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Implementation of Artificial Neural Network (ANN) for identifying design indicators of temporary modular shelters

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Abstract
The demand for fast, efficient, and adaptive emergency housing continues to increase, especially in disaster-prone areas and large-scale displacement situations. The determination of the design of Temporary Modular Shelter (TMS) so far still depends a lot on subjective considerations, so a more systematic and data-based approach is needed. This study develops and validates an Artificial Neural Network (ANN) model to identify the most suitable TMS design based on performance indicators and expert assessment. The approach was carried out through the Systematic Literature Review (SLR) stage, the determination of eight key design indicators, and assessment by 150 multidisciplinary respondents. The ANN model was built using a dense four-layer architecture with a total of 1,780 parameters and trained for 400 epochs using the TensorFlow and Keras libraries. The results showed a validation accuracy of 96% and a macro F1-score of 0,9146, indicating the stability and reliability of the model. Analysis of the contribution of features with the SHAP method revealed that the indicators of assembly methods, availability of human resources, and availability of local materials had the greatest influence on the classification results. This model has proven to be effective as a decision support system that is able to increase objectivity and efficiency in the TMS design process. Further development is suggested through integration into web-based digital platforms or mobile applications to support rapid and adaptive emergency response planning.

Introduction

The need for fast, efficient, and adaptable emergency housing remains critical in disaster situations and large-scale displacement. Shelters function as temporary protective dwellings that ensure safety, privacy, and dignity during emergency response and early recovery (Citaristi, 2022). Modular shelters, constructed from prefabricated and reconfigurable components, offer advantages in rapid deployment, flexibility, material efficiency, scalability, and reduced reliance on specialized labor, making them suitable for dynamic post-disaster conditions (Baghdadi et al., 2021; Makadi et al., 2025; Nekooie & Tofighi, 2020).

Various TMS models such as UNHCR tents, Better Shelter (RHU), Exo Shelter, Rapid Deployment Modules (RDM), and Foldable Container Units (FCU) have been widely used in earthquakes, floods, and refugee crises (Babu, 2025; Conzatti et al., 2022; Dash et al., 2022; Sari et al., 2025a). Although effective, these designs still predominantly emphasize physical construction and logistics, with limited incorporation of data-driven performance criteria related to comfort, usability, adaptability, and socio-cultural fit.

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Recent studies indicate that many existing shelters fail to meet minimum standards of thermal comfort, privacy, and cultural appropriateness (Ghomi et al., 2021; Montalbano & Santi, 2023). Other research highlights poor adaptability to local climatic conditions, resulting in energy inefficiency and user discomfort (Khadka, 2025; Sari, Winarno, et al., 2024).

The absence of systematic and standardized evaluation methodologies further contributes to design inefficiencies. Contemporary literature identifies recurring weaknesses such as suboptimal thermal retention, poor ventilation, high transport costs, low material durability, and limited contextual adaptability (Hamdan et al., 2021; Obyn et al., 2014). Moreover, layout decisions remain heavily dependent on expert judgment, lacking objective and data-driven benchmarks. This gap underscores the need for a structured, indicator-based assessment framework that integrates technical, functional, and contextual dimensions of TMS performance.
Artificial Neural Networks (ANNs) have emerged as promising computational techniques capable of modeling complex nonlinear interactions among architectural, environmental, and logistical variables. ANNs have been widely applied in construction engineering for risk assessment, building condition evaluation, and decision support (Boucetta et al., 2021; Pratama, Sari, & Prasojo, 2025; Sari, Pratama, & Ircham, 2024; Sari, Pratama, & Prastowo, 2024). However, their use in modular shelter planning remains limited to retrospective evaluations rather than proactive design decision-making. Although ANN-based approaches have shown success in optimizing structural configurations and improving cost efficiency and adaptiveness (Birjukov & Bolotin, 2015; Guo et al., 2021; Nabi & El-adaway, 2020; Xie et al., 2025), few studies have applied ANN at the early design stage of TMS development, particularly for rapid, data-driven decision-making in emergency contexts.
To address these gaps, this study introduces a multilayer ANN model designed to automatically classify Temporary Modular Shelter design feasibility using eight key indicators are building size, material characteristics, assembly method, human resource preparation, material transport, workforce availability, site accessibility, and local material availability. The model produces four decision outcomes Highly Acceptable (HA), Acceptable (A), Requires Additional Review (RAR), and Not Recommended (NR). In this way, the ANN functions not only as a predictive tool but also as a proactive decision-support system capable of enhancing design accuracy and contextual suitability for emergency shelter planning.

