

Application of Genetic Algorithm Neural Network in Identifying Buildings in Landslide-Prone Areas

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Article Information	ABSTRACT
Article History Received : May 27, 2025 Revised : June 12, 2025 Published : July 04, 2025	Indonesia is a disaster-prone country, one of which is landslides, which often occur in hilly areas with high rainfall. The impact damages the environment and infrastructure, especially buildings. For effective mitigation, a risk identification system based on artificial intelligence technology is needed. This study applies Genetic Algorithm Neural Network (GANN) in identifying buildings in landslide-prone areas. GANN was chosen for its ability to optimize network weights globally through selection, crossover, and mutation mechanisms, thus avoiding suboptimal local solutions. The dataset consists of 169 data with 12 structural features of the building. The model was configured with genetic parameters such as the number of generations 500, population size of 50, mutation rate of 10%, and the Stochastic Universal Sampling selection method. To Evaluate the performance of model created from dataset, we employed accuracy, precision, recall, and F1-score. The results showed an accuracy of 81% and an average F1-score of 0.82, with the best performance in the "Unsafe" class (recall 0.84). Although it still needs improvement, GANN has proven to have the potential as a decision support tool in data-driven landslide risk mitigation.
Keywords: <i>GANN; Building Identification; Landslide Susceptibility; Mitigation.</i>	

INTRODUCTION

Indonesia is one of the countries that is very vulnerable to various types of natural disasters, including landslides. This phenomenon often occurs in regions with steep topography and high rainfall intensity, such as mountainous or hilly areas. The impact not only damages the environment, but also threatens the safety of lives and causes damage to infrastructure, especially buildings (Trianda et al., 2018). Therefore, an accurate and reliable landslide risk identification system is needed to support effective disaster mitigation efforts.

The application of the Genetic Algorithm Neural Network (GANN) in identifying buildings in landslide-prone areas has gained attention due to its ability to accurately evaluate vulnerabilities through the integration between genetic algorithms and artificial neural networks. This approach utilizes selection, crossover, and mutation mechanisms to find optimal weights in model training, thus being able to explore a wider solution space and avoid getting stuck on suboptimal solutions which is often a challenge in conventional methods such as Back Propagation Neural Networks (Che et al., 2011). Various studies have shown that GANN has great potential in improving prediction accuracy as well as model stability, especially in complex or incomplete data conditions (Machdi et al., n.d.; Zheng et al., 2023).

In the context of disaster mitigation, GANN has been successfully applied to analyze various geospatial and environmental factors relevant to landslide events, such as slope angle, soil type, precipitation, and distance to river (Wang et al., 2021). A case study in South Taiwan proved GANN's effectiveness in creating a map of landslide potential with a high correlation between rainfall and landslide events (Chen et al., 2013), while (Zhu et al., 2020) reporting a prediction accuracy of 93.02% using GANN, demonstrating its reliability in real-world applications. In recent years, artificial intelligence technology has been increasingly used in disaster risk analysis, including the identification of buildings in landslide-prone areas, where high-dimensional multivariate datasets are used as inputs (Sari et al., 2024a). The dataset includes the structural characteristics of the building as well as the environmental parameters that are non-linearly interrelated.

The training and evaluation process of the model is carried out systematically with a k-fold cross validation approach to ensure proportionate and representative sharing of training and test data (Pratama et al., 2024; Sari et al., 2024b). Although GANN is performing well, some challenges are still encountered, such as the need for a large enough dataset and complex hyperparameter optimization processes (Daviran et al., 2023). Therefore, advanced research is recommended to integrate more diverse data sources as well as improve the generalization capabilities of models in order to provide more reliable and adaptive results in dynamic field scenarios (Kudaibergenov et al., 2024). The integration of other methods, such as ensemble models, can also be an alternative to enrich insights in a holistic landslide risk assessment.

The lack of studies that specifically discuss the application of GANN in the identification of buildings in landslide-prone areas is one of the main challenges, as most previous studies focused more on mapping landslide-prone zones in general, rather than on the classification of building safety status based on physical and environmental conditions. In addition, the evaluation of model performance in a number of studies is still limited to the use of accuracy metrics only, without considering other metrics such as precision, recall, and F1-score that are important to provide a comprehensive picture in the case of multiclass classifications (Safe, Less Secure, Not Safe). GANN performance is also heavily influenced by genetic parameters such as mutation rate, parent selection type, and crossover method, but there is still little research that systematically optimizes it for building identification applications. Finally, the integration of geological and structural features in the model is still limited, where the input data used has not fully covered important variables such as soil type, slope angle, and rainfall that are relevant in predicting landslide risk in buildings (Prastowo et al., 2018; Pratama et al., 2024; Sari et al., 2024a).

