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Article

# Prediction of UCS values using basic geotechnical soil parameters via regression and Artificial Neural Networks ANN

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**Abstract:** Unconfined Compressive Strength (UCS) test is a widely used lab procedure for assessing soil's undrained shear strength. However, conventional lab testing is time-, cost-, and labor-intensive. This study evaluates predictive models for UCS using basic soil parameters. Soil mixtures were prepared and tested through several laboratory experiments, including Atterberg's limits, particle size distribution, water content, bulk density using Harvard miniature compaction apparatus, and UCS. A total of 152 soil samples were utilized to train the prediction models. To achieve that, multi-linear regression (MLR), multi-nonlinear regression (MNLR), and backpropagation Artificial Neural Networks (ANN) were employed to relate the dependent variable UCS (predicted) to the independent geotechnical parameters (predictors). Results showed that the best model to predict the UCS values for soil using its soil parameters is the ANN-based model with $R^2$ of 83% and ASE (Averaged Square Error) of 0.0029, followed by the nonlinear regression model with $R^2$ = 49.2% and ASE of 3.63, and finally the MLR model with $R^2$ = 44.5% and ASE of 3.92.

**Keywords:** UCS; Artificial Neural Networks (ANN); multi-linear regression (MLR); multi-nonlinear regression (MNLR)

## 1. Introduction

Soil shear strength is a critical parameter for the design and analysis of various engineering applications, including the bearing capacity of shallow and deep foundations, retaining structures design, and slope stability. It depends on two main factors: cohesion, which binds soil particles [1], and internal friction, which resists soil grain sliding [2]. These parameters are measured using in-situ tests, such as the Standard Penetration Test (SPT) and Cone Penetration Test (CPT), or laboratory tests, including the Triaxial, Unconfined Compressive Strength (UCS), and direct shear tests [3]. Our study is focused on building a laboratory testing database to determine the UCS strength parameter of the various soil mixtures with the aid of statically based and machine learning-based approaches.

The Unconfined Compressive Strength (UCS) test measures the stress cohesive soils can withstand before failing under peak axial compressive force without confinement [4]. UCS is an undrained shear test, where the soil samples are loaded rapidly, preventing complete dissipation of pore water pressure. For this reason, UCS represents a conservative approach, representing the worst-case scenario a soil may experience in the field [5], which makes it a favored method among geotechnical engineers for determining shear strength. UCS is widely used to determine shear strength due to its simplicity but is limited by high costs, time, and labor requirements. Examples of applications for the UCS test include slope stability, foundation design, and pavement subgrade. In pavement application, UCS represents subgrade strength under undrained conditions. Studies show UCS values correlate with the California Bearing Ratio (CBR) for treated swelling soils [6]. The undrained shear strength, cu, is a fundamental design parameter for saturated clay and can be hard to determine in the field. UCS is double the value of CU [7], which adds to the UCS viability in design and analysis tasks. In the railway application, a study by [8] explained the importance of UCS values for assisting the railway ballast deterioration. The study showed a strong relation between UCS values and predicting railway ballast deterioration parameters, including settlement.

Recent studies have used machine learning to estimate UCS for various soils and rocks. Afolagboye et al. [9] investigated four distinct machine learning models, Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), and Relevance Vector Machine (RVM), to predict the uniaxial strength of crystalline rock. They trained the models on data collected from the literature. In their study, ANN showed a high predictive accuracy with $R^2$ training of 94% and $R^2$ testing of 84%. Artificial Neural Networks (ANN) is a data modeling technique that has been applied to complex geotechnical problems. ANN has shown strong potential for solving non-linear geotechnical problems [10].

