Prediction of Health Building Conditions using Artificial Neural Networks in Bondowoso Regency

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ABSTRACT

Healthcare buildings are vital infrastructure that play a role in supporting medical services to the community. Limited maintenance budgets and manual inspection methods often lead to delays in detecting building damage. This study aims to develop a predictive model for the condition of healthcare buildings using an Artificial Neural Network (ANN) with a case study in Bondowoso Regency. The variables used include building age, maintenance history, usage intensity, environmental conditions, and existing conditions. Data were collected from field surveys, technical documentation, and interviews with healthcare facility managers. The results show that the Artificial Neural Network (ANN) model is able to predict building conditions with a high level of probabilistic accuracy for the next 1, 5, and 10 years. These findings can be used as a basis for prioritizing maintenance and formulating local government policies to maintain the sustainability of healthcare facilities

Keywords: ANN, building condition, health building, Bondowoso.

INTRODUCTION

Healthcare buildings, such as hospitals and community health centers, are vital infrastructure supporting public health services. Maintaining building quality not only enhances comfort but also ensures the safety of patients and medical personnel working within them. Poor maintenance management can accelerate infrastructure deterioration, reduce operational efficiency, and increase the risk of workplace accidents [1]. This highlights the importance of a continuous building condition monitoring system, particularly in healthcare facilities serving as public service centers. Therefore, a method that can accurately, efficiently, and adaptively predict building conditions is needed to support healthcare asset management [2]

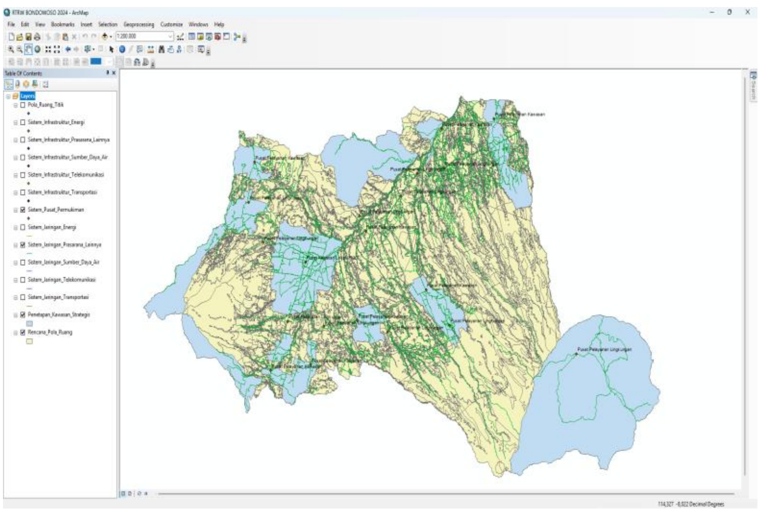

Figure 1. Research location

The development of artificial intelligence (AI) technology has opened up new opportunities in infrastructure management, particularly through the application of Artificial Neural Networks.

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ANN's have been shown to solve non-linear problems by learning patterns from historical data, thus providing more accurate condition predictions [3]. According to [4]. ANNs can predict bridge deck conditions with high accuracy, demonstrating the method's significant potential for application in healthcare facilities. Furthermore, research on the use of AI in asset management has demonstrated increased accuracy and efficiency of infrastructure maintenance planning compared to traditional methods [5]. This fact reinforces the relevance of ANN-based research in improving healthcare building damage prediction systems.

Bondowoso Regency, as the research location, faces different challenges compared to large cities. Most healthcare buildings in this region face limited maintenance funding, a lack of skilled personnel, and limited technology for inspecting building conditions. Many healthcare facilities in the area experience a maintenance backlog, resulting in accelerated structural degradation [6]. This aligns with the findings of [7] who emphasized that rural areas in Indonesia are at higher risk of building degradation due to limited resources. In this context, ANN-based methods are relevant because they can help local governments prioritize building maintenance budget allocations more effectively [8].