Therefore, this study aims to analyze and evaluate the performance of the Genetic Algorithm Neural Network (GANN) in identifying buildings in landslide-prone areas, with a more comprehensive approach and based on a more feature-rich dataset. The evaluation process is based on various metrics such as accuracy, precision, recall, and F1-Score, which provides a thorough picture of the model's strengths and weaknesses. In addition, this study will also conduct experiments to optimize the evolutionary parameters in the GANN to improve the stability and accuracy of the predictions.

The results of this research are expected to make a real contribution to the development of a disaster mitigation system based on AI technology. By using the GANN model that is able to explore solutions globally, it is hoped that more targeted mitigation recommendations can be produced, both in the form of risk zone mapping and protection infrastructure placement strategies. The use of GANN in this context can also be the basis for the development of predictive models that are more adaptive and responsive to changing environmental conditions.

RESEARCH METHODS

This study aims to evaluate the performance of the Genetic Algorithm Neural Network (GANN) in identifying buildings in landslide-prone areas. To achieve this goal, the research was designed with a quantitative approach based on machine learning models, using spatial and structural data as the main inputs (Reddy Voddi, 2023; Rivas et al., 2020; Sari et al., 2024a). The

research design was prepared to provide an objective picture of GANN's ability to classify the security status of buildings into three categories, namely Safe, Less Safe, and Unsafe.

Research Design

The research was carried out through several main stages, namely data collection, data pre-processing, GANN model formation, model training and validation, performance evaluation, and interpretation of results. Each stage is designed in such a way as to ensure that the model can learn from the data effectively and provide accurate predictions. In this process, the k-fold cross validation method is used to improve the reliability of the results and avoid biases due to certain data sharing.

Population and Sampling Techniques

The data used in the study came from a structured dataset that included information about the physical condition of the building and the surrounding environment. The dataset consists of 169 rows of data and 12 feature columns, including drawing plans, plans, foundations, sloofs, columns, beams, walls, roofs, and easements. These features were chosen because of their relevance in assessing the stability of building structures in landslide-prone areas. Sampling was carried out purposively by taking into account geographical representation and variations in building characteristics. The data used has gone through an initial selection process to ensure the availability of complete and consistent information. Furthermore, the dataset is divided into two parts: the training data and the test data, with a stratification strategy to keep the class distribution proportional.

Architecture of Artificial Neural Networks

The GANN model is constructed using the basic structure of an artificial neural network consisting of three main components. The input layer has a number of neurons that correspond to the dimensions of the data feature used as the input model. After that, there are one or more hidden layers that are equipped with the ReLU (Rectified Linear Unit) activation function, which plays a role in providing the model's ability to study data patterns non-linearly. At the output layer, the number of neurons is adjusted to the number of target classes, and is equipped with a Softmax activation function that functions to generate class distribution probabilities to allow the model to make classification predictions more accurately.

In the Genetic Algorithm Neural Network (GANN) architecture, the activation function plays an important role in determining how neurons process and transform information. The activation function helps the model learn non-linear patterns from the input data, thereby improving the network's ability to make accurate classification predictions. The two main types of activation functions used in this study are ReLU (Rectified Linear Unit) on the hidden layer and Softmax on the output layer. The following is an explanation of each activation function along with the mathematical formula used (Abood et al., 2023; Chen et al., 2013).