Many researchers have related the soil shear strength to the soil's basic geotechnical parameters such as Atterberg's limits, bulk density, water content, and particle size distribution to reduce testing effort and time. This study investigates the relationship between soil's geotechnical properties/parameters and UCS values. Previous research has explored the influence of various factors on soil shear strength. For example, Jiang et al. [11] examined the effect of clay content, moisture content, and density on cohesion and angle of friction of paddy soils. Using a direct shear apparatus, they tested twenty combinations of soil samples with different water content to determine the shear strength parameters for each mixture. The results showed that cohesion increases as the soil's clay content and density increase and decreases as water content increases. Whereas the internal friction angle enhanced as the bulk density and water content increased. Additionally, the study found that the soil's friction angle dropped drastically to zero when the soil's water content was higher than its liquid limit. A statistical analysis model was then developed to predict soil strength parameters using basic soil properties. The model achieved a mean square error of less than 11% for the soils involved.

Building on these correlations, this study investigates the relationship between basic geotechnical properties and UCS values using statistical and ANN-based approaches. This study focuses on relating the basic geotechnical parameters to the UCS of soil via the use of statistically based and ANN approaches. These findings will support ongoing research on levee soil erosion by estimating erodibility coefficients and critical shear strength from UCS values using Jet Erosion. Accordingly, we are utilizing both linear and non-linear analysis models and then comparing their accuracy measures with the one obtained via the ANN-based model. The importance of this study is exploring the potential of ANN to enhance the predictability of UCS. ANN models have not been widely adopted as practical tools for geotechnical field and design engineers. This study bridges the gap between academic studies and practical geotechnical engineering applications by providing an easy-to-use spreadsheet with over 80% accuracy.

## 2. Material and methods

### 2.1. Materials

In this study, two different types of soil were collected from the National Sedimentation Lab (NSL) in Oxford, Mississippi. Soils used in this study were low plasticity silty clay (CL-ML) with sand and high plasticity silty clay (CH-MH). Soils were stored in sealed plastic buckets. Each soil was separated by sieve #200 and used to generate different artificial soil mixtures, ranging from (95% coarse: 5% fine) to (5% coarse: 95% fine) with a 5% step. Creating a range of synthetic soils is considered in this study to enhance the soil results spectrum, in which a 152 results database were generated. **Table 1** shows soil mixtures used to perform the basic geotechnical tests of each soil separately, including Atterberg's limits, bulk density, and unconfined compressive strength. Soil mixtures were oven dried at a temperature of 105 ℃ for 24 h and kept in sealed plastic buckets. Soil mixtures were oven dried at a temperature of 105 ℃ for 24 h and kept in sealed plastic buckets. The optimum moisture content of the parent soil was 15%, as shown in **Figure 1**. Therefore, 10% and 15% water content are used for soil mixing, considering the optimum and dry side of the compaction curve. Optimum moisture is the water content at which soil is compacted in most geotechnical applications, including levees [12]. This aligns with the study's objective of providing a design guideline for practicing engineers.

**Table 1.** Sample of soil mixtures.

| **No.** | **Mixtures** | **Percentage (%)** | |
|---|---|---|---|
| | | **(Retained on Sieve No.200)** | **(Passing on Sieve No.200)** |
| 1 | 95% C:5% F | 95 | 5 |
| 2 | 90% C:10% F | 90 | 10 |
| 3 | 85% C:15% F | 85 | 15 |
| 4 | 80% C:20% F | 80 | 20 |
| . | | | |
| . | | | |
| . | | | |
| . | | | |
| . | | | |
| 16 | 20% C:80% F | 20 | 80 |
| 17 | 15% C:85% F | 15 | 85 |
| 18 | 10% C:90% F | 10 | 90 |
| 19 | 5% C:95% F | 5 | 95 |

Notes: C: Coarse particles, F: Fine particles.

