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A Hybrid I-LSTM and GA-AP Clustering Framework for Urban Building Health Monitoring

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Abstract: At present, current methods suffer from low monitoring accuracy and poor real-time performance in urban building health monitoring methods. To address these issues, this study proposes an urban building health monitoring method based on an Improved Long Short-Term Memory (I-LSTM) and a Genetic Algorithm-Affinity Propagation Clustering (GA-AP) algorithm. First, this study uses an Improved Long Short-Term Memory (I-LSTM) network to predict urban building settlement. These predictions are then used as input for a clustering model to classify health levels. By using the random forest algorithm to screen key features and inputting the selected features into a clustering model, the classification of health status levels has been achieved. This study utilizes genetic algorithms to optimize the parameters of clustering models and improve the accuracy of health status assessment. The experiment showed that the warning accuracy and response time of the research method were 94.58% and 0.18 seconds. In practical applications, the average number of errors in risk level classification was only 1 per week, and the number of missed detections was only 0.5 per week. The contour coefficient and average percentage error in the clustering process of health levels were 0.90 and 0.23. In addition, this method exhibited strong robustness in complex environments. The proposed method can effectively improve the intelligence level of the monitoring system, significantly enhance timeliness and reliability of the warning mechanism, and provide solid guarantees for urban building safety.

Keywords: LSTM, city building, health monitoring, GA, clustering, sparrow search algorithm.

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1. Introduction

The continuous growth of the social economy has led to the expansion of urban infrastructure construction year by year. If there are safety hazards in urban buildings, it will directly affect residents' lives (Beh et al., 2022). When natural disasters such as earthquakes and floods occur, buildings with health risks are more likely to collapse, causing significant casualties and property damage (Cook et al., 2022). Therefore, urban buildings require long-term and accurate health monitoring to provide a scientific basis for maintenance personnel and further ensure the safety of buildings (Wu et al., 2023). With the advancement of artificial intelligence technology, more scholars are beginning to use it to detect and evaluate the health status of urban buildings (Kim et al., 2022). Mishra et al. (2024) used the YOLOv5 model for defect detection to monitor the structural health of New Delhi tombs. This method combined YOLOv5 and used a Residual Neural Network (ResNet) to enhance feature extraction capability. The maximum average accuracy of this method reached 93.73%. Chen et al. (2023) put forward a method based on building modeling information and image semantic segmentation for automatic detection of concrete defect information. This method achieved defect image recognition and localization by integrating building modeling information data and Deep Learning (DL) technology. The detection accuracy of this method has reached over 90%. Karimi et al. (2024) found that historical bridges in Isfahan faced continuous wet dry cycles, which led to cracks and material peeling in their bridge structures, exacerbating the aging rate. To effectively monitor the bridge, a method based on ResNet and Unmanned Aerial Vehicle (UAV) images were proposed. This method combined UAV high-resolution images with ResNet to achieve recognition of bridge building defects with an accuracy of 96.58%. Khajwal et al. (2023) proposed a new network architecture for reliable automated post disaster assessment of damaged buildings, which utilizes Convolutional Neural Networks (CNN) to extract image information. The images processed by CNN came from multiple shooting perspectives. This architecture combined convolutional forest networks to comprehensively analyze the 3D damage information of buildings, with an evaluation accuracy of 81%.

Long Short-Term Memory Networks (LSTMs) have powerful processing capabilities for temporal data and can effectively capture the long-term dependencies hidden in temporal data. It was applied in multiple fields (Torres et al., 2022). Lu et al. (2024) put forth a prediction network built on multi-average LSTM to achieve safer and more accurate surgical navigation. This network used LSTM to estimate the posture of surgical instruments in real-time, combined with spatial coordinate feedback, to improve positioning accuracy and response speed. The average estimation time of this network was only 1ms. Huang et al. (2022) developed a model that integrates CNN and LSTM to achieve high-precision system fault diagnosis. This model integrated temporal data through sliding windows, extracted features through convolutional layers, and captured delay information through LSTM layers, achieving a diagnostic accuracy of 90.42%. Sun et al. (2023) designed a hybrid DL model combining CNN and LSTM to achieve performance degradation prediction of fuel cell systems and improve prediction accuracy. This model preprocessed data using Complete Ensemble Empirical Mode Decomposition (CEEMD) technology, separated features at different time scales, and then used a hybrid DL model to achieve performance degradation prediction. The prediction accuracy of this method has significantly improved. Hu et al. (2022) constructed a new traffic speed prediction model to achieve timely and accurate traffic speed prediction and provide travel decisions for urban traffic management. This method combined bidirectional LSTM and attention mechanisms to analyze the spatiotemporal characteristics of traffic data, with a prediction accuracy of over 90%.

