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Dynamic DSS for Post-Natural Disaster Sector Damage Detection Using Modified-TOPSIS and Neural Networks

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Abstract

Indonesia is a country that is highly vulnerable to natural disasters, necessitating a rapid and systematic post-disaster rehabilitation and reconstruction process. However, regional disaster management agencies frequently encounter subjective and inconsistent damage assessments from field surveyors due to the absence of clear standardized criteria. To address this issue, this study develops a web-based Intelligence Decision Support System Dynamic (IDSSD). The system integrates a classically modified Multi-Criteria Decision Making (MCDM) method, specifically Modified-TOPSIS, with an Artificial Intelligence (AI) model utilizing a Single Layer Perceptron Neural Network. The Modified-TOPSIS method utilizes Pairwise Comparison to objectively determine criteria weights, while the Neural Network dynamically adjusts criteria weights when encountering new or unpatterned data. The system was evaluated using confusion matrix parameters (accuracy, precision, recall, and F-measure) based on 16 field datasets from BPBD Blitar, East Java. The experimental results demonstrate that the Modified-TOPSIS method achieves an accuracy of 75% (classified as Fair Classification), whereas the integrated Neural Network-Modified TOPSIS method achieves an accuracy of 81% (classified as Best Classification). The integration of Neural Network significantly enhances system adaptability and objectivity in assessing post-disaster damage.

Keyword: Decision Support System, Neural Network, Modified-TOPSIS, Disaster Management.

1. Introduction

Indonesia is an archipelagic nation geographically situated in a region prone to natural disasters. This condition necessitates preparedness and rapid response from all relevant stakeholders, particularly regarding post-disaster management through rehabilitation and reconstruction phases. The rehabilitation and reconstruction process represents a tangible government effort to restore various development sectors—such as housing, infrastructure, social systems, and the economy—impacted by disasters. From philosophical and theological perspectives, the collaborative effort to rebuild the lives of disaster victims aligns with the noble values found in the Quran (Surah Al-Baqarah: 153 and Surah At-Taubah: 71), which emphasize the importance of patience in facing trials and the obligation for humans to assist one another in acts of goodness (ma'ruf).

In practice, the rehabilitation and reconstruction planning process—led by the Disaster Management Planning and Control (P3B) team under the Regional Disaster Management Agency (BPBD)—relies heavily on the availability of accurate damage data. A common empirical challenge in the field is the subjectivity of assessments made by individual surveyors. This arises from the absence of transparently standardized criteria and benchmarks for damage assessment, leading to variations and inconsistencies in the damage reports submitted to the BPBD.

To address these data inaccuracies, the use of Decision Support System (DSS) technology offers a crucial solution for minimizing subjectivity through the standardization of assessment criteria (Contrera et al., 2020; Greenal & Anilkumar, 2025; Utomo & Ipmawati, 2016). Previous research has demonstrated that Multi-Criteria Decision Making (MCDM) methods can be applied to classify damage levels, thereby enhancing the efficiency of formulating recovery action plans (Aktas et al., 2025; Zabihi et al., 2023). However, traditional Decision Support Systems (DSS) suffer from limitations due to their static and rigid nature, rendering them inflexible when dealing with dynamic field situations that often involve incomplete or conflicting data (Smarzewski & Rutka, 2020). Consequently, this research focuses on developing a Dynamic Intelligent Decision Support System (IDSSD). The system's strength lies in integrating a classic Multi-Criteria Decision-Making (MCDM) method—specifically Modified-TOPSIS—with Artificial Intelligence via Neural Networks (Chung et al., 2007). This combination aims to address data incompleteness and to update criteria weights dynamically and objectively based on the characteristics of the disaster-affected area.

Based on existing operational conditions, the primary research problem is identified as follows: How to implement and determine the accuracy level of an integrated Modified-TOPSIS and Neural Network approach for assessing sectoral damage levels following a natural disaster. The main objective of this study is to analyze and determine the accuracy of the Modified-TOPSIS and Neural Network methods when implemented within a dynamic decision support system designed to assess sectoral damage levels after natural disasters.

To maintain the research focus, the following scope limitations have been established: First, the data used for testing and modeling is derived from disaster records in the Blitar Regency area of East Java. Second, the decision analysis methods applied and evaluated are limited to Modified-TOPSIS and Neural Networks.