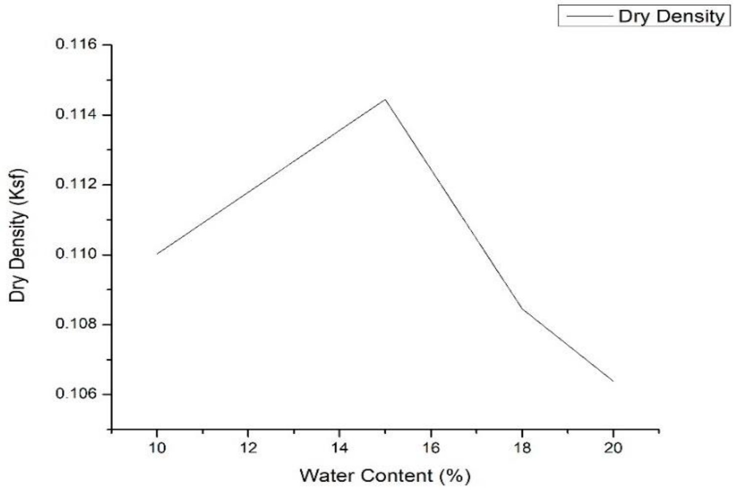


**Figure 1.** Parent soil compaction curve.

## 2.2. Laboratory experiments

To determine the bulk density, soil was compacted in 3 layers with a total of 25 blows for each layer using the Harvard miniature compaction mold. Each mixture was prepared at a water content of 10% and 15% following the ASTM standard [13]. Harvard specimens were stored in buckets with careful handling to avoid breakage or weaken the samples. Two compacted specimens were tested to determine UCS for each water content ending up with 152 total data sets. The compacted soil samples were stored in a plastic wrapping and cured for 24 h before tested.

UCS samples were tested using a uniaxial testing machine to determine the compressive strength of soil mixtures based on the ASTM standard [14]. The machine is connected to a computerized data logger that records both the load and strain every 0.001 in of axial deformation of the tested sample. The data is used to draw a stress-strain diagram for each specimen and determine the soil strength. Each laboratory test was done twice, and the average value was taken to reduce human error and increase the results' reliability. **Figure 2** shows a typical UCS failure mode for a 10% water content mixture. **Table 2** shows a sample of UCS results for the soil.

Atterberg limits are basic geotechnical lab tests that are performed on soil with clay content. ASTM [15] standard was carried out in the lab to determine the liquid limits and plastic limits for each mixture. Liquid limit is the soil's water content where the soil turns into a flowable like liquid, whereas the plastic limit is where the soil turns into plastic [16]. Results from the lab work are used to develop an ANN-based model that can predict the UCS value for a given basic geotechnical parameter.

**Figure 2.** UCS failure mode of a 10% water content soil mixture.

**Table 2.** Sample UCS and bulk density results for the soil.

| Mixture | Water Content (%) | Bulk Density (Kip/$ft^3$) soil | UCS (ksf) Soil | Liquid limit (%) | Plastic limit (%) |
|---|---|---|---|---|---|
| 95% Course: 5% Fine | 10% | 0.1200 | 8.675 | 29.05 | 18.01 |
| 95% Course: 5% Fine | 15% | 0.1300 | 6.7 | | |
| 5% Course: 95% Fine | 10% | 0.1210 | 6.04 | 73.00 | 38.00 |
| 5% Course: 95% Fine | 15% | 0.1331 | 4.70 | | |

## 3. Results and discussion

### 3.1. Laboratory tests results

**Table 3** shows a statistical summary of the laboratory test results. UCS values varied between 0.1306 and 18.37 ksf with an average of 5.014 ksf. According to [17], soil is classified as very soft if its UCS is less than 0.25 ksf and hard if its UCS is greater than 8 ksf. This indicates that the range of soil types included in our database covers a wide spectrum. Atterberg's limits show a high variance, which can be justified due to the large difference in fine material content between all mixtures. In our case, fine content varies between 95% fines in one mixture to as low as 5% fines in another soil mixture.

Based on [18] bulk density of stiff clay is typically 0.125 kcf and 0.11 kcf for soft clay. That range is contained in our database ranges and may indicate a broad range of our database. Subsequently, the failure mode of UCS samples was noted to be consistent with the one reported in the literature. To better understand the relationship among the inputs and their effect on the UCS values, a correlation matrix was determined in **Table 4**. The results indicate that inputs are interdependent and cannot be analyzed in isolation. This interdependency limits the feasibility of conducting a meaningful sensitivity analysis.

