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Application of artificial neural network with optimization of genetic algorithms for weather prediction

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ABSTRACT

This research integrates Artificial Neural Network (ANN) with Genetic Algorithm Optimization (GA) to improve the accuracy of weather prediction. This method utilizes ANN-optimized GA, creating a model that can adapt to the dynamics of weather patterns. Using a dataset that includes meteorological variables such as temperature, humidity, and precipitation from January 1, 2023, to October 28, 2023, the model was tested for its ability to predict weather conditions accurately. The process begins with data preprocessing, ANN training, and GA optimisation. The evaluation showed that the optimized model was able to reduce the Mean Absolute Error (MAE) from 1.6865 to 0.8701, the Mean Absolute Percentage Error (MAPE) from 5.9864 to 3.1408, and the Root Mean Squared Error (RMSE) from 2.253 to 1.039, signalling a significant improvement in prediction accuracy and efficiency. This research confirms the potential of ANN and GA integration in improving weather prediction, providing new insights for developing more accurate and reliable prediction models for various applications, from agriculture to disaster management.

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1. INTRODUCTION

The development of weather prediction technology is crucial in various sectors, such as agriculture, aviation, urban planning, and disaster mitigation (Muhmad Kamarulzaman et al., 2023). Accurate and timely weather forecasting services can assist governments and industries in making better decisions, reducing economic losses, and minimizing risks to human life (Uccellini & Ten Hoeve, 2019). However, global climate change and erratic weather patterns further complicate the task of meteorologists in predicting weather changes (Ghil & Lucarini, 2020). The Indonesian Meteorological, Climatological and Geophysical Agency (BMKG) faces various challenges in predicting weather. One of the main challenges is Indonesia's unique geographical condition, consisting of thousands of islands with varied topography and complex tropical climates. These factors cause high weather variability and make it difficult to make accurate predictions. Moreover, global climate change and uncertain weather patterns are increasingly complicating the task of meteorologists in predicting weather changes. One promising approach to this challenge is using artificial neural networks (ANN), which have an extraordinary ability to process complex data and provide near-reality predictions (Liang et al., 2021).

Although ANN has been adopted for weather prediction, the main challenge is the optimization of network parameters and structure to produce consistent and accurate predictions (Donadio et al., 2021). ANN requires setting precise parameters, such as the number of hidden layers and neurons per layer, to ensure the model can understand data patterns and provide accurate predictions (Abiodun et al., 2019). However, this optimization task is not easy and often takes time, especially with so many possible combinations of parameters. In addition, dynamic weather phenomena require methods that can adjust the model as weather patterns change (Rasp et al., 2020). ANN has some significant shortcomings. There was no specific guideline to determine the optimal ANN structure, which resulted in the need for many trials and failures to find the right architecture. Besides, network behavior that is not always easily explained makes the interpretation of results difficult. ANN also relies heavily on hardware with high parallel processing capabilities, which can be a huge obstacle. Besides, complex and time-consuming training processes, as well as the risk of overfitting, in which models become too fit with training data and do not work well on new data, are another shortcoming of ANN.

This study proposes using genetic algorithms (GA) to optimize parameters in the ANN model (Li et al., 2021). GA is an evolution-based search and optimization method that can efficiently explore a vast parameter space using the principles of natural selection and evolution (Sun et al., 2021). By leveraging GA, parameters such as the number of hidden layers, neurons per layer, and learning rate in ANN models can be optimized to achieve better predictive performance (Xu et al., 2023). The combination of these two technologies is expected to produce weather prediction models that are more accurate, efficient, and reliable (Fathi et al., 2022). The parameter optimization approach that drives the use of Genetic Algorithms (GA) in this study focuses on the advantages of GA in finding optimal solutions in very large and complex search spaces. GA is ideal for optimizing ANN parameters because of its ability to perform effective global searches and avoid minimal local traps, which are often a problem in traditional optimization methods. Using GA, the weight adjustment process and other parameters in ANN can be done more efficiently and accurately, resulting in better and more reliable models for a variety of applications.