This research is expected to yield several benefits, including: First, facilitating field surveyors in objectively and rapidly determining sectoral damage levels, thereby assisting the Regional Disaster Management Agency (BPBD) in accurately estimating the aid and recovery measures required for affected victims. Second, providing empirical evidence regarding the accuracy and comparative performance of the integrated Modified-TOPSIS and Neural Network algorithms.

2. Literature Review

2.1 Related Research

Research on optimizing decision-making in disaster management continues to evolve. Almais et al. (2016) developed a system using the Multi-Expert Multi-Criteria Decision Making (ME-MCDM) method to determine post-disaster recovery actions. While the decision patterns derived from the ME-MCDM training data successfully generated tactical guidelines, they remained limited by static weighting assigned by experts. Subsequently, Bachriwindi et al. (2019) designed a web-based Decision Support System (DSS) utilizing the Weighted Product (WP) method to map damage levels. Evaluation of the system revealed a low accuracy rate of 48.7%, attributed to inaccuracies in input data from the field.

To address the dynamic nature of criteria—which often shift due to government policies—Almais et al. (2020) introduced a Dynamic Decision Support System employing the Fuzzy-Weighted Product (F-WP) method. The F-WP method demonstrated the ability to adapt dynamically and achieved an accuracy rate of 53%. However, it suffers from a significant functional drawback: the system's execution time increases exponentially as the volume of pattern data in the database grows.

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Conversely, the reliability of Neural Networks (NN) in pattern matching and error minimization via backpropagation has proven effective for solving complex classification problems (Pujianto et al., 2018; Yulianti, 2013). By combining this intelligent system with decision algorithms, the limitations of traditional DSS in handling incomplete information can be significantly mitigated. Therefore, this study proposes an integration of Modified-TOPSIS and Neural Networks to achieve efficient and rapid classification without the issue of escalating execution times (Zhang et al., 2021).

2.2 Dynamic Decision Support System (DSSD)

A Dynamic Decision Support System (DSSD) is an evolution of the traditional DSS, designed to flexibly adapt to changes in criteria or alternatives without disrupting the system's ongoing workflow (Ozdemir et al., 2020). In the context of disaster rehabilitation, assessment criteria often fluctuate—increasing or decreasing—based on prevailing budget policies and government regulations. In a traditional DSS, adding new criteria requires the system to be redesigned from scratch, risking the interruption of application operations. Conversely, a DSSD accommodates these dynamics through a systematic cycle of dynamic phases, comprising: (a) inputting new criteria, (b) determining importance levels, (c) inputting alternatives, (d) processing, (e) testing results against similar data characteristics, and (f) making the final decision (Janjua & Hussain, 2012).

2.3 Modified-TOPSIS

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method is based on the principle that the chosen alternative must be closest to the Positive Ideal Solution (PIS) and farthest from the Negative Ideal Solution (NIS) (Gangurde & Akarte, 2013). This proximity is measured using the Euclidean Distance formula. However, a major drawback of traditional TOPSIS is the lack of a clear standard for determining the importance weights of each criterion; these are often based on the researcher's subjective assumptions (Kwok & Lau, 2019; Selvachandran & Peng, 2019).

To mitigate this weakness, the Modified-TOPSIS method integrates the Pairwise Comparison technique. Pairwise Comparison constructs a matrix that compares criteria in pairs—using a fundamental rating scale of 0 to 9—to assess the relative preferences of the criteria (Musthafa et al., 2015). This approach effectively minimizes weighting inconsistencies, thereby yielding weight value priorities that are far more accurate and objective than those produced by standard TOPSIS (Oswaldo et al., 2014).

2.4 Neural Network (Single Layer Perceptron)

A neural network is an information processing system that mimics the workings of human biological neural networks to learn, memorize, and identify implicit relationships within a database (Chowdary, 2007). In its simplest structure, this model is represented by the Single Layer Perceptron (SLP), which processes a linear combination of input values and neuron connection weights, supplemented by a bias value (Pujianto et al., 2018). The bias plays a vital role in providing numerical significance when input data values are zero. The result of this linear calculation is then transformed using a non-linear activation function—such as the Sigmoid function—to produce a continuous output value between 0 and 1. The SLP learning process focuses on minimizing the error value (the squared difference between the target output and the actual output) by iteratively updating weights based on a specified learning rate.

3. Method

3.1 Research Design

The research design is structured to ensure system reliability through sequential stages, as illustrated in the system design flowchart below (see Figure 1).

