake damage dataset. The model is trained to learn hierarchical features such as edges, textures, and structural patterns, which are critical for differentiating damage levels.

#### *3) Prediction Process:*

Once trained, the model is capable of categorizing input images into three classes: intact, moderately damaged, and heavily damaged. During prediction, an input image is passed through the trained VGG19 network, which analyzes structural patterns and outputs the predicted damage category.

*4) Web Application Deployment:*

To make the system accessible, a Flask-based web application is developed. Users can upload post-earthquake satellite images through the interface. The application forwards the image to the trained model, which processes it and generates the predicted damage level. Results are displayed in a user-friendly manner for quick interpretation by emergency teams and disaster management authorities.

*5) Result:*

Predicted outcomes are highlighted using a color-coded scheme for better interpretability—red for heavily damaged structures, blue for moderately damaged, and green for intact buildings. This visual representation supports rapid situational awareness and aids decision-making during disaster response.

This methodology ensures an end-to-end framework—from preprocessing and training to deployment and visualization—that is scalable, reliable, and suitable for real-world earthquake damage assessment.

## IV. EXPERIMENTAL ANALYSIS AND RESULTS

*A. Key Features*

1) Automated Damage Classification– Combines pre-processing, feature extraction, and classification in a streamlined workflow for accurate detection of earthquake-induced building damage.
2) Deep Learning Integration – Employs Convolutional Neural Networks (CNNs) for extracting complex features from remote sensing images, enhancing prediction accuracy.
3) Multi-Class Damage Assessment – intact, moderately damaged and heavily damaged assessment.
4) High-Resolution Satellite Imagery Utilization – Works with post-event remote sensing data.
5) Real-World Earthquake – Validated on earthquake datasets to ensure practical applicability.

*B. Results*

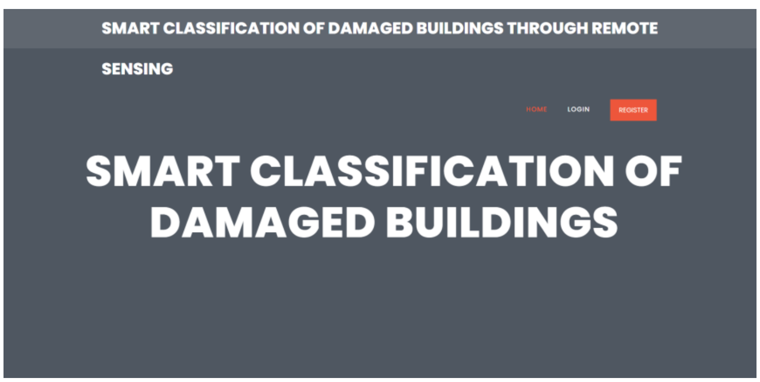



Figure-2:Home Page Interface

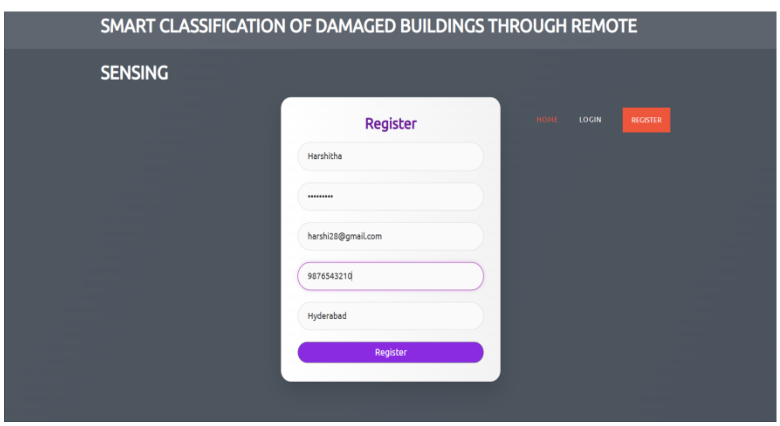



Figure-3:Registration Form

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
*ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538*
*Volume 13 Issue VIII Aug 2025- Available at www.ijraset.com*