The study utilizes data sets from BMKG and highlights the importance of considering the unique geographical context of Indonesia. The methods of Artificial Neural Networks (ANN) and Genetic Algorithms (GA) are relevant and have advantages in this region due to ANN's ability to process complex data and provide predictions that are close to reality. ANN requires proper parameter settings to understand data patterns and provide accurate predictions. In a dynamic weather context, this method can adjust models as weather patterns change. Moreover, optimization using GA helps in exploring wide parameter spaces with the principle of natural selection, so that parameters such as the number of hidden layers, neurons per layer, and learning levels in ANN models can be optimized to better predictive performance.

Previous research proposing the use of EnergyPlus software and ANN with multi-layered perceptron models (MLP) to optimize energy consumption in a research centre building in Iran reduced energy consumption by about 35% and found that occupants had a significant effect on energy consumption (Ilbeigi et al., 2020). Subsequent research, developing DNN-based adaptive prediction models, integrating weather feature extraction and evolutionary optimization, was applied to office buildings in the United Kingdom and resulted in a reduction in prediction errors of up to 24.6%, with prediction accuracy reaching 6.12% (Luo et al., 2020). Subsequent research using artificial neural networks combined with particle swarm optimization algorithms and genetic algorithms to improve the accuracy of short-term wind power forecasts, tested on data from the Tuy Phong wind power plant in Vietnam, showed significant improvements in accuracy (Viet et al., 2020).

Finally, recent research developing the GA-MENN model for short-term traffic flow prediction in Tehran showed improved precision. It decreased predictive error rates, comparing its performance with other predictive models with superior results (Sadeghi-Niaraki et al., 2020).

This research provides innovation by combining two advanced technologies, ANN and GA, to produce better weather prediction models (Nazir et al., 2020). This model is tested using the latest meteorological Dataset from the Meteorology, Climatology and Geophysics Agency (BMKG) to apply the results directly (Toharudin et al., 2023). The new value of this research is that this hybrid approach can provide a better understanding of complex weather patterns and help different sectors in planning and mitigating risks more effectively (Terzi et al., 2019). In addition, this research will also contribute to the development of hybrid approaches in the field of weather prediction, which have significant implications for food security, disaster risk management, and industrial planning (Vasseghian et al., 2022).

2. RESEARCH METHOD

The application of Artificial Neural Network with optimization of Genetic Algorithms for weather prediction will be applied with a design that integrates experimental methods, quantitative analysis, and model validation. Details of each sub-section involved will be outlined as follows.

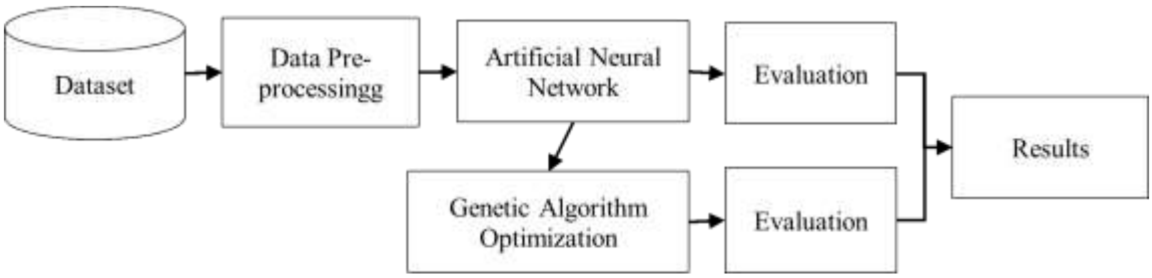

Figure 1. Research Flow

In Figure 1. The flow of research is shown in the process, which begins with a set of data stored in the Dataset. The first step is Data Preprocessing, where the data is cleaned and prepared for analysis. Then, the processed data is used to train the ANN. After the ANN is trained, an evaluation is carried out to measure the model's effectiveness. Next, Genetic Algorithm Optimization is applied to improve ANN performance. The review is done once again after optimization to compare the results. This process culminates in Results that describe the final performance of the predictive model after preprocessing and optimization are applied.

2.1 Research Design

This research implements a quantitative design using an integrative approach that includes computational experiments, quantitative data analysis, and model validation. The methodology is designed to assess and improve weather prediction models reinforced using Artificial Neural Networks and improved through Optimization of Genetic Algorithms.