Based on the above literature, although current Urban Building Health Monitoring (UBHM) methods can identify urban building risks to a certain extent, they are still difficult to comprehensively evaluate the safety status of buildings. It also has problems such as complex data processing and insufficient real-time performance. Therefore, this study proposes a UBHM method based on Improved LSTM (I-LSTM) and Genetic Algorithm-Affinity Propagation (GA-AP) clustering. This study aims to optimize the algorithm model to achieve more efficient UBHM and provide an effective basis for urban management personnel in building management and maintenance. The novelty of this study is that this method, combining the advantages of DL and intelligent optimization algorithms, has strong generalization ability and stability. By introducing the Sparrow Search Algorithm (SSA) to optimize the initial parameters of LSTM, the problem that traditional models are prone to falling into, a local optimum is effectively alleviated, and the accuracy and convergence speed of prediction are improved. The risk level classification of building settlement characteristics is carried out by combining the GA-AP clustering algorithm, which enhances the interpretability and practicability of the results. The existing models ignore the real-time deployment of urban security networks. The study further constructs a lightweight model architecture that supports real-time reasoning at the edge, achieving dynamic monitoring and early warning of urban building complexes. Moreover, it has strong adaptability and robustness in complex urban environments and can effectively deal with practical challenges such as sensor noise and data loss.

The study is divided into three sections: Section 1 is the method introduction section, which elaborates on the principles and optimization process of I-LSTM and GA-AP algorithms in detail. Section 2 is about experimental design and data analysis, analyzing the application effect in actual monitoring. Section 3 is the conclusion and outlook, summarizing the research results and proposing future improvement directions.

2. Methods and Materials

To achieve effective UBHM and provide reliable data support for urban building management, this study proposes a comprehensive monitoring model based on I-LSTM and GA-AP algorithms. This model enhances its capacity to capture long-term dependent features through the I-LSTM structure, and combines GA-AP to optimize feature clustering, improving monitoring accuracy and real-time performance.

2.1. Building Settlement Prediction Based on I-LSTM

The settlement of building foundation pits is an important indicator of UBHM. If the settlement of building foundation pits can be predicted and warned in advance, it will effectively avoid potential safety risks. LSTM has good long-term dependency processing capability, which can effectively model time series data and capture settlement trends. Therefore, this study chooses LSTM as the prediction model for urban building settlement (Abid et al., 2022; Nanjappan et al., 2024; Khleel and Nehéz, 2024). LSTM enhances its ability to remember and update historical data by introducing forget gate and input gate mechanisms, thereby more accurately predicting future settlement trends. LSTM memory units generally consist of three core components: forget, input, and output gates, in addition to a memory cell used to store long-term information. If LSTM directly adopts a random parameter configuration, it will result in low training efficiency and unstable prediction results. Therefore, this study uses SSA to perfect the Initial Weights and Thresholds (IW-Ts) of LSTM. The process of the urban building settlement prediction method based on I-LSTM is shown in Fig. 1.

In Fig. 1, this study first preprocesses historical settlement data, extracts key features, and then uses SSA to optimize the IW-Ts of LSTM. The optimized network is applied to training settlement data and generates prediction models. Finally, the model outputs the future settlement trend. During the prediction process, the accuracy and reliability of the model are evaluated by comparing and analyzing the predicted values with the actual values, thereby achieving early warning of building foundation pit settlement and ensuring urban building safety. This study uses the Root Mean Square Error (RMSE) of predicted values as the loss function to train the model, and through multiple iterations of optimization, gradually lowers the error and lifts the model's prediction accuracy. The training set used comes from actual measurement data of urban construction projects in City A from 2020 to 2024, covering various building types and geological conditions to ensure the model's generalization ability. It includes key indicators such as surface settlement of surrounding roads, top slope settlement, horizontal displacement of slopes, and building tilting, with a total of 120 points covering the building characteristics of different areas.

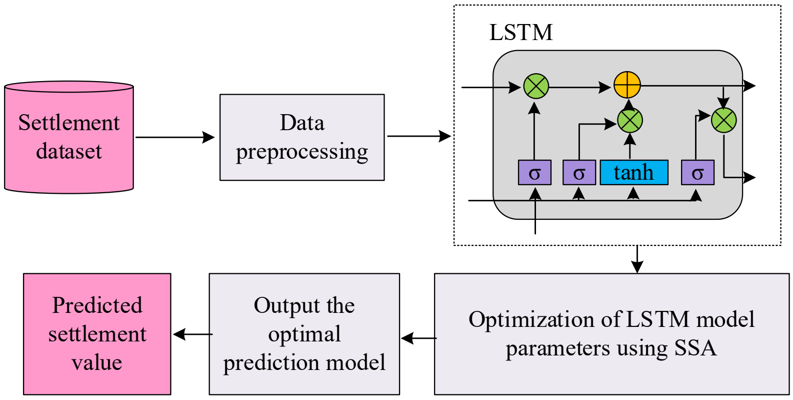


Fig. 1. Process of urban building settlement prediction method based on I-LSTM

To achieve data preprocessing, this study adopts data cleaning, data normalization, and inverse normalization. During the data cleaning process, this study eliminates outliers and missing values to ensure data quality. Subsequently, through normalization processing, the data scale is unified to improve the model training efficiency. Inverse normalization is used to restore the original scale of the predicted results, which is convenient for practical applications. The normalization and anti-normalization processes are shown in Eq. (1).

$$\begin{cases} X = \dfrac{x - x_{\min}}{x_{\max} - x_{\min}} \\ X' = X \cdot (x_{\max} - x_{\min}) + x_{\min} \end{cases} \tag{1}$$

In Eq. (1), x_{max} and $x_{m_{in}}$ are the maximum and minimum in the input dataset. X means the normalized data. x is the current input, and X' denotes the data after inverse normalization processing. This study utilizes SSA to improve the LSTM model. The optimization process of SSA is shown in Fig. 2.