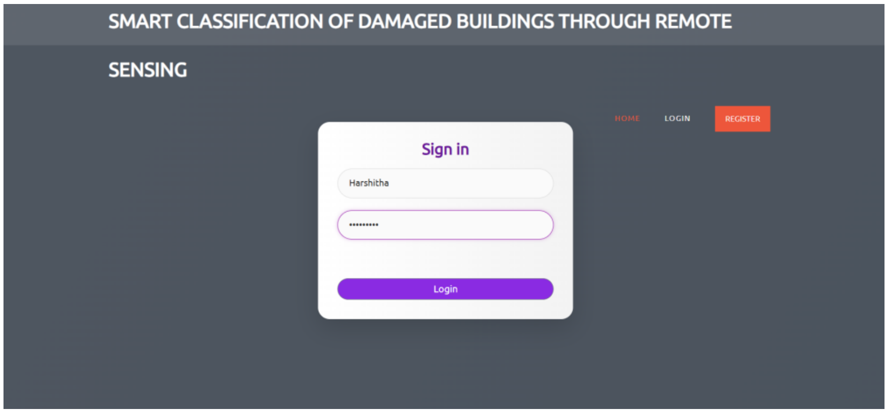



Figure-4: Sign in Page

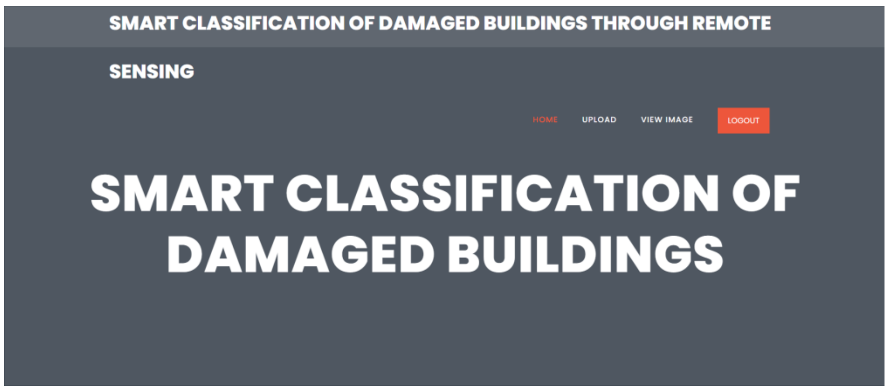



Figure-5: User Dashboard

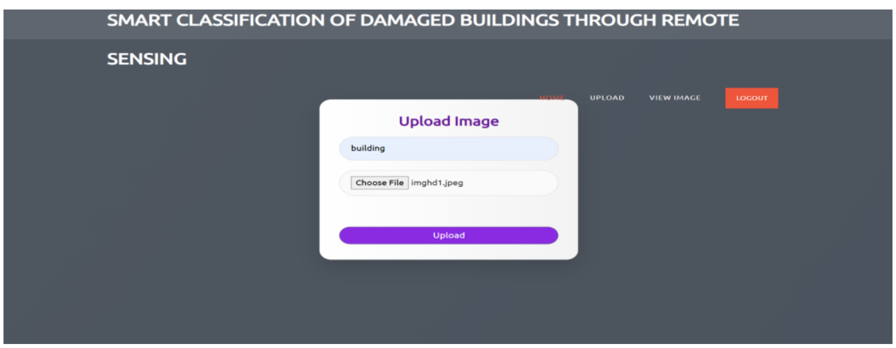



Figure-6: Upload Image Page

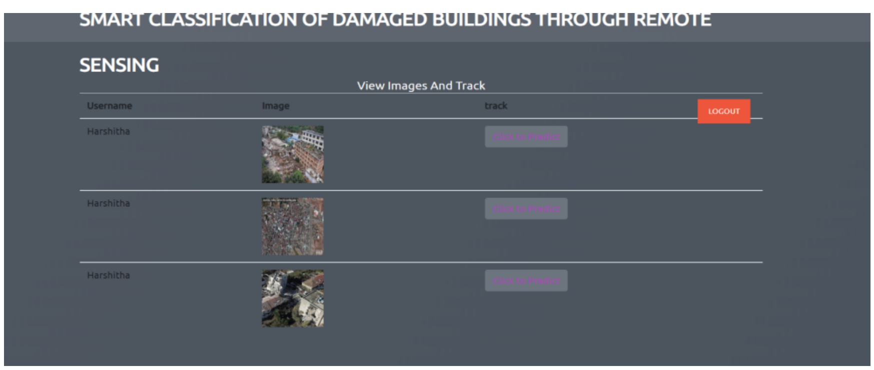



Figure-7: View and Track Interface


Figure-8: Result Page

The proposed Smart Classification of Damaged Buildings system was successfully deployed as a web-based application, providing a seamless interface for users to register, login and upload images. The home screen offered a simple and intuitive workflow, guiding users to select the images and initiate the damage assessment process.

Once images were uploaded, the system processed them using the CNN model then classifying buildings into intact, moderately damaged and heavily damaged. The final results were displayed on the interface, highlighting affected areas with clear markers.

