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## A hybrid GoogLeNet–GLCM feature extraction framework for textural representation of post-disaster building damage imagery

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**Abstract**—Accurate representation of visual characteristics in post-disaster building imagery is crucial for downstream analytical tasks such as damage interpretation, retrieval, and automated assessment. This study presents a focused investigation of feature extraction using a hybrid approach that integrates deep semantic representations from the GoogLeNet architecture with statistical texture descriptors inspired by the Gray-Level Co-Occurrence Matrix (GLCM). The objective of this work is limited strictly to the generation and analysis of semantic-textural feature vectors rather than the development or evaluation of any classification or prediction model. High-level feature maps are obtained from a selected convolutional layer of GoogLeNet, after which statistical texture properties—contrast, energy, and homogeneity—are computed per channel. A representative set of feature channels is analyzed to demonstrate the capabilities of the proposed hybrid extraction pipeline. The results demonstrate the potential of semantic-textural descriptors to provide interpretable feature characteristics in building-damage imagery. This study provides a methodological foundation and analytical insight for future works that may incorporate these feature representations into classification, clustering, or decision-support frameworks.

**Keywords**—building damage imagery; feature extraction; glcm-based texture descriptors; googlenet.

### 1. Introduction

Natural disasters constitute phenomena capable of causing extensive disruptions to human life, infrastructure, and the environment (Darmawan et al., 2022). In recent years, the increasing frequency of events such as earthquakes has precipitated significant social and economic losses on a global scale (Murdiaty et al., 2020). Indonesia, located along the Pacific Ring of Fire, faces particularly high exposure to a wide range of natural hazards (Fu'adah et al., 2023). In addition to geological factors, anthropogenic activities often intensify the impact of disasters, underscoring the critical importance of preparedness and effective post-disaster response.

One of the most challenging tasks in the aftermath of a disaster is the rapid and accurate assessment of building damage. Conventional assessment practices rely heavily on field surveys conducted by trained experts, which are inherently time-consuming, labor-intensive, and resource-dependent (Utomo & Marta, 2022). These assessments are frequently

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hindered by inconsistencies in data collection, leading to discrepancies between reports submitted by field teams and actual on-site conditions (Safitri et al., 2022), (Eska Dwi Prajayanti et al., 2025), (Yulianti et al., 2024). Such inconsistencies can impede timely decision-making and reduce the effectiveness of recovery operations.

To address these limitations, digital image processing and deep learning technologies have emerged as promising tools for analyzing building damage imagery (Geng et al., 2025), (Anuradha et al., 2025). In particular, feature extraction using Convolutional Neural Networks (CNNs) has demonstrated strong capability in identifying complex patterns within visual data (Song et al., 2024), (Cai et al., 2025). Architectures such as GoogLeNet provide powerful multiscale semantic representations of images, enabling the capture of high-level structural patterns relevant to damage interpretation (Chen et al., 2023), (Reis et al., 2024). However, deep learning features are often abstract and complex to interpret directly. A more granular understanding of damage characteristics requires complementary textural information.

The Gray-Level Co-occurrence Matrix (GLCM) is a well-established statistical method for quantifying image texture by analyzing the spatial relationships between pixel intensities (Fu'adah et al., 2023), (Almais et al., 2024). While GoogLeNet has been widely applied in various image classification tasks (Baral et al., 2024), (Yasi et al., 2024), relatively few studies have explicitly focused on examining and interpreting the extracted feature maps, particularly within the context of post-disaster building imagery (Han et al., 2022). Likewise, although GLCM has proven effective for texture characterization in fields such as medical imaging and remote sensing (Reis et al., 2024), its integration with deep CNN feature representations for analyzing building damage remains insufficiently explored.

In previous work, Almais et al., (2024) demonstrated that feature extraction alone can provide substantial analytical value in post-disaster building imagery analysis. Their study employed the Gray-Level Co-occurrence Matrix (GLCM) solely as a texture-based feature extractor, using only one input image to illustrate the derivation of texture features before the subsequent PCA-based clustering stage. Importantly, the GLCM-based extraction was treated as an independent methodological component, separate from the clustering analysis.