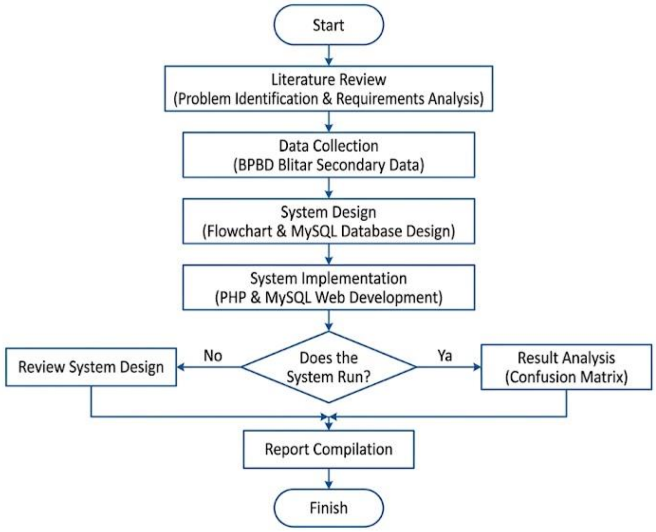

Figure 1. System Flowchart Design

3.2 Data Collection

The data used in this study consists of secondary data sourced directly from historical natural disaster records maintained by the Regional Disaster Management Agency (BPBD) in Blitar Regency, East Java, covering the years 2010, 2011, and 2013. This field data represents various instances of physical damage to structures such as residential areas, places of worship, educational institutions, and transportation infrastructure.

In the database design, the system categorizes this data into four sectors: 1) Economy (e.g., livestock, shophouses/retail outlets, fisheries, agriculture, markets); 2) Settlements (e.g., settlement infrastructure, housing); 3) Social (e.g., other institutions, community health centers, prayer rooms/mosques, education); and 4) Infrastructure (e.g., roads and bridges, clean water and sanitation, electricity, railways, embankments/irrigation, telecommunications). The system's final classification output is defined by three alternative damage levels:

- ALT001 - Minor Damage
- ALT002 - Moderate Damage
- ALT003 - Severe Damage

The system is designed using five primary assessment criteria based on the standards set by the Directorate General of Human Settlements (CV. Cipta Karya) of the Ministry of Public Works (2006) regarding earthquake-resistant building guidelines:

- K001 (Building Condition)
  The assessment scale includes: Still Standing (Minor), Leaning (Moderate), and Totally Collapsed (Severe).
- K002 (Building Structural Condition)
  The assessment scale includes: Minor Damage to a Small Portion (Minor), Damage to a Small Portion (Moderate), and Damage to a Large Portion (Severe).
- K003 (Extent of Physical Building Damage)
  The quantitative assessment scale comprises <30% (Minor), 30–50% (Moderate), and >50% (Severe).

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- K004 (Building Function)
  The assessment scale comprises Non-Hazardous (Minor), Relatively Hazardous (Moderate), and Hazardous (Severe).
- K005 (Condition of Other Supporting Elements)
  The assessment scale comprises Partially Damaged (Minor), Largely Damaged (Moderate), and Totally Damaged (Severe).

3.3 Weight Determination Using Pairwise Comparison

The pairwise comparison calculation process is carried out to obtain objective priority weights for each sub-criterion. As an example, the pairwise comparison calculation for the "Building Condition" sub-sector is presented in Table 1 below.

Table 1. Pairwise Comparison Matrix for Building Condition

Criteria	**Standing**	**Crooked**	**Total Collapse**	**Priority Weight (*Priority Sector*)**
Standing	1	1,5	2,5	0,287683284
Crooked	0,666666667	1	2	0,203910068
Total Collapse	0,4	0,5	1	0,108406647
Total	2,066666667	3	5,5	1,000000000

(Source: Weighted data from BPBD Blitar Regency criteria documents)

Based on Table 1, the "Still Standing" sub-criterion is rated 2.5 times more important than "Totally Collapsed" and 1.5 times more important than "Leaning," while "Leaning" is rated twice as important as "Totally Collapsed." Through a similar calculation process applied to all criteria, a summary of the functional weights for the sub-criteria was obtained, as detailed in Table 2 below.