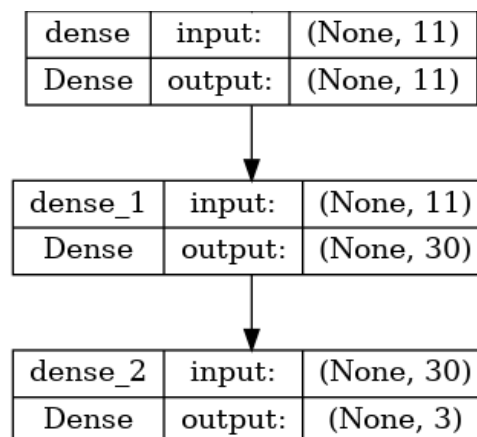


Figure 1. The Architecture of ANN

Fig 1. shows the architecture of ANN implemented on the system. The system employs 3 layers of neuron that consists of 11 input nodes, 30 nodes of hidden layer, and 3 output nodes which represent the target class (Not Safe, Less Safe, and Safe).

$$\text{ReLU } f(x) = \max(0, x) \quad (1)$$

$$\text{Softmax } (z_i) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad (2)$$

Where z_i is the output value of the i th neuron, and K is the total sum of the class

Weight Optimization Using Genetic Algorithm (GA)

In GANN, the training process does not only rely on the gradient descent algorithm, but uses the principles of biological evolution to find the optimal weight. Each individual in the population represents a tissue weight vector, and the evaluation is performed based on the fitness function derived from the prediction accuracy (Krenek et al., 2016).

In the application of GANN, the process of optimizing the weight of the neural network is carried out through several main steps inspired by the principles of biological evolution. The first step is Population Initialization, in which a number of individuals with a random weight configuration are formed to be the initial potential solution. Each individual was then evaluated based on fitness, which in this study used the model's prediction accuracy metrics as the basis for assessing the individual's quality. Based on fitness values, an Individual Selection is carried out to select the individual with the best performance as a prospective parent (Daviran et al., 2023; Rahmayanti, 2010). After that, Crossover is carried out, which is the process of combining two selected individuals to produce new offspring with the formula:

$$W_{baru} = \begin{cases} W_1 & \text{from parent A to intersection} \\ W_2 & \text{from parent B to intersection} \end{cases} \quad (3)$$

Next, Mutations are applied to introduce genetic variation with the formula:

$$W_{mutasi} = W + \Delta W \times \text{rand}(-1,1) \quad (4)$$

This process helps prevent the model from getting stuck on a local solution. The results of crossovers and mutations then form a New Generation in the Reproductive stage. The iteration will continue until it reaches the maximum number of generations or there is an Iteration Stop because there is no significant increase in fitness values for several consecutive cycles.

The GANN model optimization process is carried out using a number of parameters of Genetic Algorithms that have been systematically determined. The number of generations used in the evolutionary process is 500, with a population size of 50 individuals in each generation. The mutation rate is set to 0.01 to introduce sufficient genetic variation to avoid premature convergence to local solutions. The crossover rate is set at a value of 0.8, which indicates the proportion of individuals who will undergo the process of recombination to produce new offspring. The selection method used is Roulette Wheel Selection, which provides reproductive opportunities based on the fitness value of each individual. The type of crossover applied is Single Point Crossover, while the type of mutation used is Random Mutation to maintain genetic diversity in the population during the optimal solution search process.

Model Performance Evaluation

In order to assess the extent to which the Genetic Algorithm Neural Network (GANN) model is able to perform classification tasks in identifying buildings in landslide-prone areas, objective and comprehensive evaluation metrics are needed. These metrics not only measure how accurate the model is in making predictions, but also provide an overview of generalization capabilities and balance between classes (Pradana et al., 2022; Prathama, 2018; Zhu et al., 2020). The following is an explanation of the evaluation metrics used in this study.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

Information:

TP = True Positive; TN = True Negative; FP = False Positive; FN = False Negative

To ensure the robustness and reliability of the model's predictive performance, a 10-fold cross-validation technique was employed. In this method, the dataset was randomly partitioned into 10 equal subsets. During each iteration, one subset was used as test data while the remaining nine subsets were used to train the model. This process was repeated 10 times, with each subset used exactly once as test data. The final evaluation metrics (accuracy, precision, recall, F1-score) were averaged across all iterations to obtain a stable performance estimate and minimize bias due to random data splits. This rigorous validation strategy was chosen to enhance the credibility of the experimental results and to ensure that the model's performance was not dependent on a specific data division (Pratama et al., 2024; Sari et al., 2024a).

RESULTS AND DISCUSSION

The Genetic Algorithm Neural Network (GANN) model is configured with a number of specific settings to improve learning ability and prediction accuracy. One of the important aspects of this configuration is the sharing of datasets, which is carried out with a proportion of 75% for training data and 25% for test data. This division is designed so that the model has enough data to study complex patterns during the training phase, while also setting aside some data to evaluate the model's generalization ability against new data. With this approach, it is hoped that the GANN model will be able to produce more accurate and stable predictions in identifying buildings in landslide-prone areas.