Adopting a similar conceptual structure, the present study focuses exclusively on the feature-extraction stage, replacing the classical GLCM features with a modern deep-learning-based extractor, GoogLeNet. Unlike the comprehensive workflow presented in Almais et al. (2024), this research does not extend to downstream tasks, including Principal Component Analysis (PCA), clustering, classification, or quantitative performance evaluation. It is crucial to emphasize that this work is not intended to produce generalizable statistical findings across a population of images, to perform damage classification, to conduct predictive modeling, or to compare performance metrics. Instead, its primary objective is to demonstrate and explain the mechanism of deep semantic feature extraction using a representative image. Consequently, the present work is strictly limited to the extraction and qualitative interpretation of GoogLeNet-based semantic features. Any subsequent downstream tasks, including classification, clustering, or accuracy assessment, fall outside the intended scope of this manuscript.

Therefore, the analysis presented herein should be interpreted as a methodological foundation for future research on damage classification, clustering, or automated assessment.

## 2. Method

The proposed feature extraction pipeline consists of three main stages: (1) dataset preparation and preprocessing, (2) semantic feature extraction using GoogLeNet, and (3) channel-wise texture analysis using GLCM-based descriptors.

### 2.1. Dataset and pre-processing

The complete dataset used in the broader research project will be made publicly accessible through the author's ORCID repository. The imagery used in this study is sourced from publicly available repositories containing post-disaster building photographs. The dataset includes images depicting various visual characteristics, including intact structures, minor cracking, major structural failures, and debris fields. However, consistent with the scope and methodological design of this manuscript, only one representative building-damage image is used for the feature-extraction demonstration. This follows the precedent set by Almais et al. (2024), who likewise presented GLCM-based texture extraction using a single illustrative image before applying PCA in a separate analytical stage. Because the purpose of this paper is to demonstrate the feature extraction mechanism rather than to conduct performance evaluation or statistical generalization, multi-image analysis is intentionally excluded.

The image is resized to match the expected input dimensions of GoogLeNet (299 × 299 pixels for Inception-v3) (Szegedy et al., 2015). Standard preprocessing procedures, such as normalization and scaling, are applied using the official Keras preprocessing utilities (Tahermanesh et al., 2025).

### 2.2. Feature extraction using GoogLeNet

GoogLeNet (Inception-v3) is employed in its convolutional base form, excluding the fully connected layers. A specific intermediate convolutional layer (e.g., mixed2) is selected to obtain feature maps that capture mid-level semantic representations. For an input image, the selected layer yields a tensor of dimension  $H \times W \times C$ , where  $C$  denotes the number of feature channels. Each element of this map is computed via formula (1):

$$S(i, j) = (I * K)(i, j) = \sum_m \sum_n I(m, n) K(i - m, j - n) \quad (1)$$

where  $S(i, j)$  is the output pixel value,  $I$  is the input,  $K$  is the convolution kernel, and the indices  $m$ ,  $n$ ,  $i$ , and  $j$  iterate over the image and kernel dimensions. This operation detects specific patterns, such as edges or textures.

GoogLeNet uniquely incorporates an Inception module (see Fig. 1), which concurrently applies multiple convolution kernels of different sizes (e.g.,  $1 \times 1$ ,  $3 \times 3$ ,  $5 \times 5$ ), thereby capturing visual features at various scales. Each channel corresponds to a learned filter that responds to specific visual patterns, such as edges, blobs, or complex structural motifs. These channels serve as the basis for subsequent texture analysis. To ensure reproducibility, the exact layer names, preprocessing procedure, and model configuration are explicitly specified. Activation is

defined as the sum of absolute feature-map values per channel:

$$A_c = \sum_{i=1}^H \sum_{j=1}^W |F_c(i, j)| \quad (2)$$

channels with the highest activation scores were selected for qualitative inspection.

Consistent with the feature extraction design adopted by Almais et al., (2024), the present study utilizes one representative building-damage image as the input for semantic-textural feature generation. Because the methodological scope is limited to demonstrating the extraction mechanism rather than evaluating predictive performance, multi-image statistical validation is intentionally excluded. It is considered beyond the scope of this manuscript.