Table 2. Summary of Sub-Criterion Weights Derived from Pairwise Comparison

Main Criteria	**Sub-Criteria**	**Priority Weight (*w_j*)**
Building Status (K1)	Still Standing / Leaning / Totally Collapsed	0,28 / 0,20 / 0,10
Building Structural Status (K2)	Minor Damage to Small Portion / Partially Damaged / Largely Damaged	0,24 / 0,22 / 0,14
Physical Condition of Damaged Building (K3)	<30% / 30–50% / >50%	0,30 / 0,20 / 0,10
Building Function (K4)	Not Dangerous / Relatively Dangerous / Dangerous	0,45 / 0,24 / 0,07
Status of Other Supporting Elements (K5)	Partially Damaged / Largely Damaged / Totally Damaged	0,48 / 0,30 / 0,07

(Source: Results of system criteria data processing)

3.4 Dynamic System Architectural Design

The workflow of the IDSSD information system is systematically designed to intelligently handle discrepancies in input data provided by surveyors. When a surveyor enters parameters—such as disaster type, sector type, and criterion values—in the field, the system checks the input data against the pattern data stored in the MySQL database.

If the input data matches an existing pattern (previously validated using Modified-TOPSIS), the system immediately displays the damage level alternative. However, if the data entered by the surveyor is not found in the database's pattern data, the system automatically triggers the Single-Layer Perceptron Neural Network subsystem. This NN algorithm processes the criteria, updates the criterion weights in real-time, stores them in the database as a new pattern, and subsequently processes the new weights using the Modified-TOPSIS method to determine the final damage assessment alternative.

4. Results and Discussion

4.1 System Implementation and Interface

The IDSSD information system is a web-based application developed using HTML, PHP, CSS, and JavaScript, utilizing a MySQL database server. To ensure dynamic and smooth data operations, the system employs a relational database architecture integrating nine primary tables: `tbkriteria`, `tbcrips`, `tbpola_detail`, `tbjenis`, `tbbencana_detail`, `tbpola`, `tbbencana`, `tbsektor`, and `tbalternatif`.

The user interface is designed intuitively to facilitate operator interaction. Key menu views include:

- Home Menu
  The initial landing page, which provides an explanation of the system's functionality alongside the main navigation menu (see Figure 1).

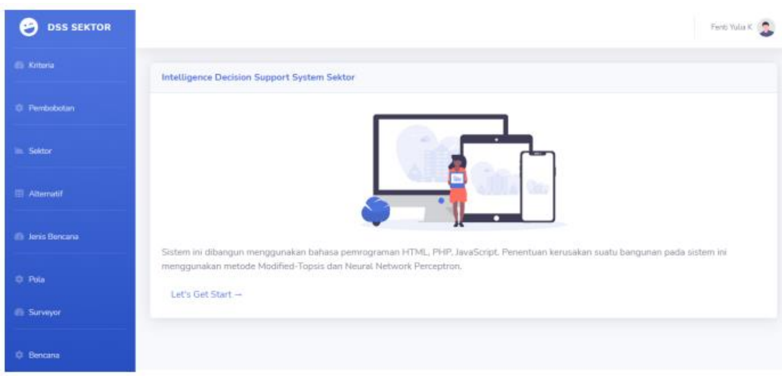
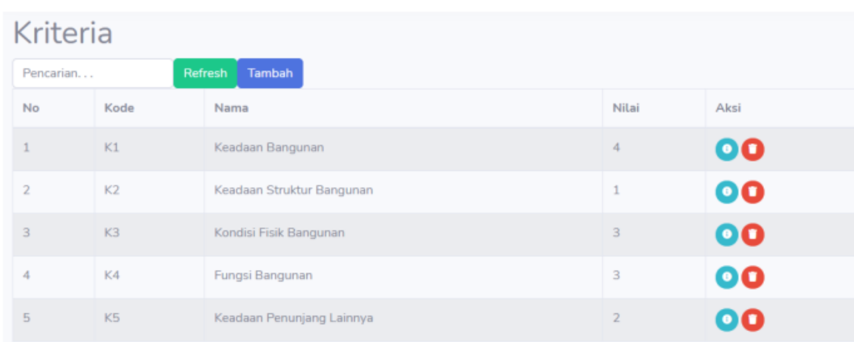


Figure 1. Main Page Design Layout

- Criteria and Weighting Data Menu
  Provides a means for the administrator to dynamically add, modify, or delete criteria and weighting scale values in the database (see Figure 2).


Kriteria

Pencarian. . . Refresh Tambah

No	Kode	Nama	Nilai	Aksi
1	K1	Keadaan Bangunan	4	
2	K2	Keadaan Struktur Bangunan	1	
3	K3	Kondisi Fisik Bangunan	3	
4	K4	Fungsi Bangunan	3	
5	K5	Keadaan Penunjang Lainnya	2	

Figure 2. Design of criteria and weighting data

- Pattern Data Menu

Displays a summary of disaster pattern data, complete with an automated TOPSIS calculation function to classify the damage level for each historical disaster case (see Figure 3).