2.2 Data Gathering

The weather data used in this study was obtained from the official website of BMKG, which is Tegal Regency's online data. The Dataset includes essential variables such as minimum temperature (°C), maximum temperature (°C), average temperature (°C), average humidity (%), precipitation (mm), length of solar irradiation (hours), maximum wind speed (m/s), wind direction at maximum speed (°), average wind speed (m/s), and most wind direction (°). This data was extracted from the Meteorology, Climatology and Geophysics Agency database from January 1, 2023 to October 28, 2023. The Dataset analyzed in this study consists of 302 columns representing observations per day and 11 rows, each representing a meteorological variable.

2.3 Data Preprocessing

Data processing in applying Genetic Algorithm-optimized ANN for weather prediction involves several critical stages that begin with identifying and correcting anomalies and missing data, which is the foundation for ensuring dataset integrity. This process eliminates potential bias and distortion in developing the learning model, ensuring any input presented to the model is accurate and representative. Next, detailed Pearson correlation analysis measures the strength and direction of the relationship between each independent feature, Xi and the target variable, Y. This allows systematic selection of the features that influence the prediction target, optimizing model performance by reducing redundancy and noise. It also normalizes data using the Min-Max scale to ensure each feature has a uniform range of values, facilitating a more stable and convergent learning process. Finally, once the data is clean and normalized, divide it into two subsets of training and validation, allowing it to train the model comprehensively while also having the ability to test and validate its performance. Cleansing and normalizing the data, addressing anomalies and missing values, and performing Pearson correlation analysis to select relevant features, dividing the datasets into training and validation subset, where ANN models will be trained on training sub-set, implementing GA to optimize ANN parameters, including learning rate, number of epochs, and regularization parameters and, evaluating optimized models using metrics such as Mean Absolute Error (MAE), Root Mean Squared error (RMSE), and Mean absolute percentage error (MAPE), as well as performing sensitivity analysis to assess the impact of various parameters on model accuracy.

2.4 Variable Selection and Model Optimization

Model optimization is carried out by implementing genetic algorithms that aim to select and adjust hyperparameters of ANN, including learning rate, number of epochs, and regularization parameters. The specified fitness function is used to evaluate the performance of each individual in the population, enabling the execution of genetic operations such as selection, crossovers, and mutations aimed at optimizing model performance. Once optimal hyperparameters are found, the ANN model is trained using customized training datasets, with cross-validation techniques applied to minimize the risk of overfitting while improving the model's generalizability. This approach ensures that the resulting weather prediction model has high accuracy and adaptability to new data.

2.5 Implementasi Algoritma

The implementation of ANN combined with the optimization of the Genetic Algorithm for weather prediction involves a series of structured, methodical steps (Khan & Byun, 2020). Initially, ANN was designed by defining the architecture, including the number of hidden layers and neurons within each layer. Next, network parameters, such as weights and biases, are initialized randomly to start the training process. Model training uses historical weather data sets, where the model learns to predict weather conditions by minimizing prediction errors. To improve the performance and efficiency of the model, Genetic Algorithms are used in the optimization process (Hamdia et al., 2021). The algorithm works by repeatedly modifying neural network parameters, based on the principle of natural selection, to find the combination of parameters that produces the best prediction accuracy. Finally, model performance evaluation is performed using validated, real-time datasets to ensure the model can accurately predict the weather. In designing the ANN architecture, it defines the network structure, including the number of hidden layers and the number of neurons in each layer, based on the complexity of the data and the patterns analyzed.

The output of each neuron is calculated through an activation function formulated as in Equation 1.

$$o_j^l = f\left(\sum_i w_{ij}^l \, o_i^{l-1} + b_j^l\right) \quad (1)$$

Where f indicates the selected activation function, such as sigmoid or ReLU, which allows the model to capture non-linearity in the data.