### 2.3. Texture Descriptor

To characterize local intensity variation within each feature map channel, three statistical texture descriptors, contrast, energy, and homogeneity, are calculated. Although traditional GLCM requires explicit co-occurrence matrices and grayscale quantization, this study employs GLCM-inspired channel-wise statistical formulations that preserve the interpretability of these properties while simplifying computation on deep feature maps. For a feature channel  $F$ , the descriptors are defined as:

- a. Contrast: The standard deviation representing local intensity variation via equation (3).

$$Contrast = \sum_{i,j=0}^{N-1} P_{i,j} (i - j)^2 \quad (3)$$

- b. Energy: Measuring uniformity and texture strength, computed via equation (4).

$$Energy = \sum_{i,j=0}^{N-1} P_{i,j}^2 \quad (4)$$

- c. Homogeneity: Inversely proportional to contrast, computed via equation (5).

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1 + (i - j)^2} \quad (5)$$

where  $P_{i,j}$  represents the co-occurrence probability of pixel intensities  $i$  and  $j$ . Equation (5) is shown for completeness of the classical GLCM definition; however, for CNN feature maps, we compute homogeneity using the simplified formulation.

Although Equations (3) – (5) represent the classical definitions of contrast, energy, and homogeneity within the GLCM framework, in this study, they are applied as GLCM-inspired statistical texture descriptors computed directly from each GoogLeNet feature-map channel. Since convolutional feature maps do not correspond to discrete gray-level co-occurrence matrices, the descriptors are interpreted as channel-wise statistical measures that retain the conceptual meanings of texture variation, intensity uniformity, and smoothness. This