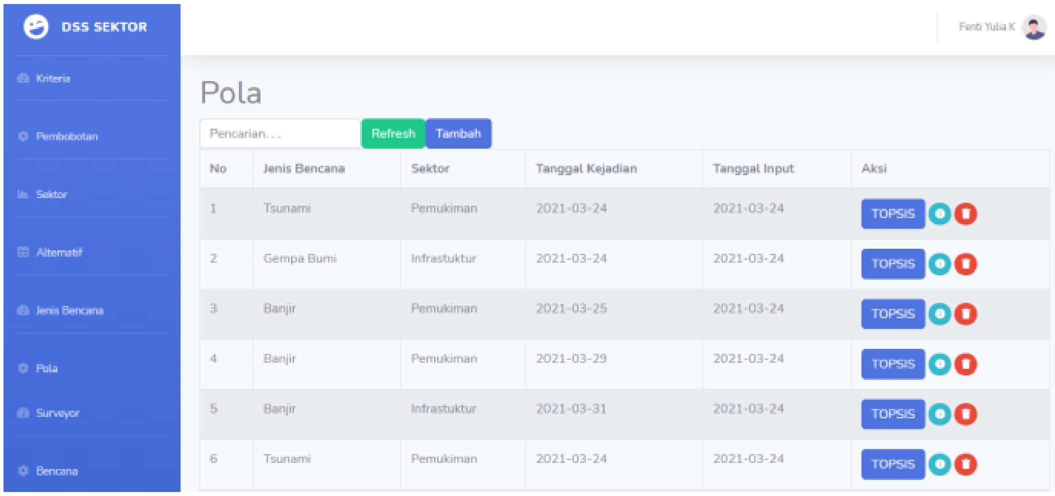


Figure 3. Pattern Data Design

- Menu Surveyor

  A visible interface for field surveyors to input new disaster data. This menu automatically displays pattern-matching results if a match is found, or shows the output of the Perceptron (Neural Network) iteration process if the new data requires a weight update (see Figure 4).

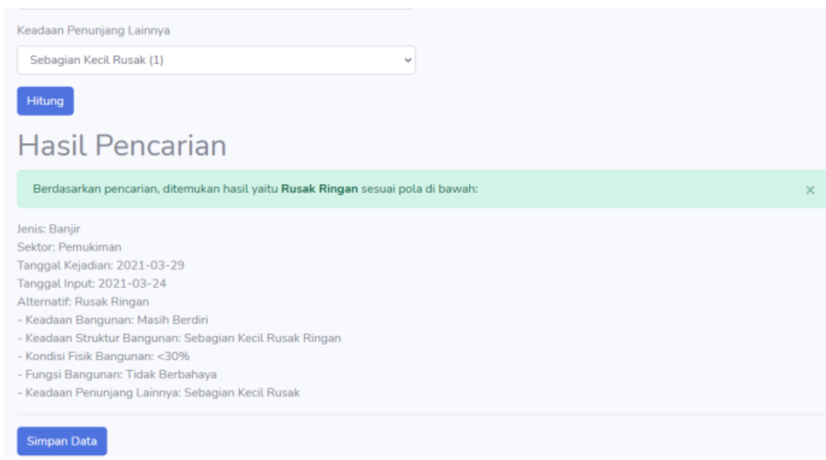


Figure 4. Surveyor Menu Design

4.2 Method Performance Test Results

To evaluate the system's reliability in accurately classifying post-disaster damage levels, a comparative test was conducted using the Confusion Matrix method. The test dataset comprised 16 actual field data points sourced from Blitar Regency BPBD documents (from 2019 and 2020) serving as the reference, which were rigorously compared against 16 system-generated decision data points. Performance was assessed based on four key parameters: Accuracy, Precision, Recall, and F-Measure. 1. Performance Evaluation of the Modified-TOPSIS Method (Without Neural Network)

Based on the classification test results for 16 test data points using the pure Modified-TOPSIS method, the Confusion Matrix mapping yielded the following values: True Positive (TP) = 6, True Negative (TN) = 6, False Positive (FP) = 3, and False Negative (FN) = 1. Based on this data, the evaluation parameters were calculated as follows:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\% = \frac{6 + 6}{6 + 6 + 3 + 1} \times 100\% = \mathbf{75\%}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% = \frac{6}{6 + 3} \times 100\% = \mathbf{60\%}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% = \frac{6}{6 + 1} \times 100\% = \mathbf{80\%}$$

$$\text{F-Measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \times 100\% = 2 \times \frac{60 \times 80}{60 + 80} \times 100\% = \mathbf{68.4\%}$$