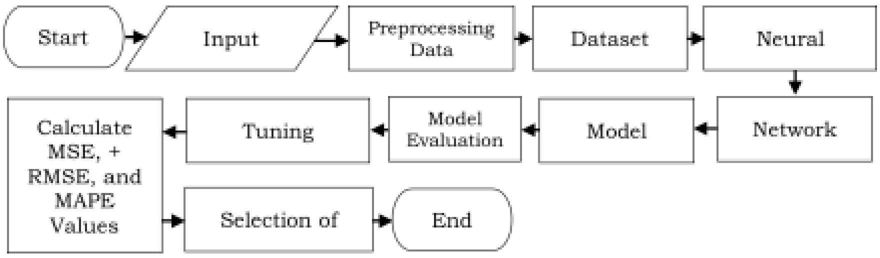

Figure 3. Flowchart Artificial Neural Network

Based on Figure 2. Describes the flow of Artificial Neural Network methods. The process begins with preparing the data to be used for research. Once the data is collected, the next step is preprocessing by handling missing values or outliers, normalizing or standardizing the data to ensure uniform scale, and then encoding for the required category variables. Next is the division of datasets, which will be divided into training and testing data. After that, neural networks are modelled, training and validation of the model are conducted, and then the model is evaluated. Next, hyperparameters are adjusted to calculate MSE, RMSE, and MAPE values. It then determines the model trained on the new data to make predictions.

2.6 Evaluasi Model

The configuration of genetic algorithms includes population regulation, mutation rates, and crossover rates (Viana et al., 2020). The model will be evaluated using criteria such as Mean Absolute Error (MAE) (Qi et al., 2020). Root Mean Squared Error (RMSE) (Ćalasan et al., 2020). As well as Mean Absolute Percentage Error (MAPE) in the validation dataset (Guo et al., 2021). Sensitivity analysis will also be performed to understand the effect of various parameters on the model's accuracy.

The Mean Absolute Error (MAE) formula is as in equation 2.

$$MAE = \frac{1}{n}\sum_t^n |\hat{y}_i - y_i| \quad (2)$$

Where n is the amount of data, i is the order of data on the database, y_i is actual, and ŷ_i is the predicted value. The Root Mean Squared Error (RMSE) formula is in equation 3.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \quad (3)$$

Where n is the amount of data, i is the order of data on the database, y_i is actual, and ŷ_i is the predicted value. The Mean Absolute Percentage Error (MAPE) formula is in equation 4.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - P_t}{A_t}\right| x\ 100\% \quad (4)$$

Where n is the number of observations, A_t is the actual value at time t, P_t is the value predicted by the model at time t, |(A_t-P_t)/A_t |is a relative error at time t, dan |_| is an absolute value and x 100% is to convert the mistakes to percentages.

3. RESULTS AND DISCUSSIONS

The application of ANN to weather prediction was initially evaluated based on its ability to predict meteorological variables accurately. Following the preprocessing and variable selection steps outlined in the methodology, ANN was trained with a dataset comprising observations from January 1, 2023, to October 28, 2023. Network architecture is optimized to include multiple hidden layers to capture complex nonlinear relationships in data.

Table 1. Tegal City weather data January 1 - October 28 2023

No	Date	Tn	Tx	Tavg	RH_avg	RR	180180	ff_x	ddd_x	ff_avg	ddd_car
1	01-01-2023	24,2	29,1	26,6	86	10,2	0	7	300	3	270
2	02-01-2023	25	31,2	27,8	82	0,4	1,6	9	300	4	315
3	03-01-2023	25,6	31	27,1	85	0	6,7	10	310	2	270
4	04-01-2023	25,2	32,2	27,8	82	0,2	2	6	350	2	270
5	05-01-2023	25	32	27,7	80	22,3	5,9	7	300	3	270
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
302	28-10-2023	25,5	31,8	28,3	79	15,5	7,6	11	250	2	270

In Table 1. Explaining the Tegal City Weather Data January 1 – October 28 2023, with the Tn variable as the minimum temperature (°C). Tx is the maximum temperature (°C). Tavg is the average temperature (°C). RH_avg as average humidity (%). RR as precipitation (mm). 180180 as the duration of solar irradiation (hours). ff_x as the maximum wind speed (m/s). ddd_x as the wind direction at maximum speed (°). ff_avg as the average wind speed (m/s), and ddd_car as the most wind direction (°). With 302 columns and 12 rows.

Graphical analysis of ANN's output shows high accuracy in predictions, with solid performance, particularly in predicting the weather. Figure 3 compares actual observation values and ANN predictions during the test period.