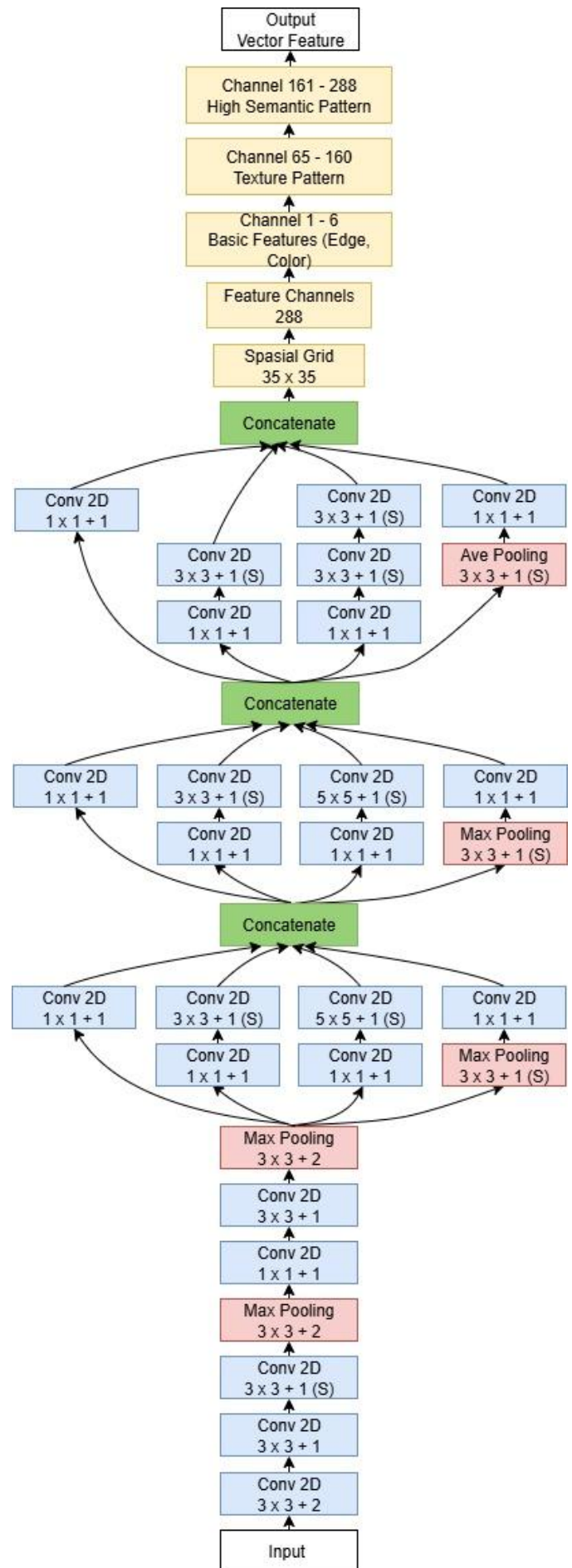


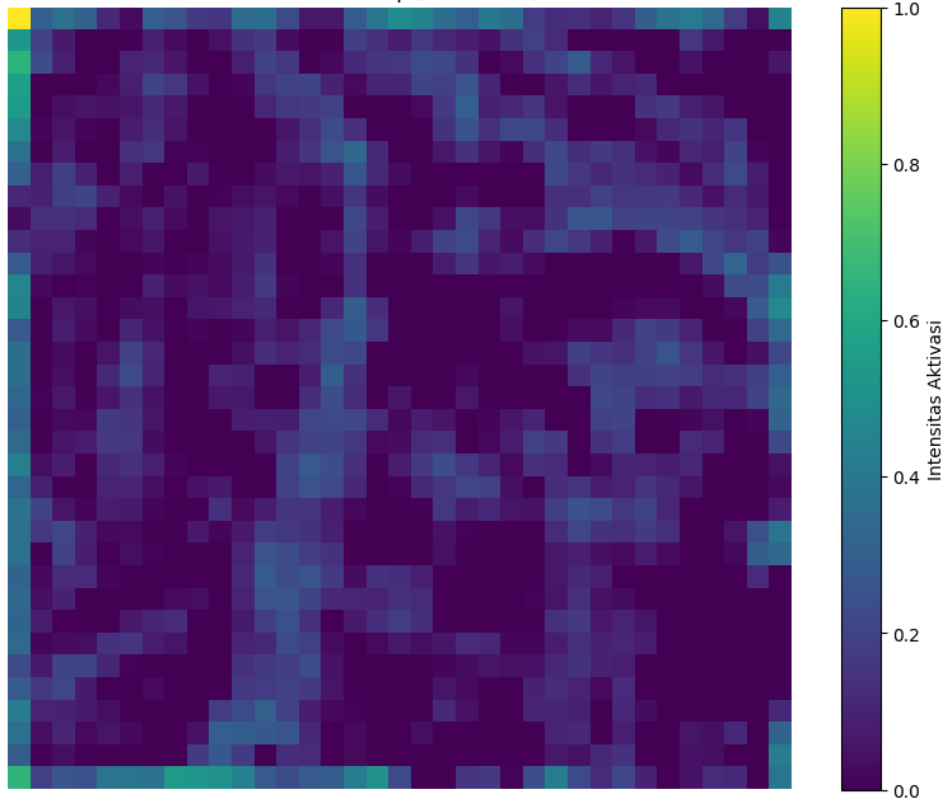
Fig. 1. Inception module architecture on GoogleNet.

Input Image



(a)

Visualisasi Feature Map (Channel 4) - mixed2



(b)

Fig. 2. Original post-disaster building image (a) and example feature map from GoogLeNet (b).

Table 1. Texture feature extraction results

| Feature Map | Contrast | Energy | Homogeneity |
|-------------|----------|--------|-------------|
| Channel 1   | 0.81     | 1.04   | 0.55        |
| Channel 2   | 0.70     | 0.59   | 0.59        |
| Channel 3   | 0.80     | 1.05   | 0.56        |
| Channel 4   | 0.37     | 0.17   | 0.73        |
| Channel 5   | 0.62     | 0.57   | 0.62        |
| Channel 6   | 0.64     | 0.54   | 0.61        |
| Channel 7   | 0.43     | 0.30   | 0.70        |
| Channel 8   | 0.83     | 1.05   | 0.55        |
| Channel 9   | 0.72     | 0.72   | 0.58        |
| Channel 10  | 0.85     | 1.27   | 0.54        |

adaptation is consistent with feature-interpretation practices commonly used in CNN-based analysis. These descriptors are computed independently for each channel. A subset of channels exhibiting the highest activation value is selected for qualitative analysis.

To ensure consistency across samples, channel activation was quantified as the sum of the absolute values of the feature maps. The ten channels with the highest activation values were selected for further analysis, as these channels contributed most significantly to the representation of semantic and textural characteristics in each image.

### 3. Results

This section presents illustrative examples of the extracted semantic-textural features. The intention is not to evaluate predictive performance but to demonstrate the descriptive nature and interpretability of the extracted feature maps and descriptors.

#### 3.1. Visual Inspection of GoogLeNet Feature Maps

Fig. 2 shows (a) an example of a building damage image and (b) one representative feature map from the chosen GoogLeNet layer. The feature map highlights structural patterns such as crack formations and debris textures, confirming that GoogLeNet effectively activates on relevant semantic regions (Wu et al., 2024), (Tahermanesh et al., 2025).