The main objective of this study is to develop and validate an ANN-based classification model capable of identifying TMS design feasibility accurately and objectively. Through real-time multivariate analysis, the model aims to support data-driven decision-making, accelerate the design process, increase consistency across stakeholders, and strengthen the integration of artificial intelligence in adaptive architecture and disaster response planning.

Methods

This study uses an experimental quantitative approach with a predictive modeling design based on Artificial Neural Network (ANN). This approach was chosen because ANN has the ability to recognize non-linear relationships between variables as well as generate accurate data-driven predictions. The main objective of the research is to develop a multilayer ANN model that is able to automatically and objectively identify TMS design indicators based on classified parameter data. This research is classified as *applied research* because the results are expected to be applied directly in the decision-making process for designing temporary housing in emergency conditions (Leavy, 2022).

Literature Review and TMS Design Identification (SLR + NVivo)

The initial stage of the research was carried out through a Systematic Literature Review (SLR) combined with qualitative analysis using NVivo 12. A total of 120 scientific articles were collected from three main databases *ScienceDirect, SpringerLink, and Google Scholar* based on inclusion criteria such as topic relevance, language suitability, and year of publication. Articles that met the criteria were extracted using standard data templates to identify the most relevant variables, factors, and attributes related to TMS design indicators.

Following the extraction process, a theme frequency analysis was conducted to determine which design indicators appeared most frequently and demonstrated strong relationships with shelter performance across various contexts. The results of this literature synthesis served as the foundation for constructing the initial dataset used in the quantitative modeling stage.

Based on this dataset, the model demonstrates stable and consistent classification patterns across all decision categories. Minor misclassifications between the RAR and NR categories indicate that the model remains highly sensitive to borderline cases in which design indicators exhibit similar characteristics. This consistency further validates the relevance of the indicators identified during the SLR and qualitative analysis stages (Sari et al., 2025b; Sari & Nugraheni, 2024).

Determination of Key Design Indicators

The results of the SLR analysis and expert validation produced eight key indicators representing the technical, functional, and contextual dimensions of TMS design (Montalbano & Santi, 2023; Nekooie & Tofighi, 2020; Xie et al., 2025). These indicators include are (1) building size, measured through effective area and occupancy ratios; (2) material characteristics classified by struktural resistance and thermal performance; (3) assembly method, evaluated based on installation duration and required labor; (4) human resource preparation, reflecting the skill level and readiness of local workers; (5) material transport method, assessing logistical feasibility; (6) availability of local human resources relative to construction demand; (7) location affordability based on accessibility and distribution distance; and (8) availability of local materials, quantified through the proportion of materials obtainable within the affected region.

To ensure consistency in classification, the four decision classes were defined using technical thresholds derived from SLR findings and expert consensus. “Highly Acceptable (HA)” refers to designs meeting all key criteria, including installation time under 6 hours (Makadi et al., 2025), thermal conductivity < 0.18 W/m·K (Ghomi et al., 2021), local material availability > 80% (Hamdan et al., 2021), and workforce readiness > 0.85 (Obyn et al., 2014). “Acceptable (A)” covers designs meeting minimum requirements installation within 6–12 hours, thermal conductivity 0.18–0.25 W/m·K, and material availability 60–80% (Baghdadi et al., 2021; Montalbano & Santi, 2023). “Requires Additional Review (RAR)” includes borderline cases such as installation times of 12–18 hours, workforce readiness < 0.6, or moderate material suitability (Khadka, 2025; Xie et al., 2025). “Not Recommended (NR)” applies to designs exceeding critical limits installation beyond 18 hours, thermal conductivity > 0.30 W/m·K, local material availability < 40%, or severe accessibility issues (Nekooie & Tofighi, 2020; Sari et al., 2025a). These thresholds served as standardized decision labels for expert evaluation and ANN training.

