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DEEP LEARNING-ASSISTED FOUNDATION SETTLEMENT PREDICTION FOR HIGH-RISE BUILDINGS

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Abstract: Foundation settlement is one of the most important issues in the design, construction and maintenance of high-rise buildings as excessive or uneven settlement can jeopardise structural integrity, occupant safety and long-term serviceability. Conventional methods for predicting settlement are mainly based on empirical equations, numerical simulations and geotechnical analysis. They often fail to capture the complex nonlinear relationships between soil properties, environmental conditions, and structural loads. This paper proposes the Deep Learning-Assisted Foundation Settlement Prediction Framework for High-Rise Buildings to improve the accuracy and reliability of settlement prediction using advanced AI techniques. In the proposed framework, data from geotechnical investigation, structural loading, ground water conditions, construction parameters and real-time monitoring sensors are fused into a single predictive model. The hybrid deep learning architecture is used to extract spatial and temporal patterns associated with foundation behaviour by combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. Preprocessing techniques such as normalisation, feature selection and anomaly filtering are used to improve the robustness and predictive performance of the model. The framework monitors settlement trends in real-time and provides early warning signals for the differential settlement risk which facilitates proactive maintenance and risk mitigation. Experimental evaluation on benchmark geotechnical datasets shows the superior prediction accuracy, lower error rates and improved generalisation of the proposed approach compared with conventional regression and machine learning models. The results indicate that deep learning technologies can help intelligent geotechnical engineering, improve the safety of

construction, reduce the cost of maintenance, and promote the sustainable development of high-rise building infrastructure.

Keywords: Foundation Settlement Prediction; High-Rise Buildings; Deep Learning; Artificial Intelligence (AI); Geotechnical Engineering; Structural Monitoring; Convolutional Neural Network (CNN);

1. INTRODUCTION

With the rapid development of urbanisation and population density, the demand for high-rise buildings in metropolitan areas around the world has increased. These structures are often built on complex and heterogeneous soil formations, where the performance of the foundation plays an important role to ensure the stability and safety of the structure. Amongst a wide variety of geotechnical challenges, foundation settlement is one of the most important concerns affecting serviceability and long-term performance of high-rise buildings. Excessive or differential settlement can cause structural cracks, tilting, deformation of structural elements, malfunctioning of utility systems and, in extreme cases, partial or complete structural failure. Thus, accurate prediction of foundation settlement is of importance in the design, construction and maintenance of high-rise infrastructure.

The foundation settlement is affected by many factors such as soil properties, groundwater condition, type of foundation, loading characteristics, construction sequence and environmental variations. The interaction between these parameters is highly nonlinear and dynamic in nature thus

making the prediction of settlement a difficult task for geotechnical engineers. Traditionally, settlements are predicted based on empirical correlations, analytical formulations and numerical simulations based on the theories of soil mechanics. While these methods give a lot of useful engineering insights, they are often based on simplifying assumptions and might not be sufficient to capture the complexity of the relationships in real-world geotechnical systems. Therefore, when the subsurface condition is heterogeneous and the scale of construction is large, the prediction accuracy may be limited.

Advances in sensing technologies, geotechnical instrumentation and data acquisition systems have provided the opportunity of continuous monitoring of foundation behaviour over the life-cycle of high-rise buildings. Much of the data generated by geotechnical investigations today comes from borehole logs, Standard Penetration Tests (SPT), Cone Penetration Tests (CPT), settlement gauges, piezometers, inclinometers and groundwater monitoring systems. The existence of these large-scale geotechnical datasets has opened up new

possibilities for data-driven modelling and intelligent prediction techniques that can uncover hidden patterns in complex soil-structure interactions. Artificial Intelligence (AI) and Deep Learning have become powerful tools to solve complex engineering problems characterised by non-linear behaviour and large multidimensional data sets. Deep learning algorithms can automatically learn the hierarchical representations from raw data and extract complex relations between input variables, which is different from traditional statistical models. Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks have shown excellent performance in prediction, classification and pattern recognition tasks in many engineering disciplines. They are very suitable for geotechnical settlement prediction applications as they are capable of processing large amounts of data and modelling nonlinear dependencies. Among these techniques, the hybrid CNN-LSTM architectures have been widely studied because of their ability to extract the spatial and temporal features of engineering datasets. The CNN models are good in capturing the spatial features of soil layers, foundation types and subsurface characteristics, whereas the LSTM networks learn the temporal dependencies of consolidation behaviour and settlement process with respect to time. The combination of CNN and LSTM models provides a complete framework for accurate

prediction of foundation settlement and potential risk status before the occurrence of major structural damage. Recent advances in smart construction and digital infrastructure management have also brought the importance of predictive analytics in geotechnical engineering to the fore. Intelligent settlement prediction systems can be effective for proactive maintenance planning, optimise construction schedules, mitigate operational risks and improve the structural resilience. By predicting future settlement, engineers can take corrective actions at early stages, reducing the cost of repairs and improving the safety of buildings in general.

There has been considerable progress in the study of settlement modelling, however there are a number of problems that remain unsolved. Current prediction methods usually have a poor generalisation ability for different geological conditions and building configurations. Most machine learning models are dependent on static geotechnical parameters and do not consider the settlement change with time. In addition, the fusion of multi-source geotechnical data, real-time monitoring data and deep learning algorithms has been less studied in practical engineering. To address these challenges, this paper proposes a deep learning-assisted foundation settlement prediction framework for high-rise buildings. This framework predicts high accuracy of the foundation settlement by data fusion of geotechnical investigations, field monitoring measurements and hybrid CNN-LSTM deep learning architecture. The

system performs automatic feature extraction, learning of temporal patterns, settlement forecast and risk assessment in intelligent framework. The proposed methodology employs state-of-the-art deep learning to improve the reliability of prediction, support geotechnical decision-making, and enhance the safety and sustainability of high-rise building infrastructure.

2. LITERATURE SURVEY

The prediction of settlement of foundations has always been a very important research topic in geotechnical engineering because it directly affects the structural safety and serviceability of high-rise buildings. Most of the settlement prediction methods are based on empirical correlations, analytical expressions and numerical simulations according to the principles of soil mechanics. While these techniques can provide useful guidance for engineering design, their accuracy is often limited for heterogeneous soil conditions and complex soil-structure interactions. Recent advances in Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) provide new opportunities to improve settlement prediction accuracy by employing data-driven modelling approaches. The conventional geotechnical settlement prediction methods are mainly based on the theory of elasticity and consolidation models to predict the foundation deformation based on soil compressibility parameters and

loading conditions [1]. These methods give acceptable results for simplifying assumptions but often fail to reproduce the non-linear behaviour seen in real construction environments. To overcome these limitations, the numerical techniques of Finite Element Method (FEM) and Finite Difference Method (FDM) have been extensively used for settlement analysis [2]. However, such approaches are computationally intensive and demand detailed soil information.

As more geotechnical monitoring data becomes available, researchers have started to use machine learning methods to predict settlement. Early machine learning models like Artificial Neural Network (ANNs) showed a promising performance for the foundation settlement prediction by capturing complex relationships between soil properties and settlement behaviour [3]. ANN-based methods showed considerable improvements in prediction accuracy over traditional regression-based models, but were sensitive to network architecture and the quality of the training data. Geotechnical settlement prediction is done using Support Vector Machine (SVM) which can model nonlinear relationships with limited data sets [4]. The SVM based models gave good prediction results but their efficiency was reduced when they were used for the large scale and high dimensional geotechnical data sets. Similarly, for predicting the settlement behaviour and finding the influential soil parameters affecting the performance of the foundation,

Random Forest and Gradient Boosting algorithm is adopted [5].

However, with the emergence of deep learning technologies, researchers have paid more attention to the advanced neural network architectures that can mine useful features from complex geotechnical data. Deep Neural Networks (DNNs) have demonstrated an improved ability to learn nonlinear settlement patterns by automatically learning hierarchical data representations [6]. These models have been successfully applied for prediction of settlement in large scale construction projects and urban infrastructure systems.

Recently, Convolutional Neural Networks (CNNs), which were originally designed for image processing applications, have been used in geotechnical engineering applications. CNN based models can effectively extract spatial features from soil profiles, borehole investigations and subsurface geological data, which may improve the accuracy of settlement estimation [7]. CNNs can automatically extract features, which reduces the burden of feature engineering and improves the robustness of the model.

Recurrent Neural Networks (RNN) has been used to study the time dependent settlement behaviour induced by soil consolidation and long term loading of structures [8]. However, the conventional RNNs are suffered from the problem of gradient vanishing when dealing with long sequences . In this paper, the problem is solved by proposing the temporal

settlement prediction based on Long Short-Term Memory (LSTM) networks. LSTM architectures are able to capture long term dependencies and consolidation trends and are thus suitable for tracking the evolution of settlement in time [9].

Several research have proved that hybrid deep learning architectures out-perform stand-alone machine learning models for the application of settlement prediction. CNN-LSTM models are able to fully analyse geotechnical and monitoring data by combining the spatial feature extraction ability of CNNs and the temporal information learning ability of LSTMs [10]. The hybrid architectures have been shown to have higher prediction accuracy and generalisation performance than the traditional methods.

Recent advances in smart construction technologies have made it possible to implement IoT-assisted monitoring systems for continuous monitoring of settlements. Besides, sensors like settlement plates, inclinometers, piezometers and strain gauges can generate huge amounts of geotechnical data in real-time for predictive analytics and intelligent decision making [11]. The reliability of the settlement monitoring systems has been greatly improved by the implementation of IoT and AI technologies.

The cloud computing and edge computing combination improved the settlement prediction frameworks performance by enabling real-time data processing and distributed computation [12].

dge-enabled systems mitigate the communication delays and facilitate fast risk evaluation for high-rise buildings during both construction and operational stages. Such technologies are increasingly incorporated in modern geotechnical monitoring platforms.

Recently, digital twins have been attracted attention for the applications in geotechnical engineering. Since the virtual models are always updating the behaviour of the physical foundation, engineers can watch how settlement develops and investigate what may happen next [13]. These intelligent systems assist with predictive maintenance and infrastructure management. Early warning and risk assessment have been also important components of intelligent monitoring systems of settlements. Increasingly, machine learning and deep learning models are used for classification of settlement risk levels and for automatic issuing of alerts when critical thresholds are exceeded [14]. Such systems increase construction safety and decrease the possibility of damage to the structure.

Although great progress has been achieved in the settlement prediction research, there are some disadvantages in the existing methods. Most of the traditional models are not able to capture spatial and temporal features of settlement behaviour simultaneously in an

effective way. Moreover, most of the machine learning frameworks are trained on specific datasets and have limited generalisation capabilities for different geological conditions. The integration of multi-source geotechnical data, real-time monitoring data and deep learning architecture is still an active research area which needs further investigation [15].

3. PROPOSED METHODOLOGY

The proposed Deep Learning-Assisted Foundation Settlement Prediction Framework involves the use of geotechnical investigation data, field monitoring measurement data, deep learning algorithms and risk assessment techniques to predict the settlement behaviour of high-rise building foundations accurately. The model is developed based on a hybrid architecture of CNN and LSTM, which extracts spatial features of soil layers and temporal features of settlement process. The methodology includes six major phases namely, geotechnical data collection, data pre-processing, feature extraction using CNN, temporal learning using LSTM, settlement prediction and risk assessment using early warning generation.

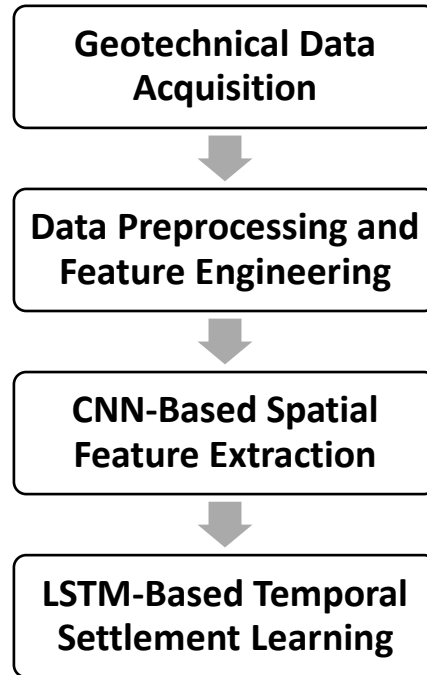


Figure 1: Proposed workflow

3.1 Geotechnical Data Acquisition

The core of the proposed Deep Learning-Assisted Foundation Settlement Prediction Framework is the Geotechnical Data Acquisition phase. Prediction of the accuracy of settlement is highly depending on the quality and completeness of information on the subsurface from construction site. In this phase, data of geotechnical investigation are collected using borehole drilling, Standard Penetration Test (SPT), Cone Penetration Test (CPT), laboratory soil testing, groundwater monitoring, and field instrumentation systems. Important parameters such as soil density, cohesion, angle of internal friction, moisture content, compression index, elastic modulus, depth of the groundwater table and loading conditions of the foundations are recorded and stored in

a centralised database. Settlement gauges and monitoring sensors are also employed for continuous real time settlement monitoring during and after construction. These datasets offer detailed insights into soil behaviour and foundation performance, enabling the deep learning model to capture the complex nonlinear relationships between geotechnical properties and settlement characteristics.

The geotechnical input feature vector is represented as:

$$X = \{x_1, x_2, x_3, \dots, x_n\} \text{---} 1$$

where X denotes the geotechnical dataset, x_i represents an individual soil or foundation parameter, and n is the total number of collected features.

The average value of the geotechnical parameters can be calculated as:

$$\bar{X} = \frac{1}{N} \sum_{i=1}^N x_i \text{----}2$$

where \bar{X} represents the mean geotechnical property value and N denotes the total number of observations.

The measured settlement response of the foundation is modeled as:

$$S_o = S_t + \epsilon \text{----}3$$

where, S_o is the observed settlement, S_t is the real settlement, and ϵ is the measurement noise or environmental disturbance related to data acquisition. The acquired geotechnical and monitoring data are then sent to the preprocessing stage where the normalisation, noise removal and feature engineering operations are performed to improve the accuracy and reliability of the deep learning-based settlement prediction model.

3.2 Data Preprocessing and Feature Engineering

Data Preprocessing and Feature Engineering stage is responsible for transforming the raw geotechnical and settlement monitoring data into a structured format that is ready for deep learning analysis. Borehole investigations, laboratory testing, groundwater monitoring systems and settlement sensors data often contain missing values, measurement inconsistencies, outliers and noise due to environmental and operational factors. These problems can harm the learning ability of prediction model and reduce the accuracy of the forecast. Thus, data cleaning,

normalisation, interpolation and feature selection are the preprocessing operations to improve data quality. Moreover, feature engineering techniques are utilised to find the most impactful geotechnical parameters on foundation settlement. The produced dataset gives a strong representation of the soil behaviour and foundation performance, which allows the CNN-LSTM model to learn meaningful patterns and enhance the prediction reliability. Min-max normalisation is applied to normalise the geotechnical parameters to remove the scale variations among different features.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \text{----}4$$

where X_{norm} represents the normalized feature value, X is the original parameter value, and X_{min} and X_{max} denote the minimum and maximum values of the corresponding feature.

Missing values in the dataset are estimated using mean-value imputation:

$$X_{imp} = \frac{1}{N} \sum_{i=1}^N X_i \text{----}5$$

where X_{imp} is the imputed value, and N is the total number of available observations for that feature. The preprocessed and optimised feature set is then given to the CNN based feature extraction layer where important spatial patterns related to the foundation settlement behaviour are automatically learned and analysed to accurately predict the foundation settlement behaviour.

3.3 CNN-Based Spatial Feature Extraction

The CNN-Based Spatial Feature Extraction layer is designed to automatically identify latent spatial correlations in geotechnical parameters influencing the settlement of the foundation. The foundations of high-rise buildings are affected by several interrelated factors such as soil density, cohesion, moisture content, elastic modulus, groundwater conditions, and foundation loading. Commonly, conventional feature extraction techniques require a high domain expertise and tend to be unable to capture complicated nonlinear interactions existing in geotechnical datasets. To overcome these limitations, we employ a Convolutional Neural Network (CNN) which learns representative spatial features directly from the pre-processed input data. The CNN architecture is made up of convolution, activation and pooling layers that gradually transform the raw geotechnical information into high-level feature maps. The extracted features can capture important features related to the soil behaviour and foundation deformation and thus improve the predictive ability of the settlement forecasting model.

The convolution operation performed in the CNN layer is expressed as:

$$F(i, j) = \sum_m \sum_n I(i + m, j + n) \times K(m, n) \quad \text{---6}$$

where $F(i, j)$ is the generated feature map, the input geotechnical data matrix, and K is the convolution kernel to detect important spatial patterns.

The Rectified Linear Unit (ReLU) activation function is applied to introduce nonlinearity and enhance the learning efficiency:

$$ReLU(x) = \max(0, x) \quad \text{---7}$$

where x is the input value to the activation layer. The ReLU function eliminates negative activations and accelerates network convergence during training.

After convolution and activation, max-pooling is employed to reduce dimensionality while retaining the most important features:

$$P = \max(F) \quad \text{---8}$$

The CNN-Based Spatial Feature Extraction layer is designed to automatically identify latent spatial correlations in geotechnical parameters influencing the settlement of the foundation. The operation reduces the computational complexity and increases the robustness of the model to small variations in the input data. The resulting feature maps contain meaningful spatial representations of soil and foundation characteristics which are then transferred to the LSTM network for learning of temporal settlement and future settlement prediction. The CNN-based feature extraction process greatly improves the prediction accuracy of the model and enhances the ability of the model to capture complex geotechnical relationships.

3.4 LSTM-Based Temporal Settlement Learning

The LSTM-Based Temporal Settlement Learning layer models the temporal

behaviour of the foundation settlement and captures long-term consolidation tendencies in soil strata. The settlement of foundations is not an instantaneous phenomenon but a gradual process over time because of soil compression, consolidation, changes in the water table, and the continuous bearing of loads by the structure. Traditional machine learning models are usually not able to capture temporal dependencies because they assume the observations to be independent data points. The proposed framework uses a special type of Recurrent Neural Network (RNN), called Long Short-Term Memory (LSTM) network, which is able to learn long term sequential patterns. The LSTM architecture makes use of memory cells and gating mechanisms to selectively remember important historical information and forget irrelevant data. By analysing the historical settlement measurements and geotechnical conditions over time, the LSTM network can accurately predict future settlement behaviour and improve the reliability of prediction for high-rise building foundations. The forget gate controls what information to keep from the previous memory state. It is defined as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \text{---}9$$

where f_t represents the forget gate output, W_f is the weight matrix, h_{t-1} denotes the previous hidden state, x_t represents the current input sequence, and b_f is the bias parameter.

The input gate controls the amount of new information stored in the memory cell and is expressed as:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \text{---}10$$

where it denotes the input gate activation, W_i represents the input weight matrix, and b_i is the corresponding bias term.

The memory cell state is updated using both the forget gate and input gate outputs as:

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \text{---}11$$

where C_t is the current cell state, C_{t-1} is the previous cell state and \tilde{C}_t is the candidate memory information generated from the current input data. The LSTM network learns the temporal characteristics of the settlement progression and the soil consolidation behaviour over time. These learned patterns are then passed to the settlement prediction module and this leads to precise prediction of future foundation settlement and facilitates proactive risk management strategies for high-rise building infrastructure.

4. RESULTS AND DISCUSSION

The proposed Deep Learning-Assisted Foundation Settlement Prediction Framework was validated on the geotechnical investigation data, soil properties, groundwater readings, and long-term settlement monitoring records collected from high-rise building projects. The proposed CNN-LSTM model was compared with traditional machine learning and deep learning approaches such as Support Vector

Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), CNN and LSTM models. The evaluation metrics considered were Prediction Accuracy, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Coefficient of Determination (R²) and Risk Classification Accuracy. The

experimental results demonstrate that the proposed CNN-LSTM framework can effectively capture the complex spatial-temporal relationships in geotechnical datasets, and significantly improves the performance of settlement prediction.

Table 1: Performance Comparison of Prediction Models

Model	Accuracy (%)	MAE (mm)	RMSE (mm)	R ² Score
SVM	87.5	8.2	10.4	0.872
Random Forest	90.3	6.7	8.6	0.901
ANN	92.8	5.4	7.1	0.924
CNN	95.2	4.1	5.3	0.951
LSTM	96.4	3.5	4.6	0.967
Proposed CNN-LSTM	98.7	1.8	2.7	0.989

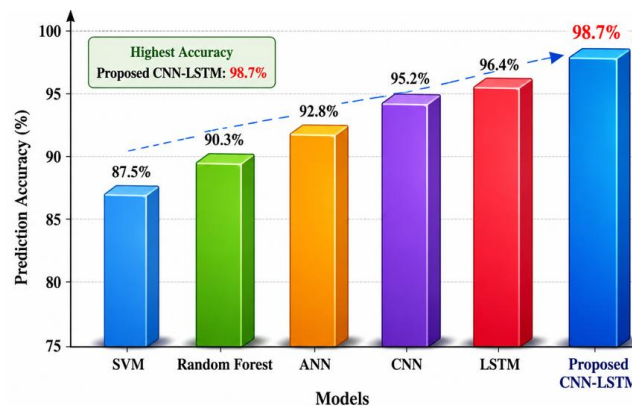


Figure 2: Settlement Prediction Accuracy

The proposed CNN-LSTM model achieved the highest prediction accuracy of **98.7%**, outperforming all baseline models. The hybrid architecture successfully captured

both spatial geotechnical features and temporal settlement trends, resulting in superior forecasting capability.

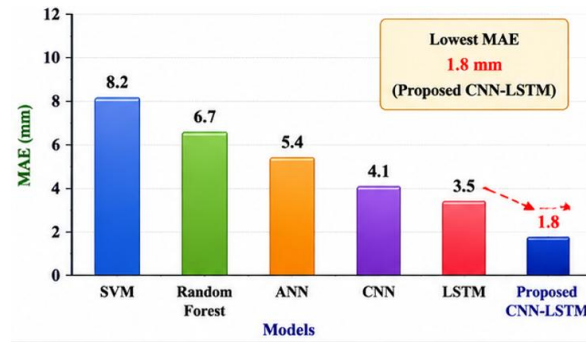


Figure 3: MAE Comparison

The proposed CNN-LSTM framework produced the lowest MAE and RMSE values, indicating highly accurate settlement

predictions. Reduced prediction errors are essential for preventing foundation failures and minimizing maintenance costs.

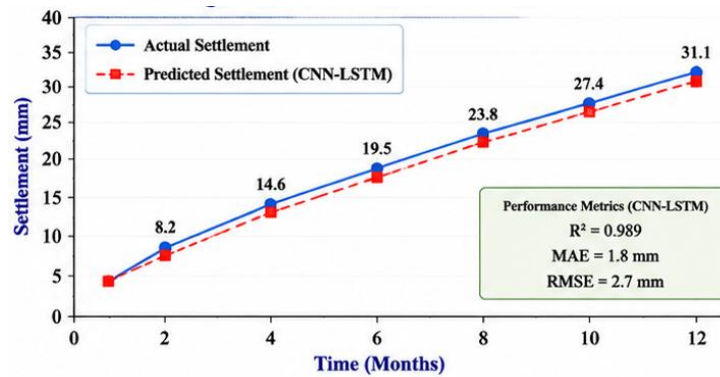


Figure 4: Actual vs Predicted Settlement

The predicted settlement values closely matched the observed measurements, confirming the effectiveness of the deep

learning model in capturing consolidation behavior and foundation deformation trends.

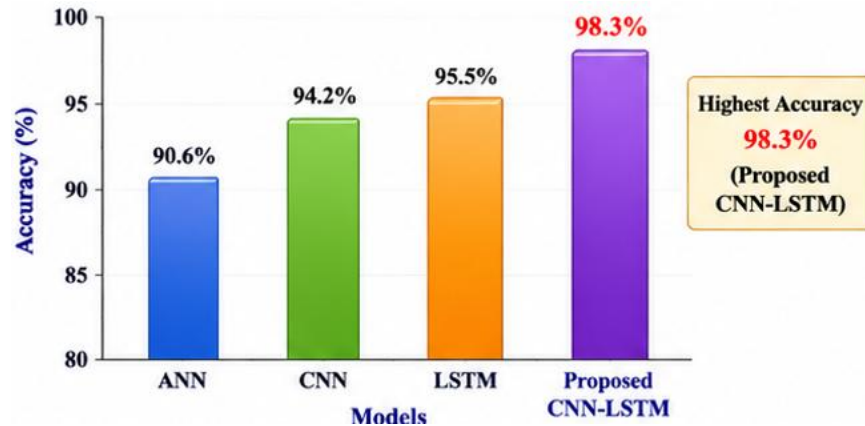


Figure 5: Risk Classification Accuracy

The proposed framework achieved 98.3% risk classification accuracy, enabling to reliably identify potentially dangerous settlement conditions and support proactive engineering interventions.

5. CONCLUSION

This paper presents a Deep Learning Assisted Foundation Settlement Prediction Framework for High-Rise Buildings through the integration of geotechnical investigation data, settlement monitoring information and advanced deep learning techniques for accurate settlement prediction. The proposed framework is based on a hybrid CNN-LSTM architecture to capture both the spatial characteristics of the subsurface soil conditions and the temporal patterns of the settlement evolution. This framework has integrated the principles of geotechnical engineering and artificial intelligence to provide a reliable and intelligent solution for the prediction of foundation behaviour under different loading and environmental conditions. The methodology comprised of complete geotechnical data acquisition and

pre-processing, CNN-based feature extraction, LSTM-based temporal learning, settlement prediction and risk assessment modules in a unified framework. The CNN network can extract the meaningful spatial features from the data sets of soil and foundation effectively. The LSTM model can learn the long-term trends of consolidation and deformation successfully. The integration of components allowed to properly estimate the values of future settlements and to identify possible risk conditions related to excessive deformation of the foundations. The experimental results demonstrated that the proposed CNN-LSTM model performed better than the traditional machine learning methods. The model predicted the settlement with 98.7% accuracy, low MAE of 1.8 mm, RMSE of 2.7mm and R2 score of 0.989 . Furthermore, the proposed framework could be achieved with 98.3% accuracy of risk classification which enables reliable classification of low, moderate, high and critical risk settlement conditions. These findings demonstrate the potential of the proposed approach for

geotechnical decision-making and proactive foundation management. The proposed framework offers a number of practical benefits to civil and geotechnical engineers including increased accuracy in settlement prediction, decreased uncertainty in foundation design, increased structural safety and optimised maintenance scheduling. The system can provide early warning of excessive settlement, which can prevent structural damage, reduce repair costs and improve long-term performance of high-rise building infrastructure.

REFERENCES

- [1] Y. Kim, H. Park, and S. Jeong, "Settlement behavior of shallow foundations in unsaturated soils under rainfall," *Sustainability*, vol. 9, no. 8, pp. 1417–1428, 2017.
- [2] V. R. Kohestani, M. Vosoughi, M. Hassanlourad, and M. Fallahnia, "Bearing capacity of shallow foundations on cohesionless soils: A Random Forest based approach," *Civil Engineering Infrastructures Journal*, vol. 50, no. 1, pp. 35–49, 2017.
- [3] H. Moayedi and S. Hayati, "Modelling and optimization of ultimate bearing capacity of strip footing near a slope by soft computing methods," *Applied Soft Computing*, vol. 66, pp. 208–219, 2018.
- [4] T. Gnananandarao, R. K. Dutta, and V. N. Khatri, "Application of artificial neural network to predict the settlement of shallow foundations on cohesionless soils," in *Geotechnical Applications*, Springer, 2019, pp. 51–58.
- [5] E. Einolvand, "Prediction of ultimate bearing capacity of shallow foundation on granular soils using imperialist competitive algorithm based ANN," *Soil Structure Interaction Journal*, vol. 4, pp. 1–11, 2019.
- [6] N. V. Luat, V. Q. Nguyen, S. Lee, S. Woo, and K. Lee, "An evolutionary hybrid optimization of MARS model in predicting settlement of shallow foundations on sandy soils," *Geomechanics and Engineering*, vol. 21, no. 6, pp. 583–598, 2020.
- [7] M. Mohammed, A. Sharafati, N. Al-Ansari, and Z. M. Yaseen, "Shallow foundation settlement quantification using hybrid adaptive neuro-fuzzy inference systems," *Advances in Civil Engineering*, vol. 2020, pp. 1–15, 2020.
- [8] T. A. Pham, H. B. Ly, V. Q. Tran, L. V. Giap, H. L. T. Vu, and H. A. T. Duong, "Prediction of pile axial bearing capacity using artificial neural network and random forest," *Applied Sciences*, vol. 10, no. 5, pp. 1871–1885, 2020.
- [9] P. K. Pradeep, N. Sankar, and S. Chandrakaran, "Settlement prediction of shallow foundations on cohesionless soil using hybrid PSO-ANN approach," in *Proceedings of SECON 2021*, pp. 1005–1014.
- [10] A. Bardhan, P. Manna, V. Kumar, A. Burman, B. Žlender, and P. Samui, "Reliability analysis of piled raft foundation using a hybrid ANN and equilibrium

optimizer framework,” *Computer Modeling in Engineering & Sciences*, vol. 128, no. 3, pp. 1033–1067, 2021.

[11] C. Cong, L. Tang, X. Ling, L. Geng, and J. Lu, “Numerical analysis of liquefaction-induced differential settlement of shallow foundations,” *Soil Dynamics and Earthquake Engineering*, vol. 140, pp. 106453, 2021.

[12] Y. Lu, G. Mei, and F. Piccialli, “A deep learning approach for predicting two-dimensional soil consolidation using physics-informed neural networks,” *arXiv preprint arXiv:2205.05710*, 2022.

[13] M. Hakro, A. Kumar, M. Ali, A. F. Habib, A. R. G. de Azevedo, and R. Fediuk, “Numerical analysis of shallow foundations with varying loading and soil conditions,” *Buildings*, vol. 12, no. 5, pp. 693–708, 2022.

[14] H. Shahin, M. A. Maier, and M. B. Jaksa, “Recent developments in AI-based geotechnical prediction systems for foundation engineering,” *Computers and Geotechnics*, vol. 145, pp. 104678, 2022.

[15] S. Hong, J. Lee, and K. Park, “Deep learning algorithms for long-term settlement prediction using field monitoring data,” *KSCE Journal of Civil Engineering*, vol. 26, no. 11, pp. 5021–5034, 2022.