GANN Model Performance in Building Identification in Landslide-Prone Areas

The Genetic Algorithm Neural Network (GANN) model developed in this study is designed to identify buildings in landslide-prone areas based on spatial and structural data. The model is trained using datasets that have been systematically processed and validated through the k-fold cross validation approach. Performance evaluations were conducted using statistical metrics such as precision, recall, and F1-score, providing a comprehensive picture of the model's ability to predict three categories: "Safe", "Less Safe", and "Not Safe". The results showed that the GANN model was able to achieve an average F1-score of 0.82. This value suggests that while not perfect, the model has a fairly good balance between precision and recall, which is important in the context of disaster risk prediction, where misclassification can have a significant impact on disaster mitigation.

In the "Safe" class, the model achieves a precision of 1.00, meaning that all predictions of this class do not result in false positives. However, a lower recall value (0.83) indicates that some real samples of this class fail to be recognized by the model (false negative). This can be caused by complex variations in building characteristics or environmental conditions that are not fully captured by the model during training. For the "Less Secure" and "Not Safe" classes, the model provides relatively balanced results between precision and recall. F1-score values of 0.72 and 0.73, respectively, indicate that the model has a moderate ability to accurately classify the two categories. In the context of disaster mitigation, the model's ability to recognize the "Unsafe" class is critical because it represents buildings that are at high risk of being affected by landslides.

GANN Parameters and Their Impact on Performance

The GANN model is configured using a number of systematically defined genetic parameters to improve the model's ability to find optimal solutions during the training process. This parameter setting is done by considering the balance between exploration and exploitation in

the search space, so that it can result in better and stable model performance. These parameters include:

Table 1. Parameters of the Genetic Algorithm in the GANN Model

GA Parameters	Grades/Description
Parents Mating	4
	The best number of individuals selected as the parent for the crossover process.
Generations	500
	The number of iterations or generations in the evolutionary process of genetic algorithms.
Genes Mutation Percentage	10%
	The percentage of genes that undergo random mutations to maintain population diversity.
Parent Selection Type	<i>Stochastic Universal Sampling (SUS)</i>
	A selection method that provides reproductive opportunities based on fitness values.
Crossover Type	<i>Single Point</i>
	A type of crossover that performs a one-part exchange of two parent chromosomes.
Typical Mutation	<i>Random</i>
	Mutations are done randomly on some genes to prevent premature convergence.
Keep Parents	-1 (True)
	Parent individuals with high fitness scores are retained to the next generation.

Setting these parameters is critical in determining the model's performance. For example, a generation count of 500 gives the model enough time to reach the optimal solution, while a mutation rate of 10% helps avoid convergence to local solutions. In addition, the use of Stochastic Universal Sampling as a parent selection method ensures that the top-performing individuals have a greater chance of becoming part of the next generation, thus improving the efficiency of the search for solutions.

Model Fitness Over Generation

Based on the results of the GANN model performance analysis in identifying buildings in landslide-prone areas, it was found that this model showed a fairly good predictive ability. An **average F1-score** value of 0.82 indicates an adequate balance between **precision** and **recall**. In the "Unsafe" class, the GANN model was able to achieve a **precision** value of 0.9 and a perfect recall (1.0), meaning that the model was very accurate in identifying buildings that were really high risk without missing a positive sample. This makes GANN a potential method in supporting disaster mitigation, especially for the categories that have the most significant impact.