All eight indicators were expressed in numerical or ordinal form and subsequently normalized using Min–Max scaling to ensure consistent processing within the ANN. Each TMS design alternative was represented as a single input vector consisting of these eight normalized indicators, forming the structured dataset used for model training and validation.

Data Collection and Evaluation by Respondents

Data were collected from 150 expert respondents selected through purposive sampling, representing six key stakeholder groups are BPBD–BNPB officials, civil engineering practitioners, academics, disaster-affected communities, humanitarian NGOs, and local material suppliers. Such multi-stakeholder engagement is consistent with best practices in shelter evaluation and disaster research (Ghomi et al., 2021; Montalbano & Santi, 2023). This composition ensured a balanced integration of technical, social, and contextual perspectives.

Each respondent evaluated 27 TMS design alternatives using eight normalized indicators covering building size, material properties, assembly duration, workforce and material availability, transport difficulty, workforce readiness, and site accessibility. The use of Likert-based expert scoring and Min–Max normalization follows established methods in multi-criteria design assessment and ANN-based decision support (Obyn et al., 2014; Xie et al., 2025).

A total of 4,050 evaluations were obtained (27 × 150). Respondents also assigned a feasibility category (HA, A, RAR, NR), which was aggregated using an expertise-weighted scheme, a procedure widely applied in expert judgment integration and emergency planning studies (Hamdan et al., 2021; Nekooie & Tofighi, 2020). The final class distribution consisted of HA = 6, A = 8, RAR = 7, and NR = 6.

Descriptive statistics show substantial variation across indicators such as building size (12–24 m²), thermal conductivity (0.12–0.32 W/m·K), assembly duration (4–18 hours), and local material availability (40–95%). Such heterogeneity aligns with previous findings on modular shelter diversity and highlights the complexity of the design problem (Baghdadi et al., 2021; Khadka, 2025). This variability underscores the need for ANN-based nonlinear pattern recognition to capture relationships among indicators (Birjukov & Bolotin, 2015; Boucetta et al., 2021).

ANN Model Development and Training

The ANN architecture was developed using TensorFlow–Keras and consists of an input layer with eight features, two hidden dense layers with 28 and 44 neurons, and a Softmax output layer with four feasibility classes. ReLU activation and HeNormal initialization were applied across hidden layers to maintain stable gradient flow, following established guidelines for deep neural network design (Chollet, 2021).

Model robustness was enhanced through L2 regularization ($\lambda = 0.001$) and a 0.2 dropout rate, while optimization used the Adam optimizer (learning rate 0.001) with a batch size of 32. These hyperparameter settings align with recommended practices for preventing overfitting and improving convergence stability (Kingma & Ba, 2015; Srivastava et al., 2014). Training was configured for up to 400 epochs, with early stopping (patience = 20) implemented to halt training once validation loss plateaued, ensuring computational efficiency without sacrificing performance (Jahn & Jin, 2024).

For generalization assessment, the dataset was split into 70% training, 15% validation, and 15% testing, complemented by five-fold stratified cross-validation an evaluation approach widely used to ensure stability across imbalanced or heterogeneous datasets (Tsamardinos et al., 2018). The model consistently achieved strong performance, with accuracy in the 95% CI range of 0.94–0.97 and macro F1-scores in the 0.89–0.93 range. These results confirm that the chosen architecture, regularization strategy, and hyperparameters produced a stable and well-generalized ANN for classifying TMS design feasibility, in line with findings from ANN performance evaluations in construction and modular design research (Boucetta et al., 2021; Xie et al., 2025).