2. Performance Evaluation of the Integrated Neural Network and Modified-TOPSIS Method

Subsequently, when testing was conducted by activating dynamic pattern recognition based on a Neural Network (Single Layer Perceptron) prior to Modified-TOPSIS processing, a far more optimal Confusion Matrix mapping result was obtained, namely: True Positive (TP) = 12, True Negative (TN) = 1, False Positive (FP) = 2, and False Negative (FN) = 1. The calculation of evaluation parameters yields the following values:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\% = \frac{12 + 1}{12 + 1 + 2 + 1} \times 100\% = \mathbf{81\%}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% = \frac{12}{12 + 2} \times 100\% = \mathbf{85\%}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% = \frac{12}{12 + 1} \times 100\% = \mathbf{90\%}$$

$$\text{F-Measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \times 100\% = 2 \times \frac{85 \times 90}{85 + 90} \times 100\% = \mathbf{43\%}$$

4.3 Comparative Analysis Discussion

To determine the credibility of the classification based on accuracy measurement results, a quality mapping was performed using the classification index standard by Musthafa et al. (2015). This standard divides accuracy levels into five categories: Excellent classification (90% – 100%), Best classification (80% – 90%), Fair classification (70% – 80%), Poor classification (60% – 70%), and Failure (50% – 60%).

Based on this standard, the results of the performance comparison analysis can be described as follows:

1. The Modified-TOPSIS method alone yields an accuracy of 75%, placing the algorithm's performance in the "Fair Classification" category.
2. The integrated Neural Network-Modified TOPSIS method records a higher accuracy of 81%, placing this intelligent system's performance in the "Best Classification" category.

This 6% increase in accuracy scientifically demonstrates that incorporating a Neural Network—using the Single Layer Perceptron learning algorithm—can overcome the structural limitations of classical decision-making models. By adaptively updating weights when faced with incomplete field data, the Neural Network successfully reduces assessment bias, resulting in decisions that are far more objective and reflective of the actual physical damage on the ground.

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4.4 Integrating Human Values with Science and Technology

The development of IDSSD technology to address the impact of this disaster represents a tangible manifestation of the moral message found in Surah Ar-Rum, verse 41, of the Quran. This verse affirms that corruption and damage have appeared on land and at sea due to human actions, yet within such calamities lies a lesson intended to guide humanity back to the right path. One way to implement this concept of "returning to the right path" within the realm of science and technology is by applying human intellect to create technological innovations that foster the common good and alleviate the suffering of others. Furthermore, the integration of this system serves as a catalyst for the government to realize the promise of Allah found in Surah Al-Insyirah, verses 5–6: that after hardship, there is inevitably ease. IDSSD functions as a technical instrument that simplifies and accelerates the bureaucratic processes involved in disaster recovery, enabling victims to emerge more quickly from the difficult post-disaster period.

5. Conclusion

This study successfully designed, implemented, and evaluated the performance of a web-based Dynamic Intelligent Decision Support System (IDSSD) to determine the severity of damage across sectors following natural disasters in Blitar Regency. Testing using Confusion Matrix parameters led to the scientific conclusion that the integrated Neural Network and Modified-TOPSIS method performs significantly better, achieving an accuracy of 81% (classified as "Best Classification"), compared to the standalone Modified-TOPSIS method, which achieved only 75% accuracy (classified as "Fair Classification").

The system's accuracy also proved far more reliable when compared to previous decision support systems, such as the web-based WP system by Bachriwindi (2019)—which recorded 48.7% accuracy—and the Fuzzy-WP system by Almais (2020), which achieved 53% accuracy. Consequently, this integrated IDSSD information system serves as a valid digital tool for local governments and surveyors to accelerate the formulation of post-disaster rehabilitation and reconstruction action plans.

To refine the information system and advance future research, the following technical recommendations are proposed: First, AI Model Development: Future research should explore the application of more complex artificial intelligence algorithms to determine if higher accuracy levels can be achieved. Second, Optimization of the Evaluation Process: The calculation of functional accuracy using the Confusion Matrix should be directly integrated into each stage of the algorithm's execution to yield more precise validation results. Third, Platform Portability: As the current system is limited to a web-based architecture, future development should focus on mobile platforms (Android/iOS) to enhance user-friendliness for surveyors operating in disaster zones.

Acknowledgments

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