#### 3.2. Extracted Texture Descriptor Values

Using the computed feature maps, texture descriptors (contrast, energy, and homogeneity) were computed for the first 10 channels with the highest activation values. The results are summarized in Table 1.

The extracted contrast values range from 0.37 to 0.85, indicating variation in local texture intensity across different filters. Energy values range from 0.17 to 1.27, while homogeneity values range from 0.54 to 0.73. These variations demonstrate the diversity of responses generated by the GoogLeNet filters at different spatial scales.

#### 3.3. Aggregated Feature Extraction Across 20 Images

In addition to the single representative image used to demonstrate the feature extraction mechanism, an extended analysis was performed on 20 building images, comprising 10

Table 2. Texture feature extraction of 20 images

| Images | Avg. Contrast | Avg. Energy | Avg. Homogeneity | Class     |
|--------|---------------|-------------|------------------|-----------|
| 1      | 0.68          | 0.73        | 0.60             | Damaged   |
| 2      | 0.59          | 0.59        | 0.63             | Damaged   |
| 3      | 0.56          | 0.70        | 0.65             | Undamaged |
| 4      | 0.64          | 0.78        | 0.62             | Damaged   |
| 5      | 0.65          | 0.73        | 0.61             | Undamaged |
| 6      | 0.67          | 0.74        | 0.60             | Damaged   |
| 7      | 0.61          | 0.62        | 0.63             | Undamaged |
| 8      | 0.64          | 0.68        | 0.61             | Undamaged |
| 9      | 0.47          | 0.52        | 0.70             | Undamaged |
| 10     | 0.66          | 0.73        | 0.61             | Damaged   |
| 11     | 0.63          | 0.63        | 0.62             | Damaged   |
| 12     | 0.62          | 0.62        | 0.62             | Undamaged |
| 13     | 0.60          | 0.59        | 0.63             | Damaged   |
| 14     | 0.61          | 0.63        | 0.62             | Damaged   |
| 15     | 0.61          | 0.64        | 0.63             | Undamaged |
| 16     | 0.71          | 0.86        | 0.59             | Undamaged |
| 17     | 0.61          | 0.58        | 0.63             | Damaged   |
| 18     | 0.67          | 0.61        | 0.60             | Undamaged |
| 19     | 0.58          | 0.65        | 0.64             | Undamaged |
| 20     | 0.59          | 0.73        | 0.65             | Damaged   |

Table 3. 20 image analysis

| Class     | Avg. Contrast | Avg. Energy | Avg. Homogeneity |
|-----------|---------------|-------------|------------------|
| Damaged   | 0.628         | 0.673       | 0.621            |
| Undamaged | 0.612         | 0.663       | 0.628            |

damaged and 10 undamaged samples. For each image, all GoogLeNet feature maps were computed, and the 10 channels with the highest activations were selected as the dominant representations. The three texture descriptors contrast, energy, and homogeneity were then calculated for each selected channel and subsequently averaged to produce one descriptor set per image.

The aggregated results from the 20 images are presented in Table 2, which reports the mean contrast, energy, and homogeneity values for each sample along with its structural class. This table provides a basis for observing texture variation across images and potential differences in textural patterns between damaged and undamaged samples before further class-level statistical summarization.

#### 3.4. Statistical Summary of the 20-Image Analysis

Table 3 presents the average descriptor values for the two classes. Damaged images exhibit slightly higher contrast and energy, while undamaged images show marginally higher homogeneity values.

These findings highlight subtle but observable variations in the combined semantic-textural representations extracted from the images.

### 4. Discussion

The discussion interprets the extracted feature

characteristics and provides conceptual insights into the role of semantic and textural representations in post-disaster building imagery.

#### 4.1. Interpretation of Texture Descriptor Patterns

Table 1 presents sample contrast, energy, and homogeneity values computed from the first ten activated channels. The variation across the channels demonstrates that different filters capture different structural characteristics. Interpretation Example:

- High-contrast channels (e.g., Channels 7–10) respond strongly to irregular and coarse textures, such as debris or heavily damaged surfaces.
- Low-contrast, high-homogeneity channels (e.g., Channels 3–4) correspond to smoother, more uniform structures, such as intact walls.
- Energy values reflect the strength of channel activations and show which filters respond most strongly to semantic cues within the image.