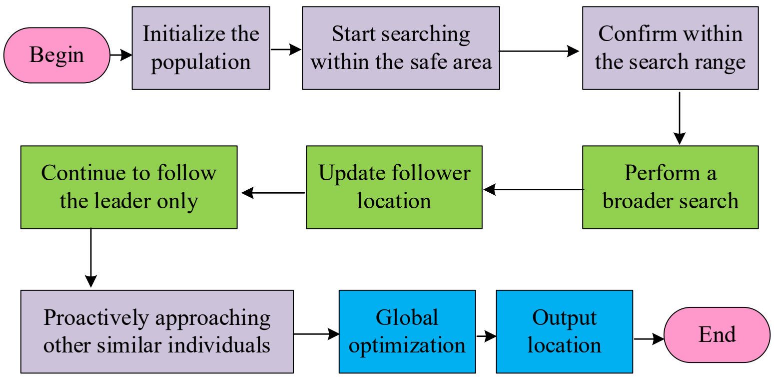


Fig. 2. The optimization process of SSA

In Fig. 2, sparrows in SSA are divided into discoverers and followers, gradually approaching the optimal solution through location updates and information sharing. During the algorithm iteration process, the ratio of discoverers to followers is dynamically adjusted to enhance search efficiency. The process of the I-LSTM model is displayed in Fig. 3.

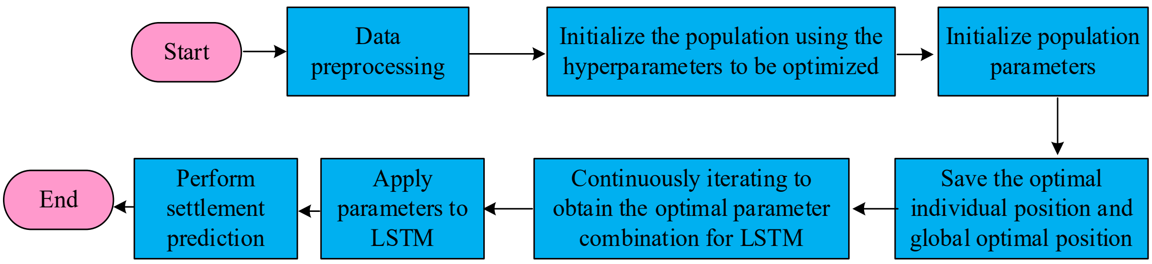


Fig. 3. The overall process of the I-LSTM model

In Fig. 3, this study first preliminarily determines the network structure and parameters, and sets the hidden layer of LSTM to 3 layers, each layer containing 50 neurons. Subsequently, SSA is used to optimize the IW-Ts, with a set iteration count of 100. This study uses the mean square error during the testing process as the fitness function to dynamically adjust the position of the sparrow population, ensuring the effectiveness of the search direction. Based on the above content, the paper utilizes the I-LSTM to intelligently predict the settlement of urban buildings, providing data support for the subsequent classification and monitoring of urban building health risk levels. Before prediction, preprocessing steps, data cleaning and normalization need to be introduced to ensure the accuracy and consistency of the input data. The predicted settlement of urban buildings can be used for later risk assessment and early warning system construction, assisting decision-makers in formulating scientific maintenance strategies, extending the service life of buildings, and ensuring urban safety.

2.2. Building Health Monitoring based on GA-AP Algorithm and Settlement Prediction Results

After using the I-LSTM model to predict urban building settlement, this study applies its prediction results to the classification and monitoring of building health risks. Combining GA-AP, clustering of building health has been achieved, further accurately dividing risk levels. By comparing and analyzing buildings with different risk levels, corresponding monitoring and maintenance strategies are formulated to enhance the scientific and effective management of urban building safety (Swathi et al., 2022; Usharani, 2023). The data used in the process of building health monitoring include a building's predicted settlement, structural parameters, wind force, temperature, humidity, acceleration, and cracks. During the monitoring process, this study uses resistance strain gauges to monitor the stress on building structures in real-time, fiber optic sensors to accurately measure crack width, temperature, and humidity sensors to collect environmental data around the building. The building health monitoring process combining multi-sensor data collection and GA-AP is shown in Fig. 4.

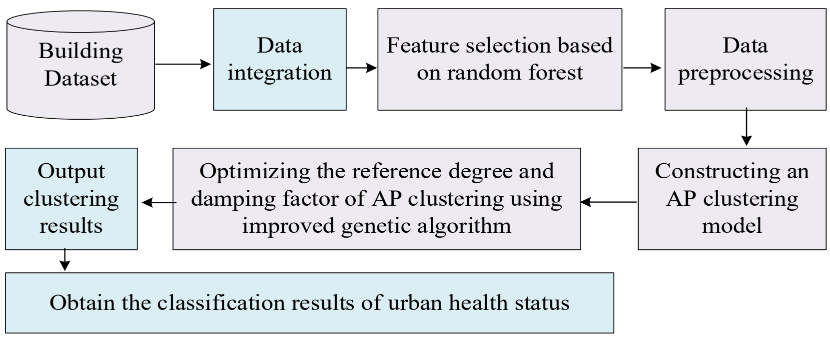


Fig. 4. Building health monitoring process combining multi-sensor data collection and GA-AP algorithm