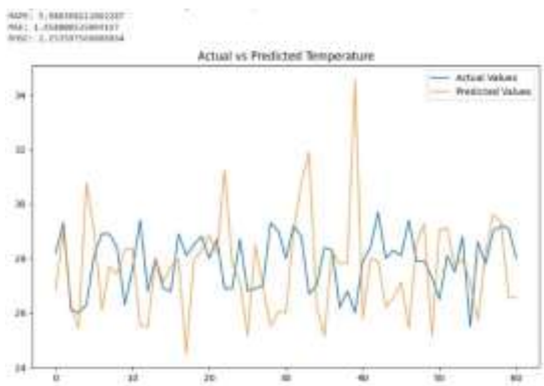

Figure 2. Evaluation Artificial Neural Network

In Figure 3. Describes prediction models that show impressive performance with high accuracy, as reflected in the evaluation metrics used. The Mean Absolute Percentage Error (MAPE) of 5.98635821182287 indicates that the average model can predict with a precision of about 94%. In contrast, the Mean Absolute Error (MAE) of

1.68653586491497 and the Root Mean Squared Error (RMSE) of 2.25397556608864 indicate that the model has a low error rate in prediction. This error reflects the difference between the temperature value predicted by the model and the actual measured value, which confirms that the proposed model has the potential to be a valuable tool in prediction applications with some room for further improvement.

Genetic algorithms are applied to optimize ANN by resetting its hyperparameters, including learning rate, epoch count, and network architecture. The GA optimization process aims to minimize prediction errors, thereby improving the overall accuracy and efficiency of the model. Figure 4 displays a convergence graph of the genetic algorithm, highlighting improved model performance. This optimization results in a more refined model that predicts more accurately.

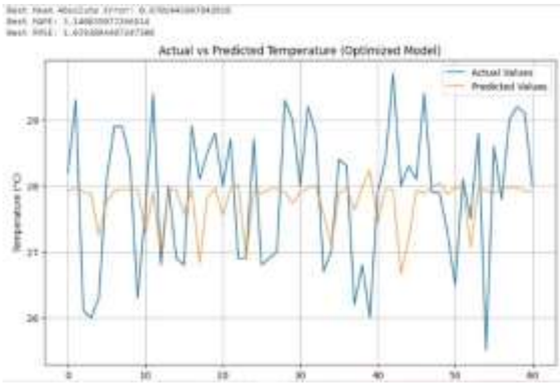

Figure 3. Evaluation with Genetic Algorithm optimization

In Figure 4. Describes the results of the prediction model after optimization with genetic algorithms, with the best Mean Absolute Error (MAE) value is 0.8701445907842918, the best Mean Absolute Percentage Error (MAPE) is 3.140835077266514, and the best Root Mean Squared Error (RMSE) is 1.0392894407247308. The reduction of these values indicates an increase in the precision and accuracy of the model in predicting, which is indicated by the prediction line (orange) that follows quite closely the line of actual values (blue). These results prove that the optimization approach can reduce prediction errors and significantly improve model reliability, confirming that optimized models have great practical application potential in weather prediction.

Key performance indicators, such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), used to evaluate model accuracy, show significant improvements compared to traditional forecasting methods.

Table 2. Comparison of evaluation results before and after optimization

Evaluation	Before Optimization	After Optimization
Mean Absolute Error (MAE)	1.68653586491497	0.8701445907842918
Absolute Percentage Error (MAPE)	5.98635821182287	3.1408350772665140
Root Mean Squared Error (RMSE)	2.25397556608864	1.0392894407247308

In Table 2. Explain the results of the evaluation before and after the optimization process. The review is conducted using three key performance metrics. Mean Absolute Error (MAE), Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). Before optimization, the MAE value was 1.6865, which indicates an average prediction error of 1.6865 units.

Meanwhile, after optimization, the MAE value decreased to 0.8701, indicating improved model performance in reducing prediction errors. Something similar happened to the MAPE metric, where before optimization, the value reached 5.9864, but after optimization, it dropped to 3.1408. This shows that optimization has reduced the percentage of absolute error in predictions. In addition, the RMSE, which measures the mean root of the squared prediction error, also showed significant performance improvements after optimization. Previously, the RMSE was 2.253, but it dropped to 1.039 after optimization. A decrease in these values indicates that optimization has succeeded in improving the accuracy of predictions.