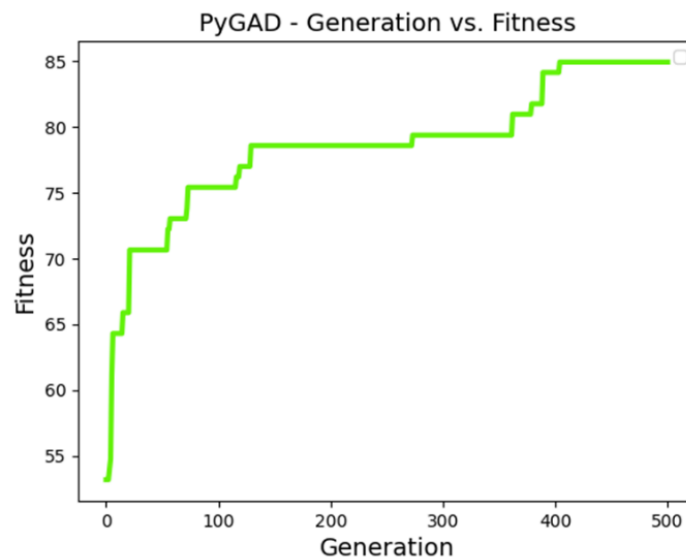


Figure 2. The Development of the Fitness Value of the GANN Model Over 500 Generations

In addition, the graph shown in figure 2 shows the development of **fitness** values over 500 generations showing a steady upward trend, with the final score reaching **84.9%**. These results prove that genetic algorithms are effective in the process of optimizing the weight of artificial neural networks through selection, **crossover**, and mutation mechanisms. Although not as fast as BPNN in terms of convergence, GANN was able to find more optimal solutions with the exploration of a wider search space, thereby reducing the risk of being stuck on suboptimal local solutions.

Confusion Matrix Model GANN

Based on the results of the **Confusion Matrix** analysis on the GANN model, this model shows a fairly good performance in identifying buildings in landslide-prone areas. In the "Safe" class, the model managed to correctly predict 10 of the 12 samples, despite one **case of False Negative** and one **case of False Positive**. This suggests that the model tends to miss a few positive samples or misclassify buildings from other classes as "Safe". For the "Less Safe" class, the model was able to correctly recognize 9 of the 12 samples, but there were 3 samples that were supposed to be in this class but were predicted to be "Not Safe", indicating an overlap of characteristics between classes that made the classification process a bit more complex.

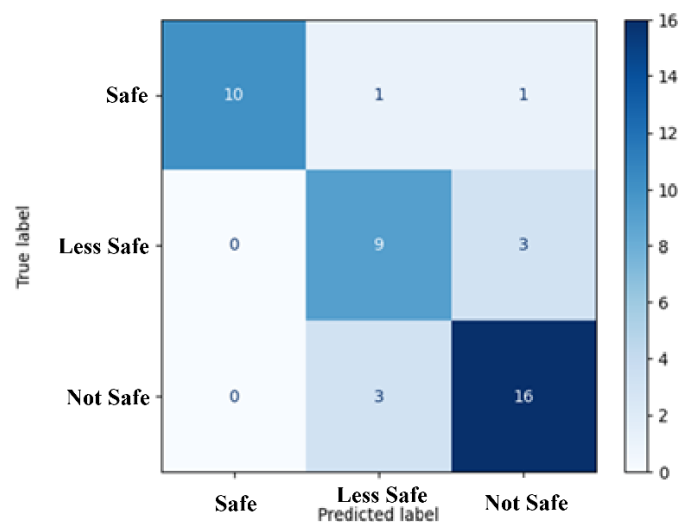


Figure 3. Confusion Matrix GANN Model for Safe, Less Secure, and Unsafe Category Classification

In the "Unsafe" class, the GANN model gave the best results by correctly classifying all 16 samples without any **False Positives**. The **precision**, **recall**, and **F1-score** values for this class reached high numbers, at 0.9, 1.0, and 0.95, respectively, indicating that the model was highly effective at detecting truly high-risk buildings. These results are particularly relevant in the context of disaster mitigation, as the ability to appropriately recognize "Not Safe" buildings can be the basis for prioritizing handling and protection decisions.

By configuring genetic parameters such as the number of generations (500), mutation rate (10%), as well as the selection and crossover methods used, the GANN model is able to find the optimal solution in the training process. Although there are still some misclassifications in the "Safe" and "Less Safe" classes, this model proves its stable and accurate predictive capabilities, especially in the most critical classes. Thus, GANN has the potential to become a reliable decision support tool in a data-driven landslide risk identification system.

Performance Score Genetic Algorithm Neural Network (GANN)

The **Performance Score table** displays the evaluation metrics of the **Genetic Algorithm Neural Network (GANN)** model in classifying data into three categories: **Safe**, **Less Safe**, and **Not Safe**. Each metric, such as Accuracy, Precision, Recall, and F1-Score, provides important insights into the model's ability to classify data precisely.