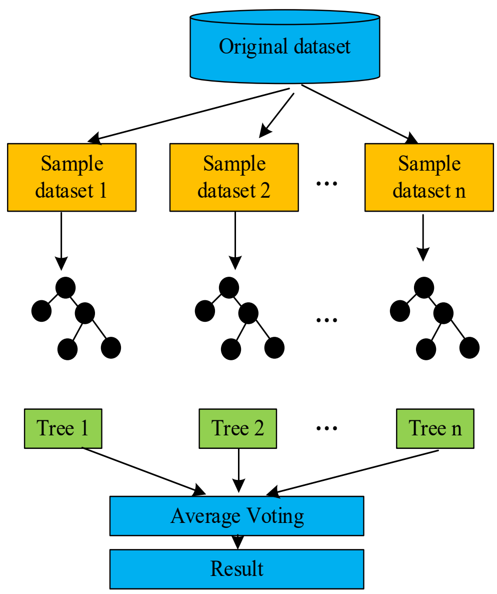


Fig. 5. The structure of RF model

In Fig. 4, firstly, the data collected by multiple sensors are fused and input into the Random Forest (RF) algorithm for feature selection. Afterwards, the data are preprocessed and input into the GA-AP clustering model for iterative optimization. At the same time, a mutation probability adaptive adjustment strategy is introduced to optimize GA. In the process of data fusion, this study adopts the weighted average method to synthesize the data from various sensors, ensuring the comprehensiveness and reliability of the data. Among them, the weighting coefficient is dynamically adjusted based on the accuracy and importance of the sensor. This study adopts the measurement error and response time of sensors as the main indicators, and incorporates their weights into the comprehensive evaluation system to ensure the scientific nature of data fusion. In the process of feature selection, this study uses an RF model to rank the importance of features and select features that have a significant impact on building health. The RF's structure is exhibited in Fig. 5.

In Fig. 5, the RF model processes data in parallel through multiple decision trees. Each tree independently generates feature importance scores and finally summarizes the scores of each tree to determine key features. This study uses the Gini coefficient as the basis for node splitting to ensure maximum purity of each node splitting. The calculation method of the Gini coefficient is shown in Eq. (2).

$$G(p)=\sum_{i=1}^{N} p_i(1-p_i) \tag{2}$$

In Eq. (2), N represents the number of sample categories, p_i is the probability that the sample belongs to category i, and $G(p)$ represents the Gini coefficient value. After obtaining the Gini coefficient, this study calculates the out-of-bag data error to evaluate the importance of features and selects the top 20% of features as key feature sets. After feature selection, this study uses the GA-AP model to further analyze data and improve clustering accuracy through iterative optimization. However, this study also found that the conventional GA is prone to dropping into local optima when iterating, causing unsatisfactory clustering performance. To address this issue, this study introduces a mutation probability adaptive adjustment strategy in the evolution process of GA, as shown in Eq. (3).

$$P_b\begin{cases} \dfrac{(P_{\max}-P_{\min})}{P_{\max}\exp\left(\dfrac{f-f_{avg}}{f_{\max}-f_{avg}}\right)}, f \geq f_{avg} \\ P_{\max}, else \end{cases} \tag{3}$$

In Eq. (3), f_{avg} is the average fitness value, P_{min} is the minimum mutation probability threshold, and f is the current individual fitness value. P_{max} is the maximum mutation probability threshold, and P_b is the mutation probability of the current individual. This study applies the optimized GA to the AP clustering model, optimizing the model reference and damping coefficient. The algorithm structure of GA-AP is shown in Fig. 6.