Evaluation and Interpretation of the ANN Model

A comprehensive assessment of the model's effectiveness employed several fundamental metrics that have become standard benchmarks in evaluating classification systems built on artificial neural network architectures. These include accuracy, precision, recall, F1-score, specificity, and false positive rate. Every individual metric serves to evaluate distinct dimensions of how well the model performs, with their mathematical formulations being transparently documented within this segment to ensure the numerical analysis remains clear and verifiable (Pratama, Sari, & Yuliani, 2025; Sari, Pratama, & Prastowo, 2024). The accuracy metric specifically quantifies what fraction of all test samples were correctly classified by the model, following the mathematical expression shown in Equation (1).

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \tag{1}$$

Precision describes the accuracy of the model in providing correct positive predictions, as stated in Equation (2).

$$\text{Precision} = \frac{TP}{(\text{TP} + \text{FP})} \tag{2}$$

Recall is used to measure the extent to which the model is able to identify all the correct positive data, as shown in Equation (3).

$$\text{Recall} = \frac{TP}{(\text{TP} + \text{FN})} \tag{3}$$

The F1-score is calculated as the harmonic mean of precision and recall to assess the balance between the accuracy and completeness of the model's predictions, as in Equation (4).

$$\text{F1 Score} = \frac{2\,x\ (\text{Precision x Recall})}{(\text{Precision} + \text{Recall})} \tag{4}$$

Specificity measures the extent to which the model is able to correctly recognize negative data, as described in Equation (5).

$$\text{Specificity} = \frac{TN}{(\text{TN} + \text{FP})} \tag{5}$$

False Positive Rate is used to assess the proportion of misclassification when negative data is predicted as positive, as in Equation (6).

$$False\ Positive\ Rate = \frac{FP}{(\text{FP} + \text{TN})} \tag{6}$$

Beyond the primary evaluation metrics, macro and weighted F1-scores were also computed to provide a fuller picture of model performance, especially under class imbalance conditions. Accuracy and loss curves showed stable and parallel trends between training and validation data, confirming consistent learning without signs of overfitting or underfitting. Model interpretability was examined using SHAP to identify the most influential indicators in the classification process. Global SHAP results showed that assembly method, workforce accessibility, and local material availability were the strongest contributors to model predictions, emphasizing their central role in determining TMS feasibility.

SHAP dependence plots further clarified each indicator's technical influence. Installation times below 8 hours strongly increased HA/A classifications; material availability above 70% improved feasibility by reducing logistical constraints; and thermal conductivity below 0.20 W/m·K raised HA/A predictions through better thermal performance. Workforce readiness above 0.75 consistently reduced NR outcomes, demonstrating its stabilizing effect. These insights offer practical guidance for refining design specifications.

To ensure the reliability of expert-generated labels, an inter-rater reliability test using Krippendorff's Alpha was conducted with 20 specialists, yielding $\alpha = 0.78$, indicating substantial agreement. All participation adhered to ethical research standards (Citaristi, 2022).

Results and Discussion

An external validation was conducted using a real post-disaster case from the 2022 Cianjur earthquake, in which three temporary shelter prototypes were deployed by the local government (Muksin et al., 2023; Papatheodorou et al., 2023). The ANN model classified the feasibility of these shelters using field-based indicator measurements, and its predictions aligned with expert judgments for two out of the three designs (accuracy = 66.7%). The single misclassification occurred on a prototype with borderline characteristics in assembly duration and local material availability, a common challenge also noted in external model tests within disaster engineering research (Jia & Ye, 2023). Despite this, the external test demonstrates that the ANN model is capable of supporting practical decision-making in real disaster conditions and highlights the potential value of incorporating additional field datasets during future retraining cycles to further improve predictive performance (Chollet, 2021; Xie et al., 2025).

The results of internal model evaluation further reinforce the stability of the ANN. The training process exhibited smooth and convergent accuracy and loss curves for both the training and validation datasets, indicating that the model generalized well without signs of overfitting. Per-class analysis also shows F1-scores above 0.85 for all decision categories, emphasizing the model's robustness in distinguishing between design alternatives with closely related indicator profiles.