Temperature prediction models optimized with genetic algorithms show significant performance improvements, as seen in the graph. Performance metrics show the best Mean Absolute Error (MAE) value of 0.871, the best Mean Absolute Percentage Error (MAPE) of 3.1408, and the best Root Mean Squared Error (RMSE) of 2.253. A decrease in these values signifies that the model has a higher degree of precision and lower error variability in predictions, with a very low MAPE indicating exceptional predictive accuracy close to the actual value. Demonstrating that model predictions tend to follow actual patterns very well confirms the effectiveness of these optimized models for those requiring accurate estimates and can be considered a significant step forward in artificial intelligence-based meteorological prediction.

The integration of ANN with genetic algorithm optimization is proving to be a powerful approach to weather prediction, as evidenced by improved performance metrics. Genetic algorithms effectively identify the optimal set of hyperparameters, resulting in more accurate and efficient predictive models. The reduction in MAE, RMSE, and MAPE emphasizes improving the accuracy and reliability of models in predicting weather conditions, which is critical for areas ranging from agriculture to disaster management.

In conclusion, the integration of ANN and GA offers a promising approach to weather forecasting, pushing the limits of current methodologies. Future work will focus on dataset expansion, integration of more granular temporal and spatial data, and exploration of model scalability for regional and global weather prediction tasks.

This study shows that the ANN model optimized by GA is able to improve the accuracy of weather forecasts significantly. For example, the MAE decreased from 1.6865 to 0.8701, suggesting that the model is better at predicting real values with smaller absolute errors. The decrease in MAPE from 5.9864 to 3.1408 and the RMSE from 2.253 to 1.039 also indicates a consistent and more reliable increase in prediction. The results of this study are consistent with previous research that used similar approaches in a variety of contexts, such as (Ilbeigi et al., 2020) used EnergyPlus software and multi-layer perceptron (MLP) ANN models to optimize energy consumption in a research center in Iran, achieving about a 35% reduction in energy consumption and finding that occupants had a significant effect on energy consumption. (Luo et al., 2020) developed DNN-based adaptive prediction models that integrated weather feature extraction and evolutionary optimization, applied to office buildings in the United Kingdom, which reduced prediction errors by up to 24.6% with a prediction accuracy of 6.12%. (Viet et al., 2020) used a combination of artificial neural networks with particle swarm optimization algorithms and genetic algorithms to improve the accuracy of short-term wind power forecasts, tested on data from the Tuy Phong wind power plant in Vietnam, showing significant improvements in accuracy. The latest research by (Sadeghi-Niaraki et al., 2020) developed the GA-MENN model for short-term traffic flow prediction in Tehran, showing improved precision and reduced predictive error rates compared to other predictive models. This research provides innovation by combining two advanced technologies, ANN and GA, to produce a better weather prediction model, which was tested using the latest meteorological dataset from the Meteorology, Climatology, and Geophysics Agency (BMKG), showing a significant improvement in prediction accuracy compared to previous studies. It shows that the ANN-GA method has a wide application potential and is relevant in a wide range of regions with complex weather conditions. However, there are some limitations in this study. First, the model may not be fully generalizable to other regions outside Indonesia without significant adjustment of parameters. Secondly, the model relies heavily on the quality and completeness of the data from the BMKG. The lack or inaccuracy of data can affect the performance of the model. Besides, the GA optimization process can take a lot of time and computing resources.

4. CONCLUSION

The research integrates ANN with GA to improve the accuracy of weather predictions, showing significant improvements in MAE, MAPE, and RMSE. Recommendations for future research include expanding datasets, integrating more detailed data, and exploring models on a regional and global scale. The practical implications of this study include improved accuracy of weather forecasts that are beneficial to the agricultural sector in planning planting and irrigation activities, determining the right time to plant and harvest, reducing the risk of harvest failure due to extreme weather, the aviation sector in improving safety with accurate weather information, as well as urban planning and disaster mitigation for preventive action. The research also paves the way for the development of advanced prediction models for a wide range of disaster risk management and industrial planning applications.

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