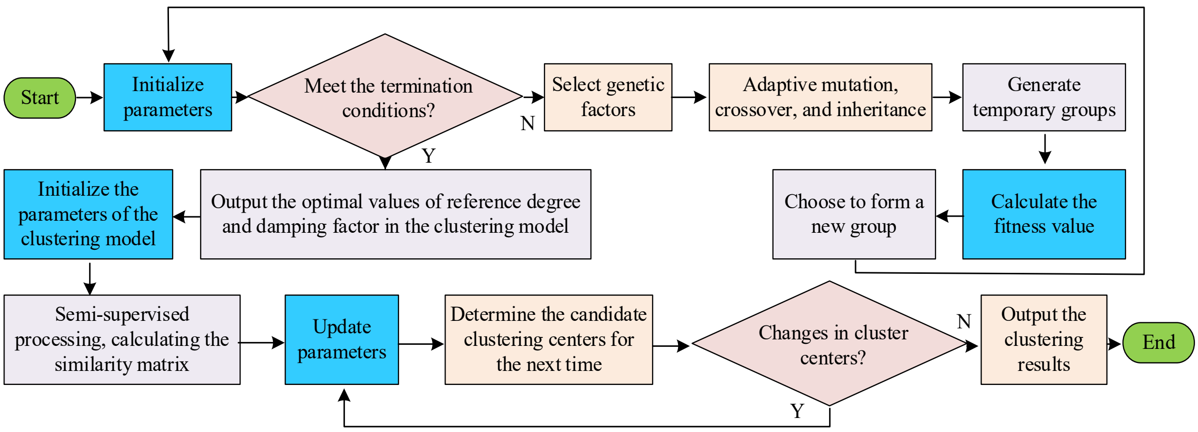


Fig. 6. The algorithm structure of GA-AP

In Fig. 6, the algorithm first initializes the population, calculates individual fitness, and then performs selection, crossover, and mutation operations to adaptively adjust the mutation probability, inputting the optimal reference degree and damping factor of the clustering model. The optimized parameter values are input into the AP clustering model, and the semi-supervised processing calculates the similarity matrix to achieve clustering of urban building health. Therefore, the classification of health risk levels for buildings has been achieved, providing a scientific basis for urban building safety. In this study, the Pearson Correlation Coefficient (PCC) is utilized to measure the linear correlation degree between two variables during the clustering process. By calculating the PCC between each feature, highly correlated features are further screened to reduce redundant information and improve clustering accuracy. By using PCC to calculate the similarity between data points, a more accurate similarity matrix is constructed. This matrix serves as an input for the AP clustering model, enhancing the stability and reliability of the clustering results. In summary, this study first uses I-LSTM to predict the settlement of urban buildings and applies the prediction results to clustering to achieve an accurate evaluation of building health. Based on the clustering results, targeted maintenance strategies have been developed to enhance the level of urban building safety management.

The study combines the current national building safety regulations with the development policies of smart cities, incorporates the clustering results of GA-AP into the urban infrastructure risk prevention and control system, and promotes the establishment of a differentiated supervision mechanism based on health classification. Under the urban resilience policy, classified control is implemented based on the health risk level of buildings. High-risk buildings are given priority to be included in the maintenance, and reinforcement plan, while medium and low-risk buildings are dynamically monitored and resource allocation is optimized to enhance emergency response and long-term resilience. The data provided by the research methods offer practical guidance for urban engineers and policymakers.

3. Results

To evaluate the performance of the proposed UBHM, this paper presents a series of simulation experiments and practical applications. The performance of each method is compared, and the advantages and disadvantages of the research methods are analyzed.

3.1. Performance Analysis of Settlement Prediction Methods

To test the improvement effect of the proposed model, the study compares the training situation before and after improvement, including the loss value of LSTM, the trend of prediction accuracy, and the convergence times, as shown in Fig. 7.

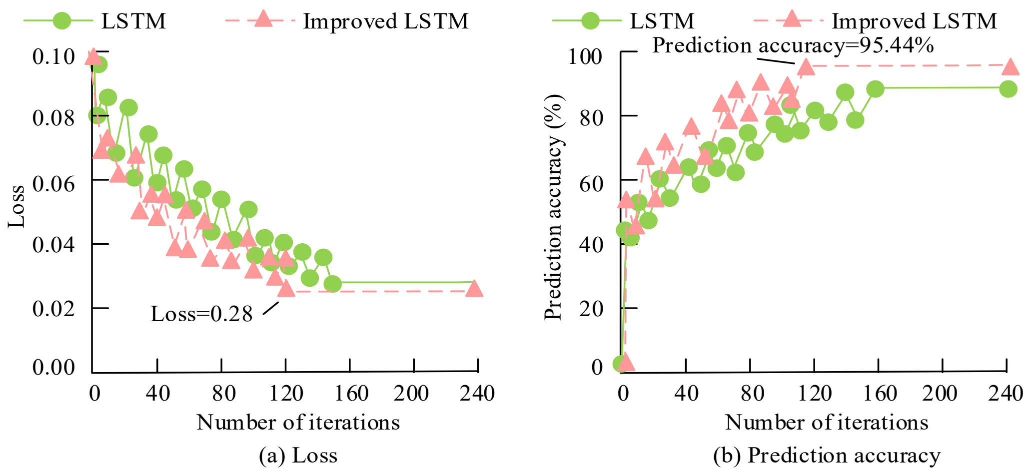


Fig. 7. Comparison of the loss value, prediction accuracy trend, and convergence times of LSTM models before and after improvement

In Fig. 7 (a), the loss value of the improved model is significantly reduced, with only 120 convergence times, a decrease of 23 convergence times compared to the original model, and a convergence value of only 0.28. In Fig. 7 (b), the prediction accuracy of the improved model has significantly improved, reaching 92.5%, which is 5.3% higher than before the improvement. The improved model reaches a stable state after only 117 iterations, demonstrating higher training efficiency and prediction accuracy.

Table 1. Comparison of settlement prediction effects of several methods

Project		RMSE	MAPE (%)	R2	Accuracy (%)
Case 1	I-LSTM	7.63	1.48	0.94	93.74
	LSTM	22.84	13.37	0.89	89.35
Case 2	I-LSTM	7.66	1.37	0.94	93.76
	LSTM	22.57	13.25	0.88	89.23
Case 3	I-LSTM	7.60	1.40	0.95	94.01
	LSTM	22.36	13.28	0.89	89.18
Case 4	I-LSTM	7.61	1.46	0.94	93.97
	LSTM	22.41	13.41	0.89	89.15

To further validate the performance of the research method, RMSE, Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2), and prediction accuracy are introduced to comprehensively evaluate the model. Table 1 compares the evaluation indicators for four scenarios: building settlement (Scenario 1), regional ground settlement (Scenario 2), top settlement of steep slope sections (Scenario 3), and soil displacement around the building (Scenario 4).