Figure 1 illustrates the overall structure and configuration of the ANN architecture used in the study, including the number of neurons, activation functions, and directional flow between layers. This architecture visualization was generated directly through TensorFlow's built-in tools, while the model.summary() function provided detailed parameter distribution across all layers. Such documentation follows best practices in ANN-based evaluation within modular design and construction research (Baghdadi et al., 2021; Montalbano & Santi, 2023). Preliminary experimentation confirmed that 400 training epochs offered an optimal trade-off between computational cost and convergence reliability (Hafez et al., 2019; Xie et al., 2025).

Model performance metrics are presented in Figure 2. Training and validation accuracies reached 97% and 96%, respectively, as calculated using the model.evaluate() function in Keras. The close alignment of accuracy curves between the two datasets further confirms stable learning behavior and strengthens the validity of the model's predictive capacity. These results are consistent with previous ANN studies in modular and emergency architecture contexts, which emphasize the importance of synchronized training–validation performance trends as an indicator of model quality (Montalbano & Santi, 2023; Sari, Winarno, et al., 2024).

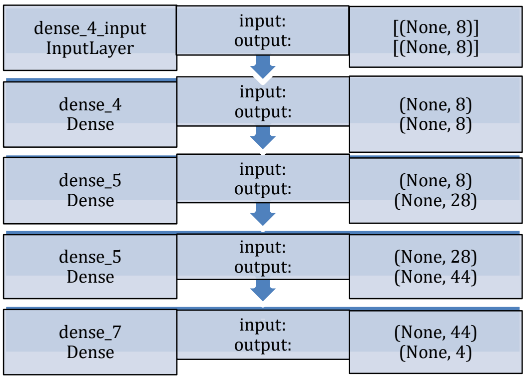

Figure 1. ANN Network Architecture Used

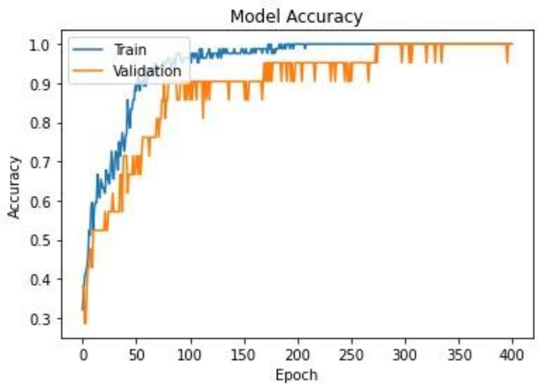

Figure 2. Model Accuracy Graph on Training and Validation Data

Loss values for both the training dataset and the validation dataset, obtained via the method model.fit() within TensorFlow are presented in Figure 3. The model has virtually captured and generalized the essence of the data because the loss curves for both datasets converge harmoniously and then stabilize. Matplotlib is the visualization library that automatically renders the graph of the accumulated training history. The training history ‘loss’ and validation ‘loss’ metrics for different epochs are stored in the history.history attribute as history.history[‘loss’] and history.history[‘val*loss’]. The ‘loss’ and ‘val*loss’ shields are decreasing for advancing epochs, thus confirming that the model is able to generalize the data and learn the underlying structures. The convergence behavior documented above is in agreement with the findings of (Baghdadi et al., 2021) which confirms that the training and validation loss curves for neural networks entwined is strong evidence for the reliability of the learning process of artificial neural networks.