RESEARCH METHODS

The study was conducted across several health centers in Bondowoso Regency. Variables considered include building age, maintenance history, usage intensity, environmental condition, and current condition. Data were obtained from field surveys, technical reports, and interviews with facility managers. The ANN architecture consists of an input layer (five variables), hidden layers optimized through training, and an output layer representing building condition categories. The study procedure includes:

1. Analysis of Health Buildings in Bondowoso
2. Application of Artificial Neural Network (ANN)
3. Prediction of Building Condition

Model validation employed probabilistic analysis over prediction horizons of 1, 5, and 10 years.

The population in this study included all healthcare buildings in Bondowoso Regency, including hospitals, community health centers, and clinics. The total population was 5 buildings, ranging in age from 10 to over 20 years. According to [2], quantitative research requires selecting a representative sample to produce generalizable findings. Therefore, a purposive sampling technique was used, taking into account the criteria of building age, intensity of use, and availability of maintenance data [9].

Table 1. Data Sampling

Name of Building	Facility Type	Age of Building	Condition
Puskesmas Taman Krocok	Health Center	23 y.o	Moderately Damaged
Puskesmas Binakal	Health Center	22 y.o	Moderately Damaged
Puskesmas Tamanan	Health Center	18 y.o	Fine
Puskesmas Tapen	Health Center	22 y.o	Fine
Puskesmas Cermee	Health Center	10 y.o	Fine

This sample selection is expected to reflect the varying conditions of healthcare buildings in Bondowoso. By involving both old and new units, the study can test ANN in various building degradation scenarios. This aligns with [10], who emphasized the importance of condition representation in building maintenance studies. Therefore, the prediction results are expected to be more valid and useful for local governments in prioritizing infrastructure improvements [11].

The research stages consisted of primary and secondary data collection, data processing, ANN model design, model training and validation, and prediction analysis. These stages were designed based on a quantitative research methodology with an experimental approach. According to [2], a systematic research structure will increase the reliability of the findings. The data collection process was carried out through field surveys, visual observations, and analysis of building maintenance documents [7]. The research procedure used consisted of several stages.