In Table 1, I-LSTM outperforms traditional LSTM in all indicators, with significant reductions in RMSE and MAPE, in R^2, and accuracy, verifying the effectiveness and superiority of the improved method. The average values of its RMSE and MAPE indicators are 7.62% and 1.42%, with an average R^2 of 0.94 and an accuracy rate exceeding 93.7%, indicating that the I-LSTM exhibits higher stability and reliability in various settlement prediction scenarios.

3.2. Performance Analysis of Urban Building Health Status Classification Method

To test the optimization effect of using the GA-AP clustering model for improvement, the paper analyzes the model's performance before and after. Comparative indicators include F1-Score, Adjusted Rand Index (ARI), and Variance Ratio Criterion (VRC). Fig. 8 compares the clustering performance of various algorithms as the data size increases.

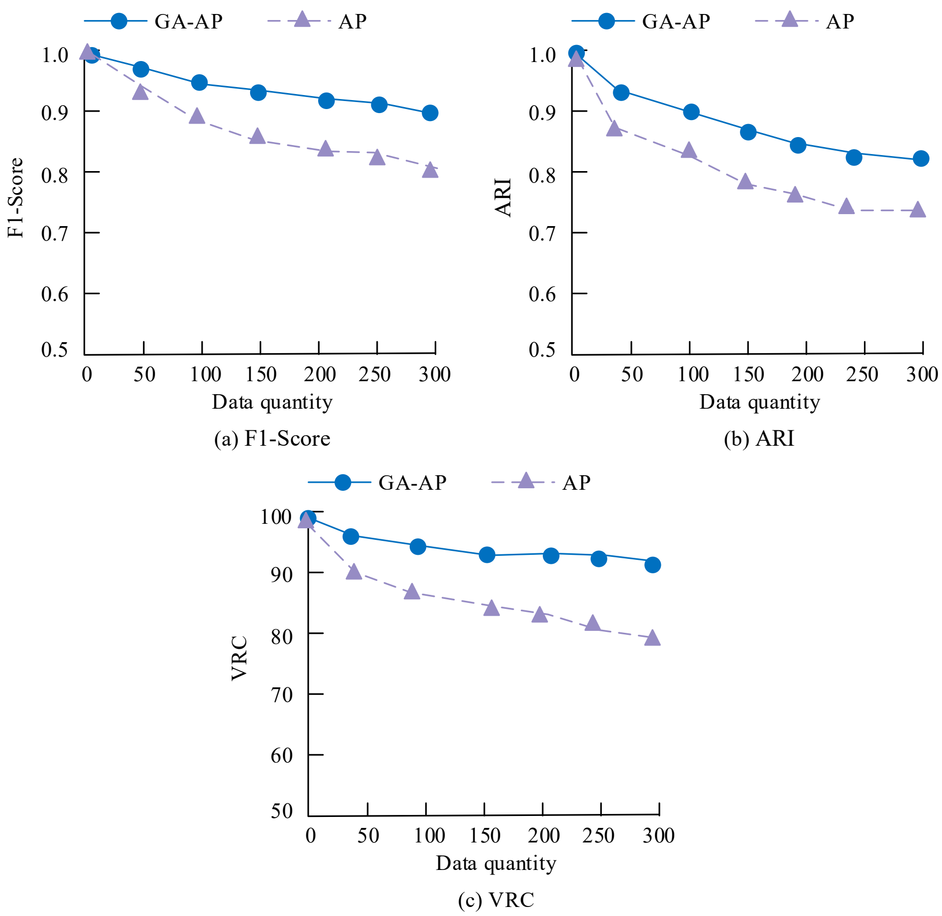


Fig. 8. Clustering performance of each algorithm

In Fig. 8 (a), as the data size increases, F1-Score gradually decreases for the improved GA-AP and AP models. The F1-Score decrease of the improved GA-AP is significantly smaller than that of AP. Its average F1-Score is 0.90. In Fig. 8 (b), the ARI value of the improved GA-AP remains at a high level as the data size increases, with an average ARI of 0.85, which is better than the AP's 0.78. In Fig. 8 (c), the VRC value of the improved GA-AP is significantly higher than that of AP, indicating its advantage in clustering stability, with an average VRC value of 90.34. The improved GA-AP exhibits stronger robustness and clustering performance in big data environments.

To evaluate the performance of the proposed UBHM (Method 1), it is compared with Masciotta et al. (2023), Mosleh et al. (2023), Liu and Chen (2022), and Molina Hutt et al. (2022) (Methods 2-5). Five methods are used to classify the health status of buildings into four levels: A, B, C, and D. The levels represent the building's health status as healthy, good, average, and poor. The accuracy and processing time of different levels of classification are listed in Table 2.