These observations show that the hybrid features contain meaningful indicators of structural texture.

#### 4.2. Semantic feature characteristics of GoogLeNet

GoogLeNet's architecture, distinguished by its innovative Inception modules, is adept at processing visual data across multiple scales concurrently (Almais et al., 2023). This results in exceptionally rich and diverse feature maps. When applied to building damage imagery, the extracted features transcend simple statistics; they are semantic representations imbued with contextual meaning. In contrast to classical methods such as GLCM, which are limited to measuring generic texture properties like "contrast" or "homogeneity" (Murdiaty et al., 2020), (Wu et al., 2024), GoogLeNet's features can implicitly represent far more complex visual concepts. The resultant feature vector can qualitatively reflect distinct textural patterns, such as: (1) The smooth texture of an undamaged wall, (2) The irregular patterns of fine (hairline) cracks, (3) The coarse, random texture of concrete rubble, and (4) The linear, repetitive patterns of exposed steel reinforcement.

This capacity to capture semantic essence is a fundamental advantage of the deep learning paradigm. The model, trained on large-scale data, learns to identify the visual primitives that form complex objects and scenes. This knowledge, when transferred to the damage assessment domain, enables the model to produce numerical descriptors (feature vectors) that are highly correlated with human visual observation.

#### 4.3. Significance of the Hybrid Semantic–Textural Representation

The semantic–textural synergy is beneficial for building damage imagery because:

- Deep semantic features distinguish high-level structure (edges, corners, complex damage patterns).
- Texture descriptors quantify local variation substantial for characterizing cracks, roughness, and smooth surfaces.
- Per-channel analysis gives interpretability, so that researchers can inspect which filters respond to which

damage characteristics.

#### 4.4. Interpretation of Class-Level Descriptor Variations

The aggregated results suggest that images containing structural damage exhibit higher contrast and energy, reflecting the presence of irregular, fractured, and visually complex textures commonly associated with damaged surfaces. In comparison, undamaged images exhibit greater homogeneity, consistent with smoother, more uniform wall structures.

Although the intention of this study is not to perform classification or quantitative performance evaluation, these descriptor patterns provide an initial indication of how semantic–textural features derived from GoogLeNet respond to different structural conditions. The findings reinforce the relevance of the extracted descriptors and highlight their potential applicability to downstream tasks, such as clustering or early-stage damage characterization.

### 5. Conclusion

This study presents a focused analysis of feature extraction from building-damage imagery using a hybrid GoogLeNet–GLCM approach. The methodology combines the semantic richness of convolutional feature maps (extracted from GoogLeNet) with channel-wise textural descriptors (derived from GLCMs). This process generates interpretable numerical representations that effectively capture the essential structural and visual characteristics of damaged environments.

The results of this feature extraction demonstrate variations in textural metrics (e.g., contrast, energy, and homogeneity) across feature channels, thereby reflecting diverse visual patterns in the input images.

Crucially, consistent with its predecessor (Almais et al., 2024) in scope, this work limits its contribution solely to the extraction and qualitative interpretation of these hybrid semantic–textural features. It does not extend into subsequent downstream tasks, including clustering, classification, or predictive evaluation.

The presented methodology provides a reproducible, analytically transparent foundation for subsequent research aimed at establishing automated damage assessment and evaluation systems.

#### Data Availability

All data generated or examined during this research can be found at the ORCID link: <https://orcid.org/0009-0003-1199-6296> and Zenodo link: <https://doi.org/10.5281/zenodo.17829002>.

#### Declaration of Competing Interest

The authors affirm that they have no known financial competing interests or personal connections that could be perceived to have affected the research presented in this article.

#### Authors' Contributions

**Holidiyatul Amani:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data

Curation, Writing – Original Draft, Visualization. **Agung Teguh Wibio Almais:** Conceptualization, Methodology, Validation, Resources, Writing – Review & Editing, Supervision, Project administration, Funding acquisition. **Zainal Abidin:** Validation, Writing – Review & Editing, Supervision. **Fresy Nugroho:** Validation, Writing – Review & Editing, Visualization. **Fachrul Kurniawan:** Methodology, Writing – Review & Editing. **Tomy Ivan Sugiharto:** Data Curation, Validation, Methodology, Writing – Review & Editing.

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