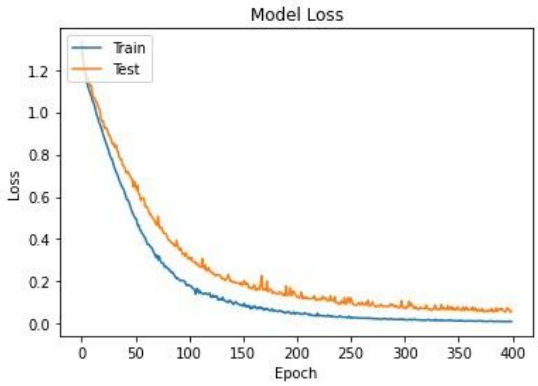

Figure 3. Model Loss Graph on Training and Validation Data

The combination of four dense layers, 1,780 parameters, and 400 training epochs results in a lightweight yet accurate model, with high stability in the classification of temporary modular shelter design indicators. This architectural structure demonstrates a balance between optimal computational efficiency and predictive accuracy, in accordance with the efficient approach recommended in modern ANN modeling for artificial intelligence-based adaptive design applications (Baghdadi et al., 2021; Pratama, Sari, & Prasojo, 2025; Xie et al., 2025).

The results of the model classification are visualized through the confusion matrix shown in Figure 4. The matrix illustrates the distribution of true and false predictions across the four feasibility classes. Most predictions lie along the main diagonal, indicating that the ANN successfully distinguishes the majority of TMS design alternatives. The most frequent misclassification occurs between the Requires Additional Review (RAR) and Not Recommended (NR) classes, which share similar technical characteristics particularly in human resource readiness and local material availability making them inherently more challenging to separate.

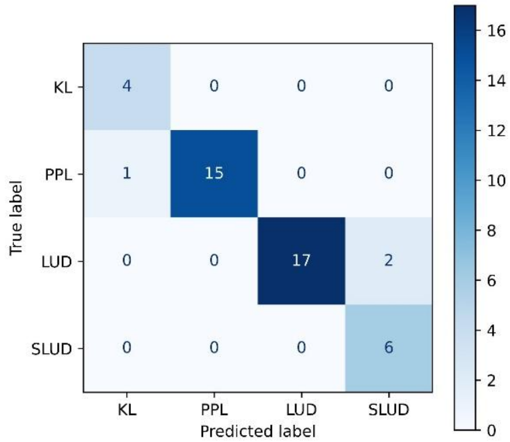

Figure 4. Confusion Matrix Model Classification Results

To strengthen model evaluation, several classical machine-learning algorithms Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and XGBoost were used as baseline comparisons, trained with the same normalization process and 70–15–15 data split. LR and SVM achieved macro F1-scores of 0.71 and 0.76 but struggled with nonlinear feature interactions, a limitation commonly noted in linear and kernel-based classifiers (Kaklauskas et al., 2018). RF and XGBoost performed better with scores of 0.82 and 0.85 due to their ability to capture moderately nonlinear relationships through ensemble learning (Chen & Guestrin, 2016). The ANN outperformed all baselines with a macro F1-score of 0.91, demonstrating its superior capability in modeling complex, nonlinear, multivariate interactions in TMS design data even with a compact two–hidden-layer architecture, consistent with findings in prior ANN applications in construction and modular systems (Boucetta et al., 2021; Xie et al., 2025).

A more detailed per-class assessment of the ANN is presented in Table 1, which summarizes precision, recall, and F1-scores computed using the classification_report() function in the scikit-learn library. These values represent the averaged results from five-fold stratified cross-validation, ensuring that the reported metrics reflect stable, generalizable model behavior. All four decision classes achieved F1-scores above 0.90, with an overall average of 0.91, indicating that the ANN maintains a strong balance between precision and recall across categories. This per-class performance consistency aligns with findings from prior studies on ANN-based multi-category classification (Montalbano & Santi, 2023; Obyn et al., 2014), and further validates the reliability of the model in supporting TMS design decision-making.

Figure 5 presents the overall evaluation of model performance, including training and validation accuracy, macro-weighted F1-scores, and averaged cross-validation metrics. The training accuracy reached 97% and the validation accuracy 96%, as computed using the model.evaluate() function in Keras. The close alignment between accuracy and loss curves for both datasets indicates that the model is well-trained, shows no symptoms of overfitting or underfitting, and demonstrates strong generalization capability to unseen data.