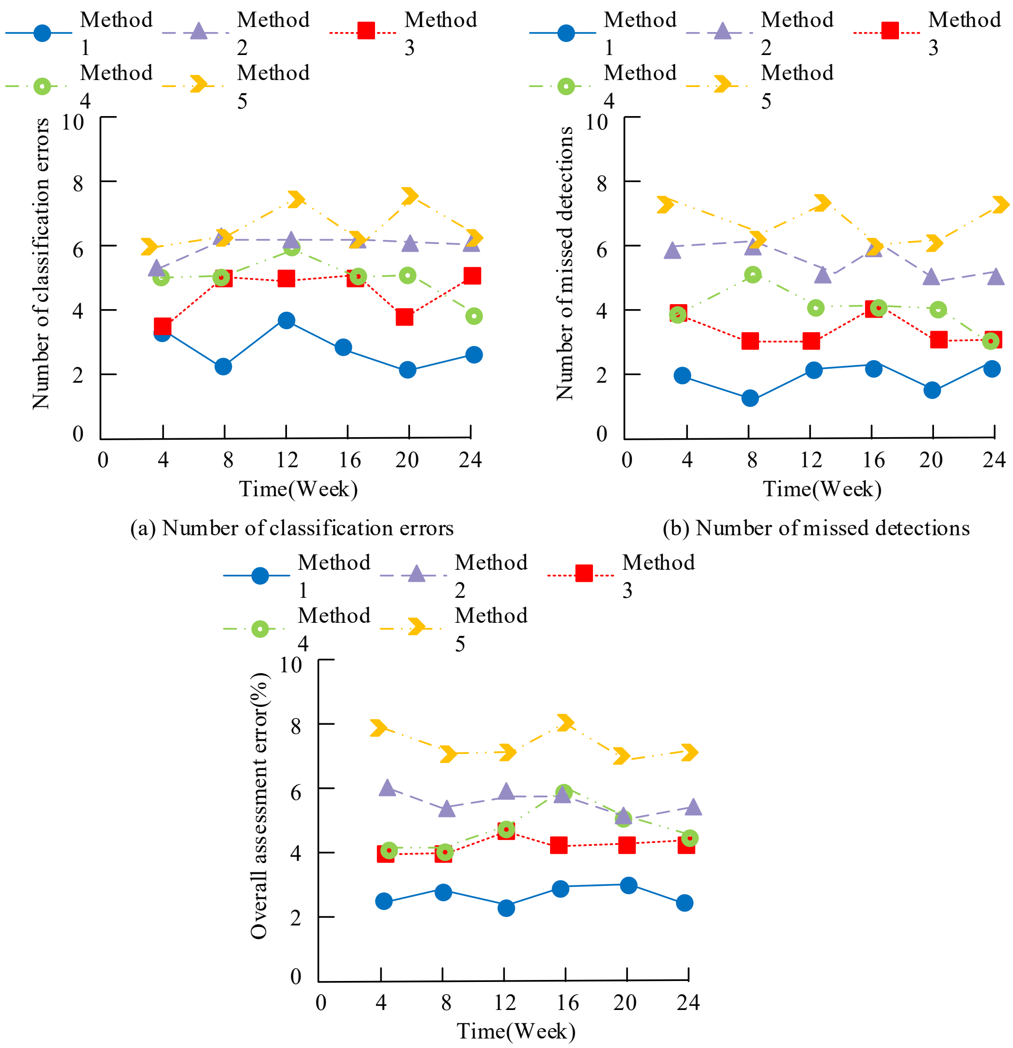
In Table 2, Method 1 significantly outperforms other methods in all indicators, especially in terms of accuracy and processing time, verifying its efficiency and accuracy. Its average division accuracy is as high as 94.36%, and the average processing time is only 0.24 seconds. In contrast, research methods have faster response times and lower error rates in data processing, making them suitable for large-scale building health monitoring and significantly improving the efficiency and accuracy, providing strong support for urban safety management.

Table 2. Comparison of the effectiveness of various methods in dividing the health status of buildings

Project	Grade A		Grade B		Grade C		Grade D	
	Accuracy (%)	Processing time (s)	Accurac y (%)	Processing time (s)	Accuracy (%)	Processing time (s)	Accuracy (%)	Processing time (s)
Method 1	94.26	0.23	95.48	0.24	93.47	0.22	93.78	0.25
Method 2	85.37	0.71	85.28	0.71	85.13	0.74	85.16	0.73
Method 3	90.33	0.41	90.14	0.45	90.22	0.40	90.13	0.41
Method 4	88.74	0.52	88.34	0.53	88.47	0.52	88.16	0.54
Method 5	82.67	0.89	82.11	0.91	82.45	0.90	82.16	0.91

3.3. Analysis of the Practical Application Effect of UBHM Methods

To further verify the practical application effect of the research method, five typical cities are selected for field testing, and five methods are used to evaluate the health status of buildings. The experiment lasts for six months and covers different climates and building types. The number of division errors, missed detections, and overall evaluation errors of each method are shown in Fig. 9.