## V. LIMITATIONS AND FUTURE SCOPE

Despite the effectiveness of the proposed damage classification system, several limitations need to be considered. Firstly, the current implementation relies primarily on overhead satellite imagery, which may not capture detailed structural damage in areas with dense urban canopies or occlusions. This constraint can limit the accuracy of damage assessment in regions with complex building layouts. Secondly, the system has been tested on a limited number of earthquake events; therefore, its generalizability to diverse geographical locations and different disaster scenarios may be constrained.

Looking ahead, several opportunities exist to enhance and extend the system. Incorporating additional data sources such as LiDAR, UAV imagery, and oblique aerial photographs can overcome the limitations of traditional overhead satellite images. Utilizing multi-temporal and multi-sensor datasets, including SAR imagery, would improve performance in cloud-covered or obscured regions. Further advancements in AI, including vision transformers, hybrid architectures, and transfer learning, may significantly boost classification accuracy. Moreover, developing real-time processing pipelines integrated with geospatial decision-support platforms can enable faster, more actionable disaster response. These enhancements aim to improve both the technical performance and practical utility of the system for emergency management and post-disaster recovery efforts.

## VI. CONCLUSION

The proposed CNN-based framework for classifying damaged buildings from remote sensing imagery demonstrates significant potential in enhancing the accuracy, speed, and reliability of post-disaster damage assessment. Unlike conventional approaches, which often rely on labor-intensive manual inspections or rule-based techniques with limited adaptability, the CNN model can automatically extract complex spatial and texture features from satellite images, enabling precise differentiation between varying levels of building damage.

By minimizing reliance on human interpretation, the system not only reduces processing time but also ensures consistency and objectivity in classification results. In the context of large-scale natural disasters, such as earthquakes, floods, or cyclones, this capability is particularly valuable, allowing emergency response teams to rapidly identify severely affected areas. Consequently, authorities can prioritize rescue operations, optimize resource allocation, and implement recovery strategies more effectively. Overall, this approach provides a robust, scalable, and practical solution for disaster management, supporting faster decision-making and improving resilience in post-disaster scenarios.

## REFERENCES

[1] D. Contreras, T. Blaschke, D. Tiede, and M. Jilge, “Monitoring recovery after earthquakes through the integration of remote sensing, GIS, and ground observations: The case of L’Aquila (Italy),” Cartogr. Geogr. Inf. Sci., vol. 43, pp. 115–133, 2016.

[2] E. Guirado, S. Tabik, D. Alcaraz-Segura, J. Cabello, and F. Herrera, “Deep-learning versus OBIA for scattered shrub detection with Google Earth imagery: Ziziphus Lotus as case study,” Remote Sens., vol. 9, p. 1220, 2017.

[3] J. Tu, H. Sui, W. Feng, and Z. Song, “Automatic building damage detection method using high-resolution remote sensing images and 3D GIS model,” ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci., vol. 3, pp. 43–50, 2016.

[4] L. Gong, C. Wang, F. Wu, J. Zhang, H. Zhang, and Q. Li, “Earthquake-induced building damage detection with post-event sub-meter VHR TerraSAR-X staring spotlight imagery,” Remote Sens., vol. 8, p. 887, 2016.

[5] M. Buchroithner, R. G. Gevorkian, and A. S. Karachanian, “Results of a structural-geological analysis of aero-cosmic data of the Spitak earthquake zone (Armenia),” in Proc. 10th Micro Symp. Relativistic Planetology, Moscow, Russia, Aug. 7–11, 1989, p. 2.

[6] M. Chini, N. Pierdicca, and W. J. Emery, “Exploiting SAR and VHR optical images to quantify damage caused by the 2003 Bam earthquake,” IEEE Trans. Geosci. Remote Sens., vol. 47, pp. 145–152, 2009.

[7] M. He, Q. Zhu, Z. Du, H. Hu, Y. Ding, and M. Chen, “A 3D shape descriptor based on contour clusters for damaged roof detection using airborne LiDAR point clouds,” Remote Sens., vol. 8, p. 189, 2016.

[8] M. Janalipour and A. Mohammadzadeh, “Building damage detection using object-based image analysis and ANFIS from high-resolution image (case study: Bam earthquake, Iran),” IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 9, pp. 1937–1945, 2016.