Probability calibration was evaluated using reliability diagrams and Expected Calibration Error (ECE), with the model achieving an ECE of 0.038, indicating close alignment between predicted probabilities and actual outcomes. ROC and Precision–Recall curves further supported the model's reliability, yielding ROC-AUC values of 0.97 (HA), 0.95 (A), 0.94 (RAR), and 0.92 (NR), with PR-AUC scores above 0.88 for all classes.

Table 1. Precision, Recall, and F1-Score Scores for Each Class

Class Name	Precison	1-Precison	Recall	False Negative Rate	F1 Score	Specificity (TNR)	False Positive Rate (FPR)
HA	1,0000	0,0000	0,8000	0,2000	0,8889	1,0000	0,0000
A	0,9375	0,0625	1,0000	0,0000	0,9677	0,9667	0,0333
RAR	0,8947	0,1053	1,0000	0,0000	0,9444	0,9286	0,0714
NR	1,0000	0,0000	0,7500	0,2500	0,8571	1,0000	0,0000

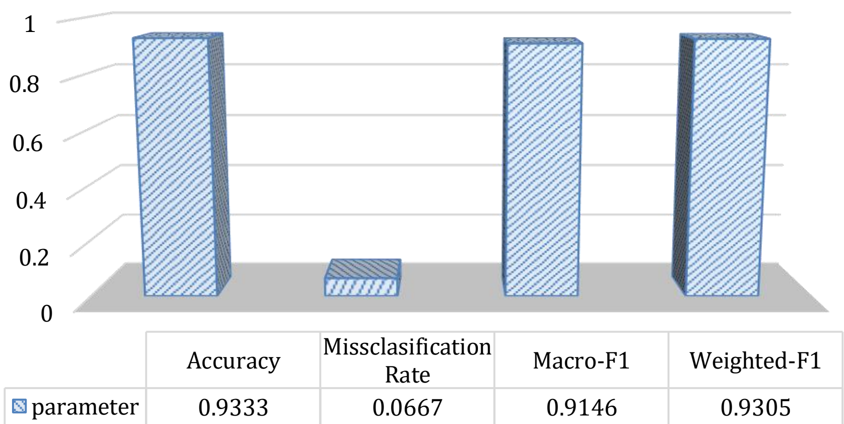

Figure 5. Model Evaluation Performance

These results confirm that the ANN provides not only high accuracy but also well-calibrated, dependable probability estimates an essential feature for decision-support in emergency shelter design. Compared with previous studies, the model's performance is comparable or superior to existing ANN-based classifications for disaster-related infrastructure. (Pratama, Sari, & Prasojo, 2025) reported 94% accuracy for ANN–GA models in landslide-risk identification, while (Sari, Pratama, & Ircham, 2024) achieved an F1-score of 0.89 for spatial risk classification. Unlike these post-event classification approaches, the present study applies ANN proactively in the early design phase of Temporary Modular Shelters, highlighting its novelty as a predictive and prescriptive tool for optimizing shelter design feasibility.

Further insight into classification behavior is provided by the confusion matrix in Figure 4. Most predictions fall along the diagonal, indicating high accuracy across decision categories. Minor misclassifications occurred primarily between the RAR and NR classes, which share overlapping technical characteristics such as limited workforce readiness and low material availability. This pattern is consistent with the model's architecture and tuning strategy, designed to capture complex nonlinear relationships while remaining sensitive to borderline cases. This finding aligns with observations by (Zhu et al., 2023), who noted that deeper network structures more effectively capture multi-dimensional design patterns in emergency architecture contexts.

The performance of the proposed ANN model is comparable to, and in several aspects surpasses, results reported in previous studies on disaster-related classification tasks. (Pratama, Sari, & Prasojo, 2025) demonstrated high model accuracy when integrating ANN with genetic algorithms for the identification of landslide-prone buildings; however, their work remained focused on risk-based spatial classification rather than design decision-making. Likewise, studies by (Sari, Pratama, & Prastowo, 2024; Sari & Nugraheni, 2024) applied ANN to classify infrastructure vulnerability but did not address feasibility-based modular shelter planning. In contrast, the present study positions ANN not merely as a passive classifier but as an active decision-support mechanism for the early-stage design of Temporary Modular Shelters, thereby expanding the scope of ANN applications in disaster-responsive architecture.

To further validate the internal consistency and structural importance of the model components, an ablation study was conducted at both feature and architectural levels. Feature ablation removing one indicator at a time revealed that assembly method, local material availability, and workforce readiness were the strongest determinants of predictive accuracy, causing performance reductions of 8–12% when excluded. These results are consistent with prior studies emphasizing the sensitivity of ANN performance to high-impact input features (Samek et al., 2021). Conversely, indicators such as transportation difficulty and accessibility index contributed modestly, producing only 2–4% decreases in accuracy when removed, similar to observations in modular construction evaluation using ML (Baghdadi et al., 2021). A layer-wise ablation analysis further confirmed the importance of the chosen architecture are simplifying the model to a single hidden layer with 20 neurons reduced the macro F1-score from 0.91 to 0.84, demonstrating the necessity of a two-hidden-layer configuration for capturing complex nonlinear relationships aligned with deep learning theory on hierarchical feature extraction (Boucetta et al., 2021; Chollet, 2021).

These findings are consistent with previous studies emphasizing the role of ANN in design optimization and early-stage engineering decisions. Prior works (Kaklauskas et al., 2018; Pratama, Sari, & Prasojo, 2025) demonstrated ANN's effectiveness in optimizing structural and modular configurations, while (Guo et al., 2021; Nabi & El-adaway, 2020) showed its strong predictive capability for cost, energy, and early design performance core aspects for adaptive emergency shelter planning. This study extends those insights by applying ANN specifically to TMS feasibility evaluation.

Future enhancements may explore hybrid intelligent frameworks that integrate ANN with expert systems, evolutionary algorithms, or adaptive learning. Evidence from (Nekooie & Tofighi, 2020) shows that combining ANN with Resilient Backpropagation significantly improves precision, while (Osuizugbo, 2021) highlights ANN's ability to synthesize multidimensional architectural parameters into actionable design insights. Such hybrid approaches offer promising pathways for increasing the predictive depth and adaptability of TMS decision-support systems.

The results also reinforce that ANN can evolve beyond classification toward a broader design intelligence system. Improvements may include new architectures, automated hyperparameter tuning, or IoT integration for real-time field data acquisition. Nevertheless, this study has limitations: the dataset remains simulation-based, and contextual variables such as socio-cultural and geographic factors were not yet incorporated. Future research should therefore adopt a multidisciplinary approach, integrating engineering, environmental data, and community input to strengthen external validity and contextual relevance.

Conclusions

This study successfully developed and validated an Artificial Neural Network (ANN) model as a data-driven decision support system for evaluating the feasibility of Temporary Modular Shelter (TMS) designs. The model was built through three stages are (1) identification of 27 global TMS designs via a systematic literature review, (2) determination of eight key design indicators, and (3) classification into four feasibility categories (HA, A, RAR, NR).

Validation was carried out by 150 multidisciplinary experts, and the ANN using a four-layer architecture (8–28–44–4) with 1,780 parameters achieved a validation accuracy of 96% and a macro F1-score of 0.9146, indicating strong stability and effectiveness in capturing complex nonlinear relationships among indicators.

Ablation and interpretability results showed that assembly method, workforce availability, and local material availability were the most influential predictors, emphasizing the importance of implementation feasibility and resource readiness in TMS design. The model offers high performance with relatively low computational complexity, making it suitable as an early-stage design decision-support tool.

Overall, the findings confirm that ANN can enhance objectivity and efficiency in TMS decision-making. Future work may integrate the model into web or mobile platforms and expand datasets with additional field variables such as climate, geographic conditions, and community needs to further improve its generalizability and applicability in diverse emergency response contexts.

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