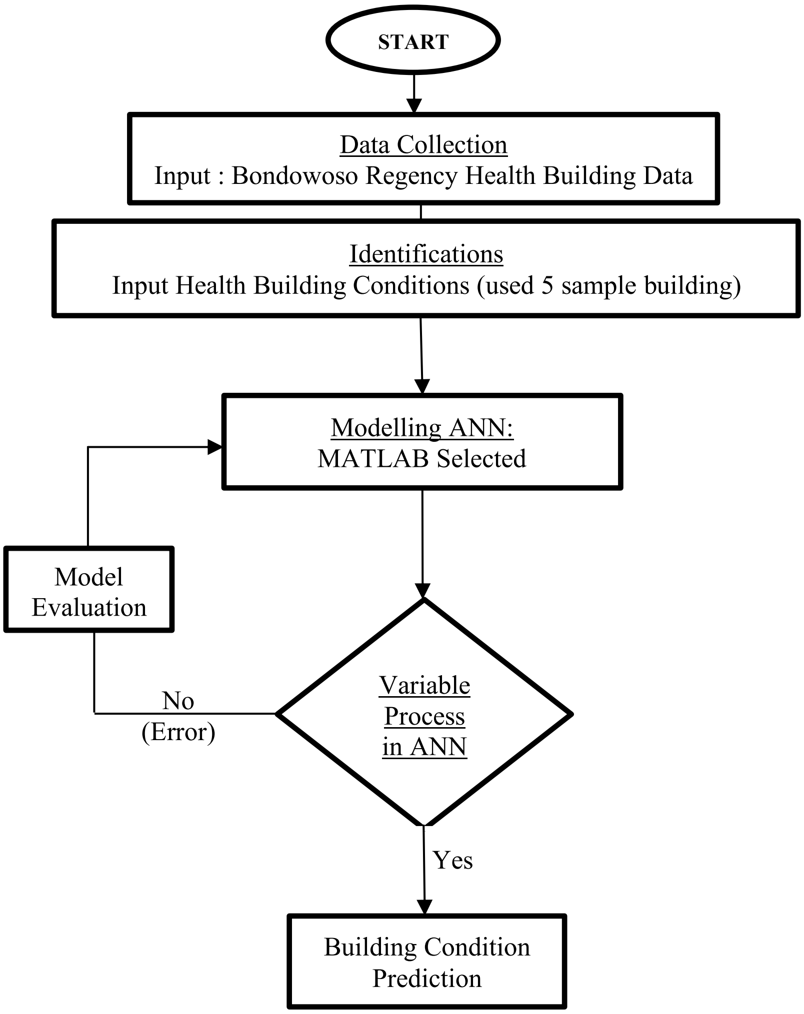

Figure 2. Flow chart

The determination of building damage variables is based on the principle that every construction component experiences a progressive degradation process of materials and structural systems over time. According to Structural Reliability theory, the probability of failure of a structural element increases with age and a decrease in material capacity due to repeated loads and environmental influences [12]. In addition, the Building Deterioration Model explains that damage depends not only on age, but also on construction quality, intensity of use, and maintenance conditions [13].

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Table 2. Validation of Research Variables Predicting Health Building Conditions

No.	Variable	Indicator	Scale	Influence on the Level of Damage	Scientific Basis / Reference Sources
1	Age of Buildings	How long the building has been standing since construction was completed	Years (ratio)	Based on the time-dependent deterioration model, where the probability of damage increases over time due to the aging process.	ISO 15686:2011; Shohet (2003)
2	Material & Construction Quality	Quality of concrete, steel, construction implementation	Ordinal (1–5)	Structural performance degradation studies show that the material has a significant effect on the rate of strength decline.	Mori & Ellingwood (1993)
3	Usage Load	Number of users, operating hours, type of activity	Ordinal (low–high)	Based on Building Performance Evaluation, high usage loads accelerate the wear of architectural and structural components.	Preiser et al. (1988)
4	Environmental Exposure	Humidity, temperature, water exposure, pollution, earthquakes, vibrations	Ordinal (good–bad)	Environmental deterioration studies, show that corrosion, weathering, and biological attack are influenced by microclimate and location.	Straub (2009); ISO 15686-2
5	Drainage & Ventilation System	Rainwater channel performance, air ventilation, damp prevention	Ordinal (good–bad)	Based on Building Pathology: poor drainage systems accelerate damage to walls and substructures	Douglas & Ransom (2013)
6	Maintenance Level	Frequency, quality, and completeness of maintenance activities	Ordinal (routine–rare)	Preventive maintenance model shows that routine maintenance slows the deterioration rate.	Shohet & Lavy (2004)
7	Extreme External Factors	History of disasters, floods, earthquakes, traffic vibrations	Nominal / Ordinal	Based on the Seismic Vulnerability Assessment: extreme external conditions accelerate structural degradation.	FEMA 154 (2015)
8	Visual Condition	Cracks, corrosion, peeling paint, deformation, wall moisture	Percentage of damage (%) / ordinal	Based on the Building Condition Assessment System (BCAS), visual condition is a direct indicator of decreased function and safety.	BCAS; Shohet (2003)

Predictive modeling was performed by dividing the dataset into training data (70%) and test data (30%). The training process used the backpropagation algorithm with the ReLU activation function in the hidden layer and Softmax in the output layer. This algorithm was chosen because of its ability to gradually reduce prediction errors by adjusting neuron weights. The integration of backpropagation and a non-linear activation function improves the accuracy of building prediction models [5].

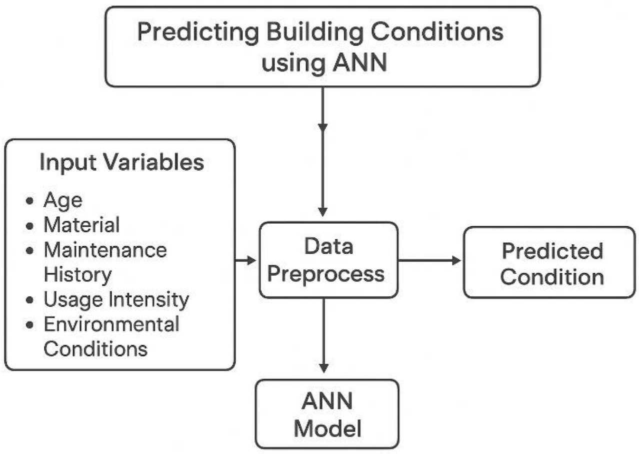

Figure 3. Artificial Neural Network (ANN) Modelling

RESULT AND DISCUSSION

The ANN test results produce probabilistic outputs in the form of the probability of each building falling into a specific condition category. For example, a 20-year-old community health center with minimal maintenance history is predicted to have a 70% probability of being categorized as moderately damaged, 20% as good, and 10% as severely damaged. The probabilistic results from ANN can be used as a basis for prioritizing infrastructure maintenance [5].