Table 2. GANN Performance Score Table

Class	Accuracy	1-Precision	Recall	1-Recall	F1 Score
Safe	1	0	0.83	0.17	0.91
Less Secure	0.69	0.31	0.75	0.25	0.72
Not Safe	0.8	0.2	0.84	0.16	0.82
Accuracy	0.81				
Misclassification Rate	0.19				
Macro-F1	0.82				
Weighted-F1	0.82				

The Genetic Algorithm Neural Network (GANN) model showed a fairly good performance in classifying buildings into three categories, namely "Safe," "Less Safe," and "Not Safe," based on the evaluation metrics used. In the "Safe" class, the model achieved a perfect precision value of 1, indicating that all "Safe" predictions were correct, even though the recall was only 0.83, meaning that 17% of the "Safe" sample was undetected. For the "Less Safe" class, the model has a precision of 0.69 and a recall of 0.75, with an F1-score of 0.72, indicating moderate performance and misclassification from other classes. In the most critical class, "Unsafe," the model achieved a precision of 0.8, a recall of 0.84, and an F1-score of 0.82, proving its good ability to detect high-risk buildings. Overall, the model's accuracy was 81%, with a Misclassification Rate of 19%, and a Macro-F1 and Weighted-F1 values of 0.82 each, demonstrating consistent performance across classes. While there is still room for improvement, especially in the "Less Safe" class, the GANN model has proven stable and reliable predictive capabilities in the identification of buildings in landslide-prone areas.

Several recent studies have emphasized the need for integrated approaches in landslide risk modeling by combining multiple methods to improve accuracy and robustness. For example, a comparison between GA-BP and PSO-BP neural network models demonstrated that hybrid approaches consistently outperform single-model techniques in landslide susceptibility mapping (Zhu et al., 2020). Similarly, (Daviran et al., 2023) demonstrated that combining SVM, ANN, and Random Forest with genetic optimization significantly improved classification performance, particularly in spatially complex regions. The results of our GANN model, which achieved an F1-score of 0.82, align with this trend and suggest that integrated optimization frameworks are crucial for reliable predictions. Unlike traditional models, GANN simultaneously handles weight tuning and solution exploration, making it suitable for real-world datasets with non-linear interdependencies. Our findings reinforce those in (Zheng et al., 2023), who highlighted GANN's

ability to reduce overfitting and increase generalization in geospatial hazard assessments. This further supports the adoption of ensemble or hybrid AI approaches in landslide risk mitigation strategies. Therefore, while GANN alone performs robustly, future work could explore combining it with other models such as BPNN or Decision Trees in ensemble schemes to capture different aspects of data variability and improve decision-making precision in high-risk zones.

These findings hold practical implications for both local governments and communities. For authorities, the GANN model can be integrated into early warning systems to identify at-risk buildings and prioritize reinforcement or relocation programs. The high recall in detecting "Unsafe" structures makes it especially useful in disaster preparedness planning. For communities, such predictive models can guide safer construction practices and raise awareness of structural vulnerabilities in landslide-prone areas. Implementing this AI-driven approach could significantly reduce casualties and material losses in future events.

CONCLUSION

Based on the results of a study on the application of **Genetic Algorithm Neural Network** (GANN) in the identification of buildings in landslide-prone areas, the GANN model showed quite good performance with an overall accuracy of **81%** and an average **F1-score** of **0.82**, indicating an adequate balance between **precision** and **recall**. The best performance was achieved in the "Unsafe" class with a **recall** of **0.84**, demonstrating the model's ability to accurately detect high-risk buildings. While there is still room for improvement, especially in the "Less Secure" class, the use of genetic algorithms in network weight optimization proves GANN's ability to explore solutions globally and avoid convergence to suboptimal local solutions, making it a potential method in data-driven disaster mitigation systems.

As a form of follow-up, this study recommends testing GANN in a broader field scenario with the integration of geospatial data and real-time sensors to improve adaptability to actual conditions in vulnerable areas. In addition, an integrated approach that combines GANN with other methods such as BPNN, SVM, or ensemble techniques is also recommended to strengthen classification accuracy on various building and geological structural conditions. These findings can be used by local governments to prioritize mitigation and strengthen early warning systems, as well as by the community as a guide in improving building structures that are safe against landslide risk.

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