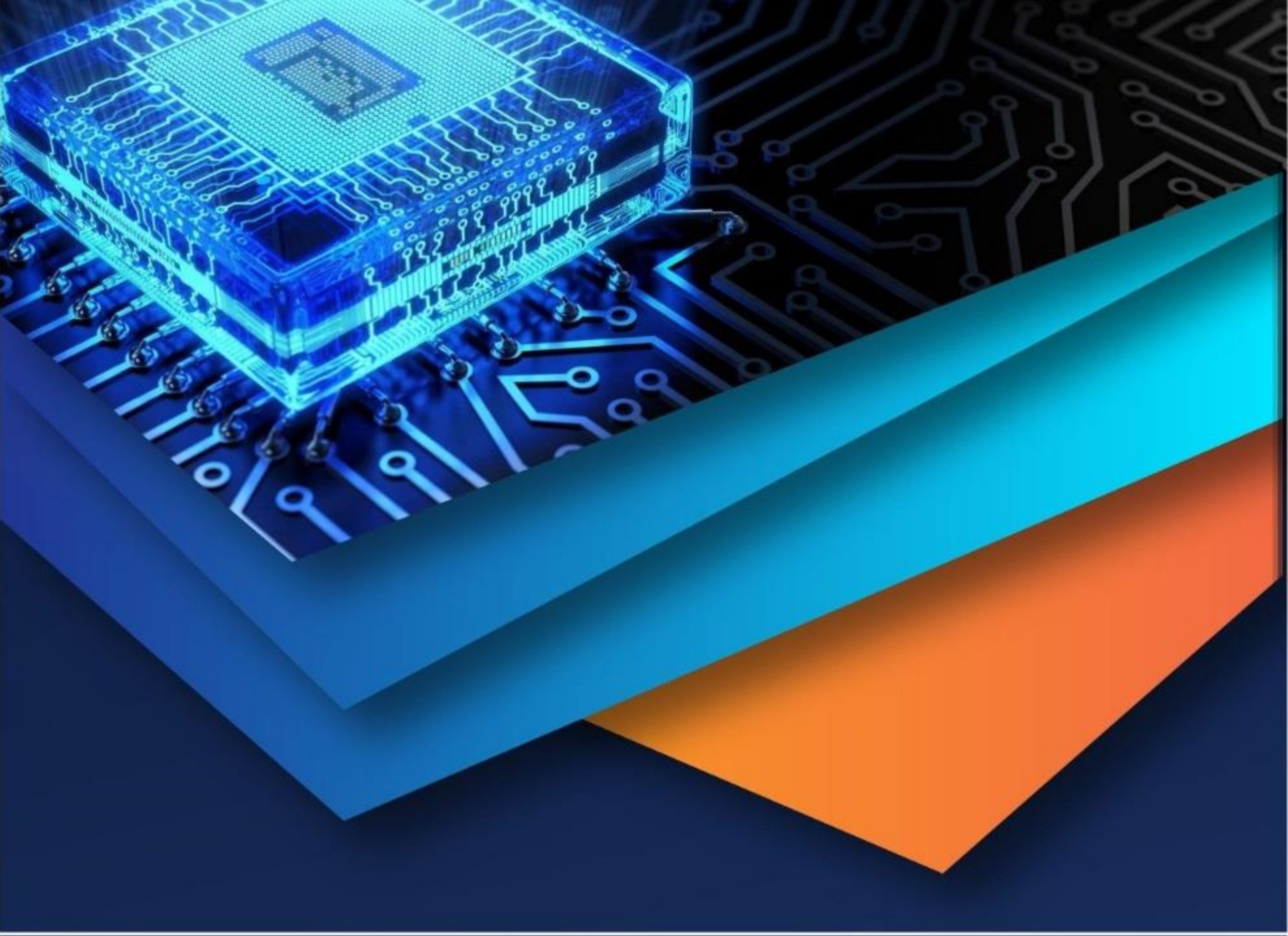
[9] P. Gamba and F. Casciati, “GIS and image understanding for near-real-time earthquake damage assessment,” Photogramm. Eng. Remote Sens., vol. 64, pp. 987–994, 1998.

[10] T. Blaschke and J. Strobl, “What’s wrong with pixels? Some recent developments interfacing remote sensing and GIS,” GeoBIT/GIS, vol. 6, pp. 12–17, 2001.

[11] T. Liu, A. Abd-elrahman, J. Morton, and V. L. Wilhelm, “Comparing fully convolutional networks, random forest, support vector machine, and patch-based deep convolutional neural networks for object-based wetland mapping using images from small unmanned aircraft system,” GIScі. Remote Sens., vol. 55, pp. 243–264, 2018.

[12] Y. Bai, B. Adriano, E. Mas, H. Gokon, and S. Koshimura, “Object-based building damage assessment methodology using only post event ALOS-2/PALSAR-2 dual polarimetric SAR intensity images,” J. Disaster Res., vol. 12, pp. 259–271, 2017.

[13] Y. Dong, Q. Li, A. Dou, and X. Wang, “Extracting damages caused by the 2008 Ms 8.0 Wenchuan earthquake from SAR remote sensing data,” J. Asian Earth Sci., vol. 40, pp. 907–914, 2011




10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429


# INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY