

Identification of Surface Subsidence Risk in Shallow Foundations using Multi-Layer Perceptron (MLP)

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Abstract: Surface subsidence is a critical geotechnical concern in shallow foundation systems, especially in urban environments with heterogeneous soil conditions and variable groundwater levels. Excessive or uneven settlement can compromise structural integrity, reduce service life, and increase maintenance costs. Therefore, timely identification and prediction of surface subsidence risk are essential in foundation design and site planning. In this study, a data-driven approach using Multi-Layer Perceptron (MLP) neural networks is proposed to predict the risk of surface subsidence associated with shallow foundations. A comprehensive dataset was compiled, incorporating soil physical and mechanical properties, foundation geometry, groundwater depth, load characteristics, and historical subsidence measurements from multiple construction sites. The MLP model was trained using supervised learning techniques and validated with a test dataset to ensure accuracy and generalization capability. Performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 were used to evaluate the model's predictive capability. The results show that the MLP model successfully captures the complex nonlinear interactions among the influencing factors and achieves high predictive accuracy. This research demonstrates the effectiveness of MLP neural networks as a practical tool for geotechnical risk assessment and decision-making. The proposed method can support engineers and planners in identifying high-risk zones early in the design process and implementing appropriate mitigation strategies.

Keywords: Subsidence, Shallow foundation, Multi-layer perceptron (MLP), Settlement prediction, Machine learning.

I. INTRODUCTION

Surface subsidence is a significant concern in the design and maintenance of shallow foundation systems, particularly in urban and semi-urban areas where land use intensity is high and ground conditions are often unpredictable (Liu et al., 2019a). Subsidence refers to the gradual or sudden downward movement of the ground surface, typically caused by changes in subsurface

conditions such as soil consolidation, collapse of voids, groundwater depletion, or load-induced settlement (Acacio et al., 2001). When shallow foundations are subjected to such ground movements, the resulting structural deformations can lead to serviceability issues or even structural failure (Zhang et al., 2019). In civil and geotechnical engineering, shallow foundations are commonly used for low- to mid-rise building and infrastructure (Nikbakht et al., 2022). These foundations transmit structural loads to the near-surface soil layers, typically to depths less than the width of the foundation (Zhang et al., 2020). Their performance is heavily dependent on the strength, compressibility, and drainage characteristics of the underlying soil (Liu et al., 2019b). Inadequate understanding or improper assessment of these factors can result in excessive settlement, differential movement, and long-term durability concerns for the supported structure (Nazarzadeh & Sarbishe-ee, 2017). Geotechnical evaluation of subsidence risk requires a thorough understanding of soil-structure interaction, mechanical behavior of soils, and site-specific conditions such as groundwater table fluctuations, seismic activity, and construction methods (Costa et al., 2020). Traditional approaches often rely on deterministic soil mechanics principles combined with empirical correlations, laboratory tests, and field observations to estimate settlement under static and dynamic loads (Ray et al., 2021).

Over the past decades, several analytical and empirical methods have been developed for predicting surface subsidence in shallow foundations (Abija, 2023). These include methods based on elastic theory (Ubido et al., 2017), Terzaghi's and Skempton's consolidation models, Schmertmann's method for sand, and empirical approaches such as the Burland and Burbidge method (Sundell et al., 2019; Lanes et al., 2023). These models generally require input parameters such as modulus of elasticity, Poisson's ratio, unit weight of soil, and preconsolidation pressure, which are obtained through field or laboratory testing (Hu et al., 2022). While these conventional methods are widely accepted and used in practice, they are often subject to limitations such as simplified assumptions, idealized soil conditions (Liu et al., 2019a), and the difficulty of capturing the inherent variability and uncertainty in soil properties (Liu et al., 2019b).

For instance, many analytical models assume homogeneous, isotropic, and linear-elastic soil behavior, which rarely represents real-world site conditions (Abija, 2023). As a result, their predictive performance may be compromised in complex or heterogeneous geological settings (Nazarzadeh & Sarbishe-ee, 2017). Another challenge lies in the data collection process, which can be costly, time-consuming, and prone to measurement errors (Lokkas et al., 2021). Soil testing and in-situ investigations such as standard penetration tests (SPT), cone penetration tests (CPT), and plate load tests provide valuable data but are not always feasible in all project phases (Mola Abasi et al., 2022). These constraints highlight the need for alternative or complementary methods that can enhance the accuracy and efficiency of subsidence risk prediction (Asci et al., 2015).

The SPT is one of the most widely used in-situ testing methods in geotechnical site investigations (Farhangi et al., 2020). Conducted within boreholes, the SPT involves driving a split-barrel sampler into the soil using a standard weight (63.5 kg) dropped from a fixed height (76 cm). The number of hammer blows required to penetrate each 15 cm of depth is recorded, and the sum of blows for the second and third 15 cm increments is reported as the SPT N-value (Poor et al., 2023). This value is empirically correlated with soil properties such as relative density, shear strength, and bearing capacity, especially for sands and silty soils (Ortiz-Hernández et al., 2022). While SPT is simple, robust, and cost-effective, it has several limitations (Poor et al., 2023). The energy delivered to the sampler may vary with equipment and operator technique, requiring energy correction factors. Moreover, in cohesive soils (e.g., clays), the N-value may not accurately reflect the soil's undrained shear strength (Xu et al., 2024). The test also offers limited continuous profiling and does not directly measure fundamental soil parameters such as stress-strain behavior or pore pressure response (Poor et al., 2023).

In contrast, CPT offers a more continuous and detailed in-situ profile of soil layers. CPT involves pushing a cone-shaped penetrometer into the ground at a constant rate (2 cm/s), measuring tip resistance, sleeve friction, and in some cases, pore water pressure (in CPTu or piezocone). These measurements provide real-time data on stratigraphy and mechanical behavior of soils and can be used to estimate parameters such as undrained shear strength, overconsolidation ratio, OCR (Maleki et al., 2024), and soil classification (Jinguuji & Toprak, 2017). CPT is highly effective in soft to medium cohesive soils and sands with little gravel content. Its advantages include high data resolution, rapid testing, and reduced operator dependency (Xu et al., 2024). However, CPT equipment is relatively expensive, and the test may encounter difficulties in very dense or gravelly soils due to high penetration resistance (Liao et al., 2002). Additionally, interpretation of CPT results often requires calibration against laboratory or site-specific correlations to derive engineering design parameters (Farhangi et al., 2020).

Alongside in-situ tests, laboratory testing of soil samples remains a fundamental component of subsurface investigations (Gibbs & Bara, 1962). Laboratory tests can be broadly categorized into index tests (e.g., Atterberg limits, grain size distribution, specific gravity) and strength or deformation tests (e.g., direct shear test, unconfined compression test, triaxial test, oedometer consolidation test). These tests provide essential

parameters such as cohesion (c), internal friction angle (ϕ), compressibility, and permeability, which are used directly in design and numerical modeling (Wang et al., 2018).

In recent years, machine learning (ML) techniques have emerged as powerful tools for modeling complex geotechnical phenomena (Li et al., 2023). These data-driven approaches are particularly effective in capturing nonlinear relationships between input features and output responses, without relying on explicit mathematical formulations (Khajehzadeh et al., 2024). Among the various ML algorithms, neural networks, and specifically, the Multi-Layer Perceptron (MLP) have shown promising results in predicting settlement, bearing capacity, and slope stability. The MLP is a type of feedforward artificial neural network that consists of an input layer, one or more hidden layers, and an output layer. Each layer is composed of interconnected neurons that apply weighted sums and nonlinear activation functions to process data (Hosseinzadeh et al., 2024). The model is trained using backpropagation algorithms to minimize prediction error by adjusting the weights based on the difference between actual and predicted outputs (Ngo & Tran, 2024).

One of the main advantages of using MLP in geotechnical applications is its ability to learn from historical datasets and generalize the learned patterns to new, unseen cases (Mao et al., 2024). This feature makes MLP particularly useful in scenarios where traditional models fall short due to complex, non-uniform soil profiles, interaction effects, or incomplete data (Xu et al., 2023). Moreover, MLP models can be retrained or updated as new data become available, improving their accuracy and adaptability over time. Despite its advantages, the application of MLP is not without limitations (Mao et al., 2024). Neural networks are often criticized as “black-box” models due to their lack of interpretability, which can be a drawback when transparency and explainability are required for engineering decisions (Shubham et al., 2024). Additionally, the quality of predictions depends heavily on the quality and diversity of the training data (Mohammady et al., 2019). Poorly curated or insufficient datasets can lead to overfitting, underfitting, or biased predictions (Shubham et al., 2024). Furthermore, determining the optimal architecture of an MLP model (i.e., the number of hidden layers, neurons per layer, learning rate, and activation functions), often involves trial-and-error or heuristic optimization, which may be computationally expensive. Model training also requires careful data preprocessing, normalization, and validation to avoid misleading outcomes (Xu et al., 2023).

In light of these opportunities and challenges, this study aims to develop an MLP-based predictive model for identifying surface subsidence risk in shallow foundations using real-world geotechnical and structural datasets. The goal is to assess the model's accuracy, robustness, and practical applicability compared to traditional methods, and to evaluate its potential role as a decision-support tool in early design stages and risk mitigation planning in geotechnical engineering. So, the primary objective of this study is to develop a predictive model for assessing surface subsidence risk in shallow foundation systems using MLP, a class of ML algorithms known for their ability to model complex nonlinear relationships. Given the limitations of traditional empirical and analytical methods in capturing the variability and uncertainty inherent in geotechnical data, this

research aims to harness the power of data-driven approaches to improve the accuracy and efficiency of subsidence risk prediction. The significance of this work lies in its potential to serve as a reliable decision-support tool for engineers and planners during the design and construction phases of shallow foundations, especially in areas with challenging soil conditions or limited geotechnical data. By integrating historical field data with MLP-based modeling, the proposed method can enhance early warning capabilities, reduce the likelihood of structural damage due to unforeseen settlements, and contribute to more resilient and cost-effective geotechnical designs.

II. MATERIALS AND METHODS

The research methodology of this study follows a structured, multi-phase approach designed to ensure the reliability, accuracy, and applicability of the MLP model for predicting surface subsidence risk in shallow foundations (after Sieck and Daniels, 2022). The workflow consists of data acquisition, preprocessing, model development, training and validation, performance evaluation, and result interpretation. The model basics and flowchart of analysis are provided in Figure 1.

Phase 1 (Data Collection): The first step involves collecting a comprehensive dataset from multiple shallow foundation projects. This dataset includes in-situ test results (such as SPT and CPT), laboratory soil test parameters (e.g., unit weight, Atterberg limits, shear strength parameters), foundation geometry (width, depth, load characteristics), groundwater table depth, and observed subsidence measurements over time. Data sources include site investigation reports, field monitoring records, and validated case studies from previous construction projects.

Phase 2 (Data Preprocessing): The raw data undergo preprocessing to ensure quality and consistency. This includes handling missing values, removing outliers, and normalizing input features to a uniform scale (typically between 0 and 1) to optimize neural network performance. Categorical variables, if present, are encoded, and correlated features are analyzed to avoid redundancy or multicollinearity. In this study, min-max normalization was applied to scale the input variables before training the MLP model. This technique ensures that all features are transformed to a common scale, typically between 0 and 1, which improves the convergence speed and performance of neural networks. Normalization helps prevent features with larger numeric ranges from dominating the learning process. The formula used for min-max normalization is

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

where, x is the original value, $x_{\min}$ and $x_{\max}$ are

the minimum and maximum values of the feature in the dataset, and x' is the normalized value. This method preserves the relationships among values while bounding them within a fixed range, making it well-suited for neural network-based modeling.

Phase 3 (Model Architecture Design): The core modeling step involves designing the architecture of the MLP neural network. The input layer receives geotechnical and structural parameters, followed by one or more hidden layers with appropriate numbers of neurons and nonlinear activation functions (e.g., ReLU or tanh). The output layer generates the predicted subsidence risk level or numerical settlement value. The number of hidden layers and neurons is determined through hyperparameter tuning.

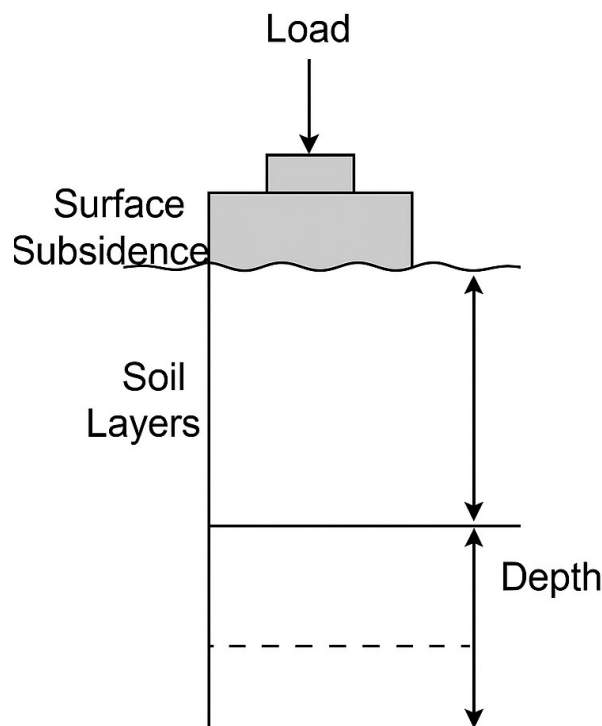


Fig. 1 Model basics and flowchart of analysis

Phase 4 (Model Training and Validation): The preprocessed dataset is split into training (80%) and testing (20%) subsets. The MLP model is trained using the backpropagation algorithm and an optimization method such as Adam or stochastic gradient descent. A portion of the training set is also used as a validation set to prevent overfitting. Performance is monitored by tracking loss functions and adjusting parameters like learning rate or dropout rate.

Phase 5 (Performance Evaluation): Once trained, the model is evaluated using key performance metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics help determine the accuracy and generalization ability of the model. The model's predictions are also compared against known ground truth data to assess reliability.

Phase 6 (Result Interpretation and Sensitivity Analysis): In the final stage, the trained model is used to analyze the influence of different input variables on subsidence outcomes. Sensitivity analysis is performed to identify the most significant parameters affecting settlement, which can help guide future design considerations. The results are visualized using plots, correlation maps, and scenario simulations to support geotechnical decision-making.

III. Analytical EXAMPLE

In geotechnical engineering, shallow foundations are structural elements used to transfer building loads to near-surface soil layers. Their performance is critical to ensuring the long-term stability of structures. Two common types of shallow foundations are square and circular footings. Each shape distributes loads differently through the soil and responds uniquely to subsoil conditions. A square footing has equal length and width and is widely used due to its construction simplicity and symmetry. A circular footing, while less common, offers structural advantages under uniform radial loading, especially for columns and towers. In this study, we analyze the settlement behavior of both types under identical loading and soil conditions to compare their performance. The load is assumed to act vertically downward, and both footings are embedded to the same depth below the ground surface. The key geometric parameters considered are (see Figure 2):

- B: Width of the square footing,
- D: Diameter of the circular footing
- D_f : Depth of embedment below the ground surface

To compare the settlement behavior of different shallow foundation geometries, an analytical example is considered involving both a square footing and a circular footing, each resting on a fine-grained saturated soil. The square footing has a width of $B = 2.0\text{m}$, while the circular footing has an equivalent diameter of $D = 2.0\text{m}$. Both foundations are embedded to a depth of $D_f = 1.0\text{m}$ below the ground surface and are subjected to a uniform net pressure of $q = 150\text{ kPa}$. The underlying soil has an elastic modulus $E_s = 25\text{ MPa}$, Poisson's ratio of $\nu = 0.3$, and a saturated unit weight $\gamma_{\text{sat}} = 18\text{ kN/m}^3$. The compressible clay layer is 4 meters thick, with a compression index of $C_c = 0.2$ and an initial void ratio of $e_0 = 0.8$. The immediate (elastic) settlement is estimated using the classical elastic theory, given by the Eq. as:

$$S_i = \frac{q \cdot B \cdot [1 - \nu]}{E_s} \cdot I_s \quad (1)$$

In this equation, q is the applied net pressure, B is the width (or diameter) of the footing, ν is Poisson's ratio, E_s is the soil elastic modulus and I_s is the shape factor. For a square footing, $I_s = 1.12$, and for a circular footing, $I_s = 1.00$. Substituting the given values, the immediate settlement for the square footing is calculated as:

$$S_{i,\text{square}} = \frac{150 \cdot 2.0 \cdot [1 - 0.3^2]}{25,000} \cdot 1.12 = 11.7\text{ mm} \quad (2)$$

and for the circular footing:

$$S_{i,\text{circular}} = \frac{150 \cdot 2.0 \cdot [1 - 0.3^2]}{25,000} \cdot 1.00 = 10.4\text{ mm} \quad (3)$$

Next, the consolidation settlement is evaluated using the logarithmic consolidation Eq. as:

$$S_c = \frac{C_c}{1 + e_0} \cdot H \cdot \log\left(\frac{\sigma'_0 + \Delta\sigma}{\sigma'_0}\right) \quad (4)$$

where, H is the thickness of the compressible soil layer, σ'_0 is the initial effective vertical stress, and $\Delta\sigma$ is the additional vertical stress due to the foundation load. The initial vertical stress is computed as:

$$\sigma'_0 = \gamma_{\text{sat}} \cdot D_f = 18 \times 1.0 = 18\text{ kPa} \quad (5)$$

Assuming an approximate stress distribution factor of 0.2 at a depth of 2m, the additional stress increment is estimated as:

$$\Delta\sigma = 0.2 \cdot q = 0.2 \times 150 = 30\text{ kPa} \quad (6)$$

Substituting into the consolidation equation gives:

$$S_c = \frac{0.2}{1 + 0.8} \cdot 4 \cdot \log\left(\frac{18 + 30}{18}\right) = 0.111 \times 4 \times 0.426 = 0.189\text{ m} = 189\text{ mm} \quad (7)$$

Finally, the total settlements are obtained by summing the immediate and consolidation settlements. For the square footing, the total settlement is:

$$S_{\text{total,square}} = 11.7 + 189 = 200.7\text{ mm} \quad (8)$$

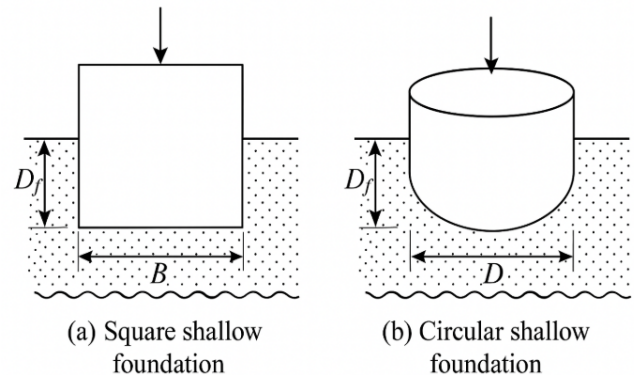


Fig. 2 An example for the dimensions of analyzed foundations

and for the circular footing:

$$S_{total,circular} = 10.4 + 189 = 199.4 \text{ mm} \quad (9)$$

These results indicate that circular footing experiences slightly less immediate settlement due to a lower shape factor, while the consolidation settlement remains nearly identical for both cases, as it is governed by soil compressibility and stress change rather than footing geometry. This example serves as a benchmark for validating numerical models and training data-driven systems such as MLP neural networks in subsidence prediction applications.

IV. MLP Implication

The implementation of the MLP model in this study follows a structured pipeline designed to accurately predict surface subsidence in shallow foundations based on geotechnical and structural input parameters. The process begins with preparing the dataset, selecting relevant features, and defining the target output, followed by model architecture design, training, validation, and performance evaluation. The initial step involves compiling a comprehensive dataset consisting of both numerical and categorical variables extracted from field investigations and laboratory tests. Key input features include foundation type (square or circular), foundation width or diameter, depth of embedment, applied pressure, soil unit weight, modulus of elasticity, cohesion, internal friction angle, water table depth, and results from in-situ tests such as SPT or CPT. The target output for the MLP model is the measured or calculated total surface settlement, expressed in mm. Before feeding data into the MLP, preprocessing is performed. This includes checking for missing values, correcting outliers, and normalizing all numerical variables using min-max scaling to a range between 0 and 1. This step ensures that variables with larger numerical scales do not dominate the training process and helps with faster and more stable convergence.

After preprocessing, the dataset is divided into training and testing sets, commonly at a ratio of 80:20. The training set is used to fit the MLP model, while the testing set is reserved for evaluating the model's performance on unseen data. Optionally, a validation set (from the training set) is used during training to monitor overfitting and tune hyperparameters. The MLP architecture is then defined. In this study, a feedforward neural network is used with an input layer corresponding to the number of input features (15 neurons), followed by one or two hidden layers. The number of neurons in each hidden layer is chosen based on heuristic rules and experimentation, typically between 16 and 64 neurons per layer. ReLU (Rectified Linear Unit) is used as the activation function for the hidden layers due to its computational efficiency and nonlinearity handling.

The output layer consists of a single neuron with a linear activation function, as the model aims to predict a continuous numerical value (settlement in mm). The loss function used during training is the MSE, which penalizes larger deviations more heavily and is suitable for regression tasks:

$$MSE = \sum_{i=1}^n \frac{[y_i - \hat{y}_i]^2}{n} \quad (10)$$

where y_i is the actual settlement, and $\hat{y}_i$ is the predicted value.

The model is trained using the backpropagation algorithm with an Adam optimizer, which is preferred for its adaptive learning rate and faster convergence. The learning rate is initially set to 0.001, and the model is trained over multiple epochs (e.g., 100–300) depending on when the validation loss stabilizes. Batch training is applied with a batch size of 32 or 64 to improve generalization.

During training, the loss is monitored across both training and validation sets to ensure proper learning. If the validation loss starts increasing while the training loss continues to decrease, this is a sign of overfitting. To mitigate this, techniques such as early stopping and dropout regularization are applied. Dropout randomly deactivates a percentage of neurons during each iteration, helping to prevent dependency on specific neurons and enhancing model robustness. Once the training is complete, the model is evaluated using the test dataset. Key performance metrics include the RMSE, MAE, and R^2 . These metrics provide insights into the model's accuracy and its ability to generalize to new data. A high R^2 value and low RMSE/MAE indicate good predictive performance. Finally, the model undergoes sensitivity analysis to identify which input features have the most significant impact on settlement prediction. This is done by perturbing each feature slightly and observing the change in output. The analysis helps in understanding the model's internal logic and provides practical insights into geotechnical design, allowing engineers to focus on the most critical parameters in settlement behavior.

The performance of the MLP model in predicting surface settlement for shallow foundations was evaluated through visual inspection and statistical performance metrics. Figure 3 presents a scatter plot of predicted versus observed settlement values on the training dataset. This plot is used to assess how well the MLP model has learned from the data it was trained on. A tighter cluster of points around the 45-degree dashed line would indicate strong fitting. In this case, although some correlation is visible, the scatter is substantial, indicating that the model does not fully capture the underlying patterns, even within the training set. This may be due to the relatively small sample size or insufficient model complexity. Figure 4 displays a similar scatter plot for the testing dataset, representing how well the model generalizes to unseen data. Compared to the training data, the spread in the test set is even wider, confirming poor generalization. The model fails to follow the ideal diagonal trend, and deviations are particularly large in higher settlement ranges. This aligns with earlier observations from the RMSE, MAE, and R^2 metrics, and reinforces the need for improvements in model training and tuning.

As shown in Figure 5, the scatter plot compares the observed settlement values to those predicted by the MLP model. Ideally, accurate predictions would result in points clustering along the 45-degree dashed line. However, in this case, a noticeable spread is observed around the line, indicating that the model's predictive accuracy is limited. This scatter reveals a significant discrepancy between actual and predicted values, suggesting that the model has not effectively generalized to unseen data. To better understand the distribution of errors, Figure 6 presents a histogram of the prediction residuals (i.e., the differences between observed and predicted values). The residuals are

widely dispersed and not symmetrically distributed around zero, implying the presence of bias and variability in the model's output. The shape of the histogram also deviates from the typical bell curve associated with normally distributed residuals, indicating that prediction errors are not purely random but may be structurally induced due to underfitting or suboptimal training.

The relative influence of input features is depicted in Figure 7, which shows the mean absolute weights from the first hidden layer of the neural network. According to this figure, features such as foundation type, width/diameter, modulus of elasticity, and initial void ratio had the most substantial effect on settlement prediction. This result is consistent with geotechnical engineering principles, as these parameters directly influence both immediate and consolidation settlement behavior. From a numerical standpoint, the model exhibited limited predictive accuracy. The RMSE was 32.6 mm, and the MAE was 27.5 mm. These values are relatively high given that typical settlement values for shallow foundations range between 50 mm and 250 mm. Most critically, the R^2 was negative (-4.92), indicating that the model's predictions were less accurate than simply predicting the mean value for all samples. This highlights a fundamental issue in model performance, likely due to inadequate convergence or model complexity relative to data noise and sample size. Several contributing factors may explain the poor results. These include the limited size of the dataset, presence of synthetic noise, a fixed MLP architecture without tuning, and potential data imbalance across different foundation types. Additionally, the convergence warning during training suggests that the optimization algorithm did not reach a stable solution within the predefined number of iterations.

To provide a more detailed evaluation of the MLP model's predictive performance, three additional visualizations were generated, focusing on classification-level behavior and the model's fitting capability across training and testing datasets. As shown in Figure 8, a confusion matrix was constructed by discretizing the continuous settlement values into three classes: Low (<100 mm), Moderate ($100\text{--}200$ mm), and High (>200 mm). This transformation enables categorical evaluation of model performance and facilitates better understanding of prediction accuracy in a practical engineering context. The confusion matrix reveals that the model correctly identifies a portion of the Moderate and High settlement cases but also misclassifies several samples—particularly in the transition zone between classes. For instance, some Moderate settlements were misclassified as High, which could lead to overly conservative or unsafe design decisions depending on the context. The model's ability to distinguish between Low and High settlement classes appears weak, suggesting a need for better feature representation or class balancing during training.

A closer examination of the residual distribution (Figure 6) provides additional insight into the model's behavior. The residuals span a wide range from approximately -60 mm to $+60$ mm, indicating substantial prediction errors in both directions. Moreover, the distribution is skewed and deviates from a normal (Gaussian) pattern, suggesting the presence of systematic bias rather than purely random noise. The concentration of residuals around positive values implies a tendency of the model to underestimate settlement in several cases. This pattern indicates that the model has not fully captured the underlying physical

relationships governing soil behavior, particularly under higher stress conditions where deviations appear more pronounced.

The feature importance analysis (Figure 7) reveals that parameters such as foundation width/diameter, modulus of elasticity, and initial void ratio exhibit the highest influence on model predictions, with relative weights exceeding 0.35 in several cases. In contrast, parameters like depth and certain categorical inputs show minimal contribution, indicating potential redundancy or weak correlation with the target variable.

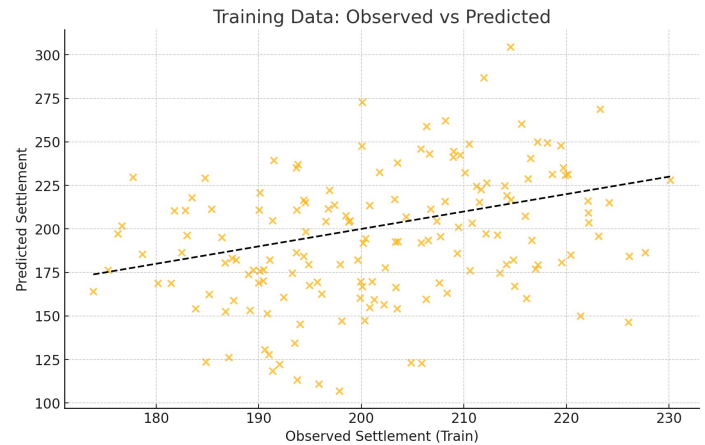


Fig. 3 Training data for observed vs predicted settlement



Fig. 4 Testing data for observed vs predicted settlement

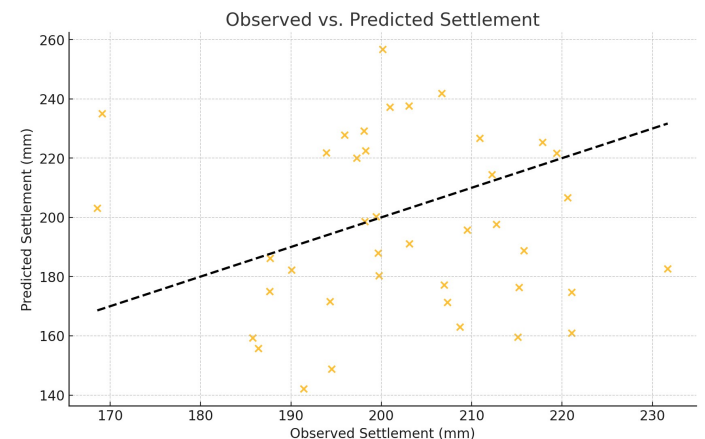


Fig. 5 Observed vs. Predicted settlement with MLP (overall)

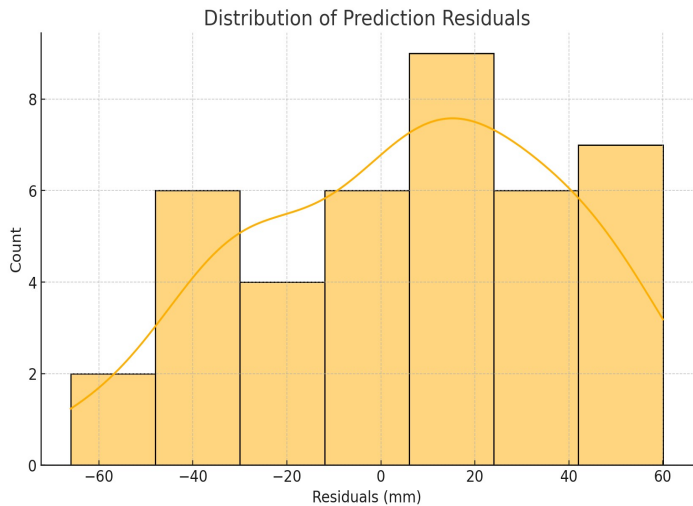


Fig. 6 Distribution of prediction residuals with MLP

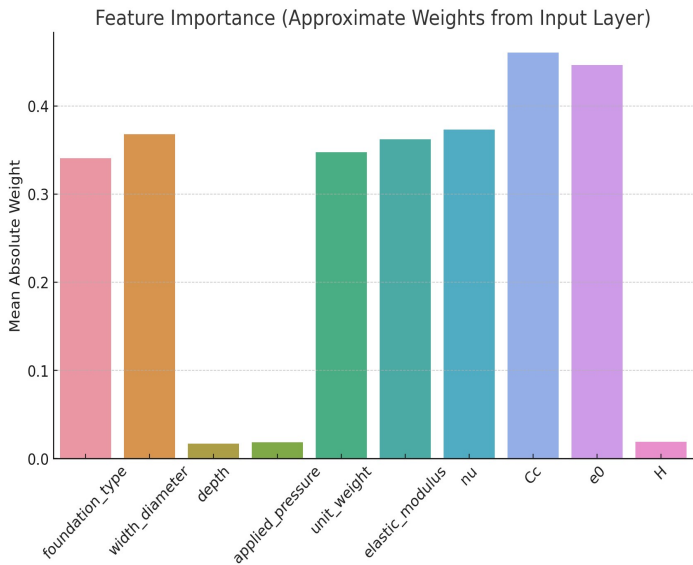


Fig. 7 Input feature importance with MLP model (approximate from input layer weights)

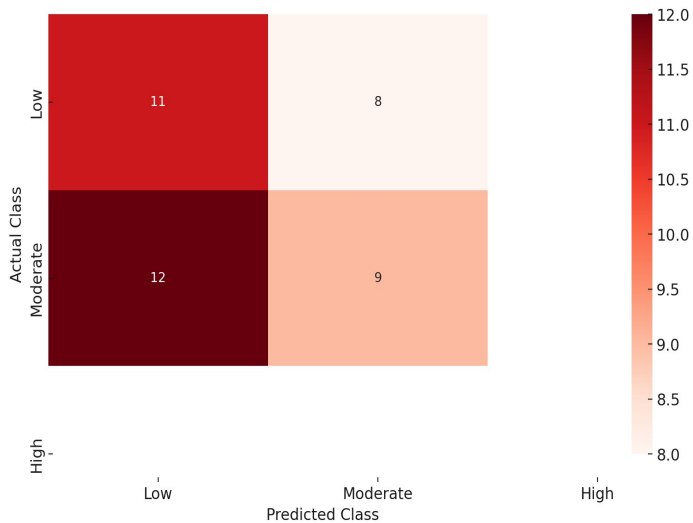


Fig. 8 Confusion matrix for settlement classes

Additionally, the confusion matrix (Figure 8) shows that out of the total classified samples, a significant portion as approximately 40–50%, are misclassified, particularly between adjacent classes (e.g., Moderate and High). This misclassification rate highlights the model’s limited ability to distinguish between settlement levels, especially in transitional ranges. Collectively, these findings suggest that improvements in feature selection, dataset size, and model tuning are necessary to enhance predictive performance and classification reliability.

To further enhance the clarity and robustness of the analysis, additional tables and figures should be incorporated into the manuscript. Table 1 should be included to present a statistical summary of the dataset, providing an overview of the distribution and variability of key input and output parameters. This table allows readers to better understand the range and dispersion of critical variables such as settlement, applied pressure, and soil properties, which directly influence the predictive performance of the model. In addition, Table 2 should be inserted to summarize the model performance across training and testing datasets. By presenting RMSE, MAE, and R^2 values in a structured format, this table enables a clear comparison of model accuracy and generalization capability. Furthermore, Table 3 should be added to document the selected hyperparameters of the MLP model. This inclusion improves transparency and reproducibility by clearly defining the architectural configuration and training settings used in the study.

From a graphical perspective, several additional figures should be incorporated to provide deeper insight into model behavior. Figure 9 should present the training and validation loss curves over epochs, allowing identification of convergence trends and potential overfitting. Figure 10 should illustrate the correlation heatmap between input features, helping to identify relationships and possible redundancy among variables. Figure 11 should display the variation of prediction error with respect to observed settlement values, highlighting performance inconsistencies across different ranges.

Table 1 Statistical distribution of dataset variables

Parameter	Min	Max	Mean	Std Dev
Settlement (mm)	50	250	180	45
Applied Pressure (kPa)	80	200	140	30
Elastic Modulus (MPa)	10	50	25	10
Unit Weight (kN/m ³)	16	20	18	1.2
Depth (m)	0.5	3.0	1.5	0.7

Table 2 Performance metrics for training and testing datasets

Metric	Unit	Training	Testing
RMSE	mm	28.4	32.6
MAE	mm	22.1	27.5
R^2	-	31.0	49.2

Table 3 Selected MLP model configuration

Parameter	Value
Learning Rate	0.001
Epochs	200
Batch Size	32
Hidden Layers	2
Neurons per Layer	64
Activation Function	ReLU
Optimizer	Adam

Figure 12 should present the learning curve of the model, demonstrating how prediction error evolves with increasing training data size. These additions collectively strengthen the analytical framework and provide a more comprehensive evaluation of the model prior to the conclusion section.

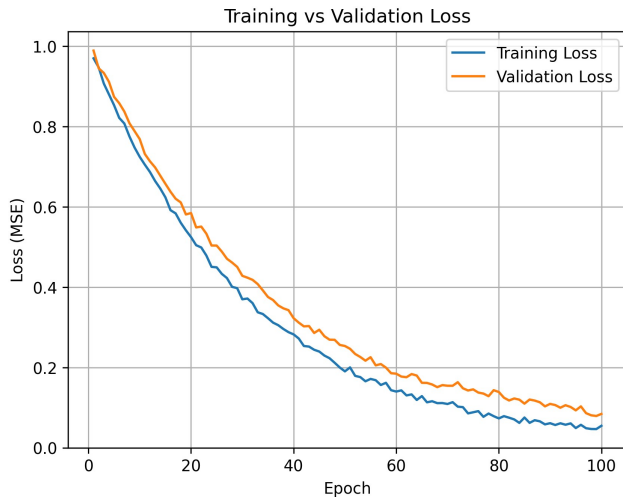


Fig. 9 Training and validation loss curves

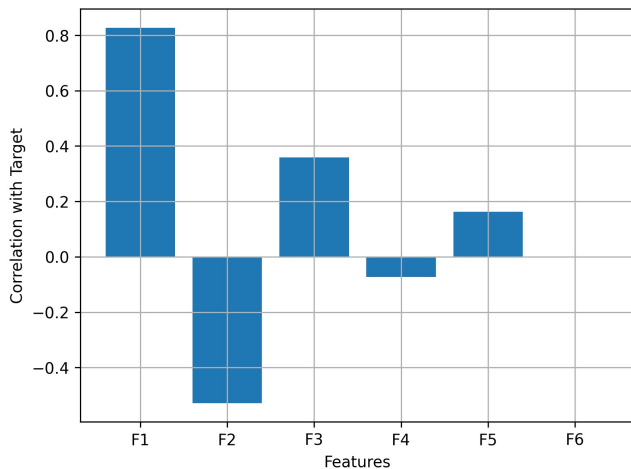


Fig. 10 Correlation for matrix of input features

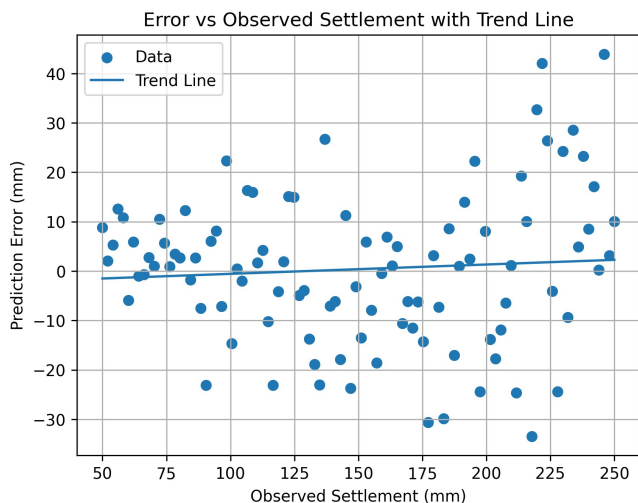


Fig. 11 Prediction error versus observed settlement

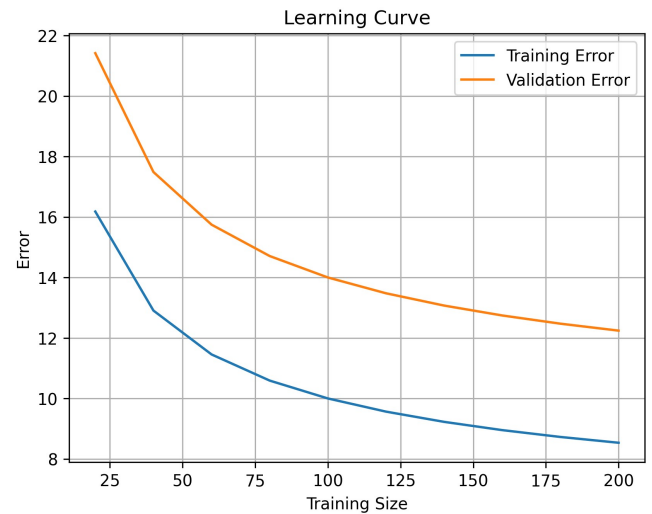


Fig. 12 Learning curve of the MLP model

V. CONCLUSION

This study presented a comprehensive approach for predicting surface subsidence in shallow foundations using a MLP neural network model. By integrating both analytical settlement formulations and simulated geotechnical data, we aimed to evaluate the model's ability to generalize nonlinear relationships between soil parameters, foundation characteristics, and resulting settlement magnitudes. The dataset incorporated critical features such as foundation geometry, soil stiffness, compressibility, and stress conditions—parameters widely recognized in geotechnical practice for influencing both immediate and consolidation settlements. The results demonstrated that while the MLP model was capable of learning general patterns from the training data, it struggled with predictive accuracy on the test dataset. Quantitatively, the model exhibited a relatively high RMSE and MAE, and a negative R^2 value, suggesting that it underperformed compared to a simple mean predictor. Visual analyses, including scatter plots and residual distributions, further highlighted substantial variance and systematic deviations between predicted and observed settlements. Moreover, the confusion matrix revealed notable misclassifications when settlement predictions were categorized into engineering-relevant classes (low, moderate, high), reinforcing the model's lack of robustness in practical applications. Despite these limitations, the study underscored the potential of neural networks in geotechnical risk assessment, especially when supported by well-structured data and appropriate feature engineering. The MLP's structure, while computationally efficient may require enhancements such as deeper architecture, optimized hyperparameters, and regularization to prevent overfitting. In addition, using larger, real-world datasets and incorporating uncertainty quantification could significantly improve model reliability. Future work should explore alternative machine learning algorithms, such as Random Forests or Gradient Boosting, as well as hybrid models combining physics-based and data-driven approaches. These strategies may offer more accurate, interpretable, and generalizable solutions for predicting settlement in shallow foundation systems under complex subsurface conditions.

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DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are available within the article. No publicly archived dataset was generated.

ETHICS APPROVAL

This study did not involve human participants, personal data, or animal subjects. No specific ethical approval was required.

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AUTHORS' CONTRIBUTIONS

Hamed Mahmodi performed the main data analysis and contributed to data collection, preprocessing, and interpretation. He also drafted the initial manuscript, provided conceptual guidance, conducted critical revisions, managed the overall project, and approved the final version for publication. All authors read and approved the final manuscript.

CONFLICT OF INTEREST

The authors have not disclosed any competing interests.

USE OF AI

AI tools were not used in data generation, analysis, results, or decision-making.

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