Table 3. Probabilistic Results of Health Building Condition Prediction

Name of Building	Age	Intensity of Use	Envi. Conditions	Existing		5th Year	10th Year	15th Year
Puskesmas Taman Krocok	23	High	0.75	Moderately Damaged	A	Moderately Damaged (65%)	Heavy Damage (75%)	Heavy Damage (85%)
Puskesmas Binakal	22	High	0.65	Moderately Damaged	N N	Moderately Damaged (60%)	Moderately Damaged (70%)	Heavy Damage (82%)
Puskesmas Tamanan	18	Currently	0.55	Fine	P R	Fine (70%)	Light Damage (55%)	Moderately Damaged (65%)
Puskesmas Tapen	22	Low	0.80	Fine	O S E	Light Damage (50%)	Moderately Damaged (65%)	Heavy Damage (78%)
Puskesmas Cermee	10	Currently	0.50	Fine	S S	Fine (60%)	Light Damage (50%)	Moderately Damaged (65%)

In the Artificial Neural Network (ANN) model, the prediction results are not directly in the form of categories (for example: good, lightly damaged, moderately damaged, heavily damaged), but rather in the form of probability values.

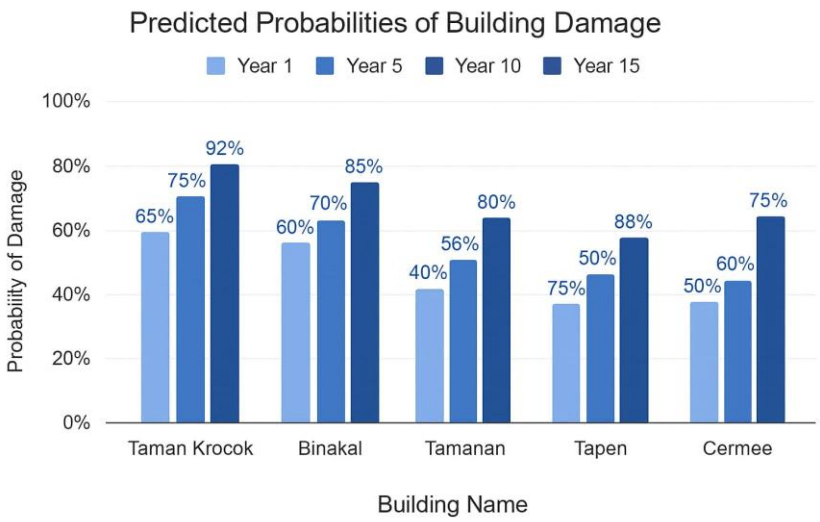

Figure 4. Predicted probabilities of building damage

CONCLUSION

Based on the results of research conducted on predicting the condition of healthcare buildings using an Artificial Neural Network (ANN) approach in Bondowoso Regency, several key conclusions were obtained. First, the determination of research variables, including building age, maintenance history, usage intensity, environmental conditions, and existing conditions, proved to have a significant influence on developing a prediction model. This is consistent with the findings of [14] and [5], which stated that multidimensional variables need to be integrated so that the ANN model produces more accurate damage estimates. Prediction logic is aligned with common patterns in ANN modeling + infrastructure maintenance literature: 1) as age increases → probability of damage increases, 2) good care → slows down deterioration, 3) high intensity of use + bad environment → accelerates damage. Based on the results and limitations of this study, several recommendations are worth considering. Future research should use a larger dataset covering a wider variety of building

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conditions to train ANN models with richer data representations. This aligns with [15] recommendation that data quantity and quality significantly impact the performance of machine learning algorithms.

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