(a) Number of classification errors (b) Number of missed detections

(c) Overall assessment error

Fig. 9. The number of division errors, missed detections, and overall evaluation errors of each method

In Fig. 9(a), Method 1 has the least number of partitioning errors, with an average of only 1 per week. As the experiment progresses, the number of partition errors in each method decreases to varying degrees, indicating that the optimization effect of method 1 is significant, and other methods are also gradually improving. In Fig. 9(b), Method 1 also has the lowest number of missed detections, with an average of less than 0.5 times per week. In contrast, methods 2 and 5 have a higher missed detection rate, which affects monitoring accuracy. In Fig. 9(c), Method 1 has the smallest overall error, only 3.2%, which is much lower than other methods, further confirming its superiority and reliability in UBHM. In long-term health monitoring, Method 1 has demonstrated extremely high stability and reliability, effectively reducing the risk of misjudgment, ensuring the accuracy of data, and providing solid guarantees for the long-term safety of urban buildings.

To further validate the superiority of the research methods, the response time, partitioning accuracy, RMSE, Silhouette Coefficient (SC), MAPE, and warning accuracy are compared, as shown in Table 3.

Table 3. Comparison of actual application effects of various methods

Method	Accuracy (%)	SC	RMSE	MAPE	Warning Accuracy (%)	Response Time (s)
Method 1	93.14	0.90	0.22	0.23	94.58	0.18
Method 2	85.11	0.75	0.60	0.59	86.17	0.38
Method 3	90.51	0.83	0.34	0.37	90.23	0.27
Method 4	88.36	0.80	0.55	0.48	88.64	0.33
Method 5	81.77	0.73	0.67	0.64	82.00	0.41

In Table 3, Method 1 performs the best in all indicators, especially in response time and warning accuracy. The division accuracy, RMSE, SC, and MAPE indicators of Method 1 are 93.14%, 0.22, 0.90, and 0.23, which are significantly better than those of other methods. Its response time is only 0.18s, far lower than the comparison method, ensuring the efficiency of real-time monitoring. The accuracy rate of early warning has reached 94.58%, further improving the reliability of the system. The research method has shown higher response speed and warning accuracy, significantly improving the real-time and accuracy of UBHM, providing strong support for preventing potential risks.

To verify the scalability and practical application effect of the research method, the study applies it to the health monitoring of large-scale building complexes in Cities A and B. City A is a coastal city in eastern China, while City B is an inland provincial capital in the west. There are significant differences in the geographical environment and architectural structure. City A consists of high-rise residential buildings and commercial complexes, with a total of 1,027 buildings. City B is composed of multi-story residences and public facilities, with a total of 683 buildings, which are relatively scattered. During the six-month continuous monitoring period, the actual operational performance of the five methods is recorded. The results are shown in Table 4.

Table 4. Analysis results of the scalability and practical application of building health monitoring methods

Method	City A			City B		
	Warning Accuracy (%)	Response Time (s)	SC	Warning Accuracy (%)	Response Time (s)	SC
Method 1	94.22	0.21	0.90	95.03	0.19	0.91
Method 2	85.18	0.39	0.76	86.45	0.40	0.75
Method 3	90.46	0.28	0.81	89.71	0.29	0.79
Method 4	88.32	0.34	0.80	86.90	0.33	0.80
Method 5	81.74	0.42	0.74	80.56	0.45	0.72

In Table 4, in the practical applications of Cities A and B, Method 1 performs the best in terms of early warning accuracy, response time, and SC index, and its cross-regional performance is stable. Its early warning accuracy rate in City A reaches 94.22%, and the response time is only 0.21 s. The accuracy rate in City B reaches 95.03%, and the response time is further reduced to 0.19 s, demonstrating good adaptability and scalability. The remaining methods show significant fluctuations among different cities, especially with a marked decline in response efficiency in complex environments.

4. Discussion and Conclusion

To achieve effective monitoring of the health status of urban buildings and provide reliable data support for urban management personnel, this study proposed a UBHM method based on I-LSTM and GA-AP. This method combined an I-LSTM to predict building settlement and used clustering models to classify building health risks into levels. In the experiment, I-LSTM outperformed traditional LSTM in all indicators. The average values of RMSE and MAPE indicators were 7.62% and 1.42%, with an average R^2 of 0.94 and an accuracy rate exceeding 93.7%. The average accuracy of the proposed urban health classification method was as high as 94.36%, with an average processing time of only 0.24 seconds. The average F1-Score of the improved GA-AP model was 0.90. The ARI value of GA-AP has been improved to 0.85, while the VRC value was 90.34. The division accuracy, RMSE, SC, and MAPE indicators of Method 1 were 93.14%, 0.22, 0.90, and 0.23. Its response time was only 0.18s, far lower than other methods, ensuring the efficiency of real-time monitoring. The accuracy of early warning reached 94.58%, further improving the reliability of the system. The proposed UBHM method can effectively respond to complex environmental changes, provide accurate warnings, assist in urban safety decision-making, and improve the level of building health management. At present, there are no in-depth analysis on whether there is an independent relationship between indicators in research. Subsequent research will further explore the interrelationships between indicators to optimize model performance and enhance the overall effectiveness of monitoring systems.

Author contributions

Wei Zhang contributed to the study conception, manuscript editing and design. Junhua Li contributed to Material preparation, data collection and analysis.

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Institutional Review Board Statement

Not applicable.

Declaration of Artificial Intelligence (AI) Tools

The authors used DeepSeek solely for language editing and readability improvement. The authors reviewed and verified all content and take full responsibility for the accuracy and integrity of the manuscript.

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