**Table 3.** Statistical analysis for the physical and mechanical properties of the tested soil mixtures.

| Parameter | Range | Mean | ST. DV | CV% |
|---|---|---|---|---|
| UCS (ksf) | 0.1036–18.37 | 5.014 | 2.7725 | 55.30 |
| Plastic Limit (%) | 18.01–38 | 25.550 | 5.3594 | 20.98 |
| Liquid Limit (%) | 27–73 | 40.362 | 14.900 | 36.92 |
| Water Content (%) | 10–15 | 12.5 | 2.5083 | 20.07 |
| Bulk density (kip/ft$^3$) | 0.1173–0.1398 | 0.129 | 0.0060 | 4.65 |
| Percent passing the #200 sieve | 95–5 | 50 | 0.2748 | 0.55 |

Notes: ST. DV: Standard Deviation, CV: Coefficient of Variation.

**Table 4.** Correlation matrix.

| | Coarse Content | Fine Content | Bulk density | Water Content | Liquid Limit | Plastic Limit | UCS (Ksf) |
|---|---|---|---|---|---|---|---|
| Coarse Content | 1 | | | | | | |
| Fine Content | −1 | 1 | | | | | |
| Bulk density | −0.1224 | 0.1225 | 1 | | | | |
| Water Content | $-1.734 \times 10^{-17}$ | $2.67 \times 10^{-18}$ | 0.8406 | 1 | | | |
| Liquid Limit | −0.5040 | 0.5040 | 0.3149 | 0.00044 | 1 | | |
| Plastic Limit | −0.5266 | 0.52669 | 0.27054752 | $1.9 \times 10^{-17}$ | 0.94389 | 1 | |
| UCS | −0.0557 | 0.0557 | −0.3900 | −0.2486 | −0.4471 | −0.3122 | 1 |

## 3.2. Multi linear regression model

MLR is mainly used in relating the one dependent parameter ($Y$) to one or more independent variables ($X$). Lab results were first processed using linear regression using the Excel Data ToolPak. The MLR model is used herein as a benchmark of accuracy for our study. Equation (1) shows the empirical MLR equation:

$$UCS = -0.6211 + 7.535 \times \mathrm{C} + 135.349 \times \text{Bulk Density} - 0.0836 \times \text{Water content} + 0.9714 \times \text{Liquid limit} - 1.3854 \times \text{Plastic limit} \quad (1)$$

The accuracy results are found to be $R^2$ = 44.5% and ASE of 3.92. **Table 5** shows a sample of the predicted and actual UCS values based on the results for the linear trained model. **Figure 3** compares the actual and model-predicted UCS values. As the linear regression model achieves a moderate precision accuracy, this indicates that the database can be characterized by utilizing better methods. In this study, accuracy measurements for all models will be compared to sort out the best performing model.

**Table 5.** Sample results of predicted vs actual UCS values.

| Mixture | Water Content (%) | Actual UCS (ksf) | Predicted UCS linear model (ksf) | Predicted UCS nonlinear model (ksf) |
|---|---|---|---|---|
| 95% Course: 5% Fine | 10% | 10.7 | 10.2 | 9.5 |
| 95% Course: 5% Fine | 15% | 6.5 | 7.7 | 7.0 |
| 90% Course: 10% Fine | 10% | 7.4 | 7.8 | 7.6 |
| 90% Course: 10% Fine | 15% | 4.3 | 5.3 | 5.0 |
| 5% Course: 95% Fine | 10% | 6.16 | 9.1 | 8.3 |
| 5% Course: 95% Fine | 15% | 4.8 | 4.5 | 5.7 |

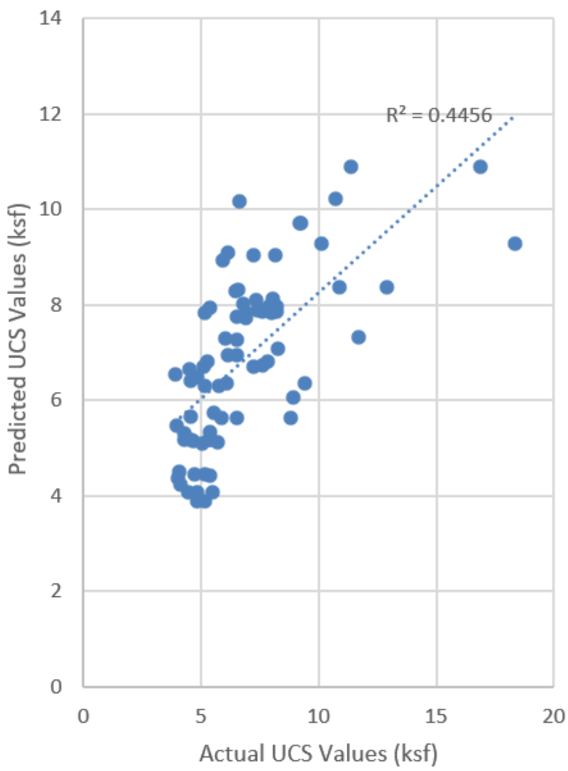


**Figure 3.** MLR prediction model.

### 3.3. Multi nonlinear regression model

The best nonlinear regression model was determined using Excel Solver, which is shown in Equation (2).

$$\begin{aligned} UCS = & -0.6211 + 7.535 \times \mathrm{C}^{0.49} + 135.349 \times \text{Bulk Density}^{1.34} \\ & - 0.0836 \times \text{Water content}^{0.96} + 0.9714 \times \text{Liquid limit}^{0.98} \\ & - 1.3854 \times \text{Plastic limit}^{0.91} \end{aligned} \tag{2}$$

MNLR showed better accuracy measurements than MLR, with $R^2$ = 49.2% and ASE of 3.63. This improvement is due to the nonlinear relation that was oversimplified using the MLR approach. **Table 5** summarizes a sample result of the nonlinear model prediction vs actual UCS. **Figure 4** visually displays accuracy measurement by plotting the actual UCS values against the predicted values by the MNLR model.

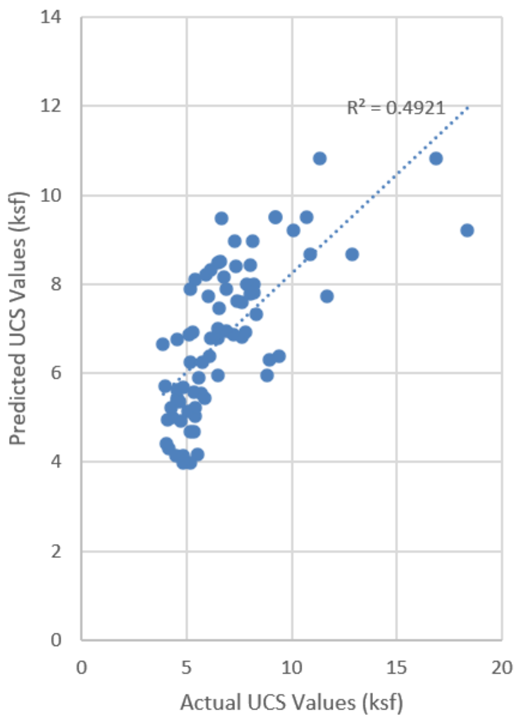


**Figure 4.** MNLR prediction model.

### 3.4. ANN-based model and structure

Due to the indirect and uncertain nature of the soil and to increase the prediction accuracy, a more sophisticated model was utilized in this study. The backpropagation feed-forward ANN is a popular approach used to investigate complex relations between inputs and output through hidden layers of computational nodes, as shown in **Figure 5**. In this study, TR-SEQ1 [19], a C++-based code, was utilized to train the desired ANN models. The model is based on a sigmoidal function (Equation (3)). Input data are normalized to fall between 0 and 1. This normalization ensures that variables with naturally low values, such as density, contribute equally during the training phase as variables with larger numerical ranges like liquid limit. The model is set at a learning rate of 0.8 and it back and forward propagates to determine the optimal connection weights. Goodfellow et al. [20] showed that one layer of hidden nodes can perform better than multiple layers for many cases. Therefore, the ANN models presented herein will only utilize one hidden layer containing multiple nodes.

$$UCS'_{\text{predicted}} = \sum_{i=1}^{N} (\text{sigmoidal}(\sum_{i=1}^{N} (w_{ij} \times X_i) + \theta_j) \times w_{jo}) \quad (3)$$

where the predicted $UCS'_{\text{predicted}}$ is the normalized value of predicted UCS and N is the number of the internal hidden nodes. $w_{ij}$ and $w_{jo}$ are the connection weights from the input node to the internal nodes and from the internal to the output node, respectively. $X_i$ is the normalized value for each input, and $\theta_j$ is the internal node bias.

The database of 152 experimentally based data sets is divided, based on the cross-validation concept [21], into three main categories: training, testing, and validation. Each category is allocated about 50%, 25%, and 25% of the entire database, respectively. Then the number of hidden nodes and iterations are adaptably determined for the optimal ANN model based on prediction accuracy statistical measures such as $R^2$ and Average Squared Error (ASE) of the trained and tested data sets. Once these steps are performed, the optimum model is then validated on its data sets. Following the 4-step approach presented by [10], the developed ANN model can then be retrained on the entire database (once the number of hidden nodes and iterations are determined) in order to capture the hidden features in the testing and validation data sets. This 4-step approach typically yields better-performing ANN models when compared with the traditional training-testing-validation sequence ANN models [10].

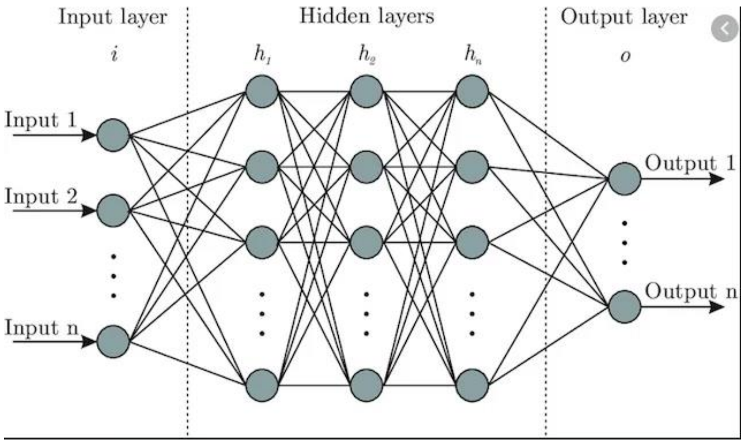


**Figure 5.** Generic ANN structure.

The ANN models were trained and tested on a total of 20 hidden nodes. This is based on the concept that the number of unknowns should not exceed the number 20 of equations. In our case, the number of unknowns is the connection weights, and the number of equations is the number 10 of datasets (152 datasets). The number of hidden nodes (HNs) is designed to fit the database size to prevent overfitting. In general practice, when the connection weights (model parameters) do not match up well with the number of training datasets, the model might not be able to capture the general trend and therefore will lean toward memorization [22]. The starting number of hidden nodes can affect the accuracy measurements of the model. Therefore, all the possible ANN models considered in this study were trained according to the following sequential order: the first model's training begins with one hidden node, the second model's training begins with two hidden nodes, etc. All models are allowed to adaptably expand up to 20 hidden nodes and a maximum of 20,000 iterations for each node structure.

The optimum model, with the highest $R^2$ and lowest ASE, was achieved when starting from 1 HN and expanded to 16 HN with 20,000 iterations. The optimal model was tested, validated, and fully retrained (according to the 4-step modeling approach presented before) over the entire dataset. **Table 6** shows the statistical prediction accuracy summary for the model. **Figure 6** shows a graphical comparison between the predicted and actual UCS values for the fully re-trained optimal model. **Figure 6** also shows a higher accuracy when UCS values are lower than 15 ksf due to the lack of training datasets with UCS over 15 ksf. Moreover, as noted in **Figure 5**, the model is more accurate in predicting UCS values in the 0 to 10 ksf range.

**Table 6.** Statistical accuracy summary for the optimal ANN model.

| | ***R*²** **(%)** | **ASE** | **Iteration/node** |
|---|---|---|---|
| Training | 89 | 0.001806 | 20,000 |
| Testing | 80 | 0.00315 | 20,000 |
| Validation | 89 | 0.001806 | 20,000 |
| Full re-training | 84 | 0.002869 | 20,000 |

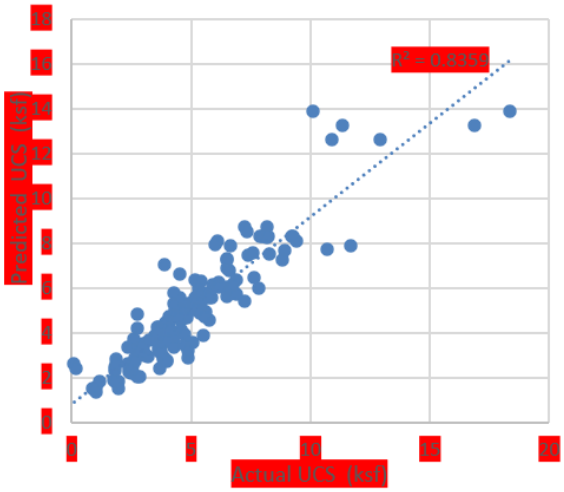


**Figure 6.** UCS (predicted) versus UCS (actual) using ANN model trained at full dataset.

### 3.5. Model performance comparison

Comparing the traditional regression-based models (MLR and MNLR) with the optimum ANN model, developed herein, it is apparent that the developed ANN model yields better prediction accuracy measures in terms of $R^2$ and ASE. For example, Linear regression model gives an $R^2$ value that is lower than the one obtained by the ANN model by more than 45% and also higher ASE error by more than 1.350%. Similarly, the non-linear regression model gives an $R^2$ value that is lower than the one obtained by the ANN model by more than 40% and also a higher ASE error by more than 1.250%. Due to the complex relations between the input variables and the desired UCS output, ANN model was able to capture these relationships in an efficient way due to the ANN structure and modeling approach. It is well known that ANN-based models are the best function approximators for databases similar to the one discussed in this study [10,19,22].

### 3.6. Model utilization via graphical user interface (GUI)

An Excel spreadsheet is designed as a workspace for ANN users. The connection weights of the ANN are implemented at the back end of the spreadsheet, making it easy to share and reuse with open access for everyone. Users only need to insert their inputs to predict UCS values based on the trained ANN model. Also, a recommended range for each input is provided for better accuracy. The stated ranges are based on the available database. Although the user is free to enter any value outside the ranges, accuracy is not guaranteed as the ANN will extrapolate outside the training ranges. **Figure 7** shows the GUI, and it is accessible to users upon request from the corresponding author. The GUI is straightforward to use. For instance, **Figure 7** illustrates the following user inputs: The fraction of coarse material retained on sieve #200 is 0.7, the fraction of fine material passing sieve #200 is 0.3, bulk density (ksf) is 0.1373, water content is 15%, the liquid limit (LL) is 41.55%, and the plastic limit (PL) is 23.76%. The trained model predicted a UCS value of 2.602779 ksf with 83% certainty. This prediction can assist field engineers and designers once they obtain basic soil properties.

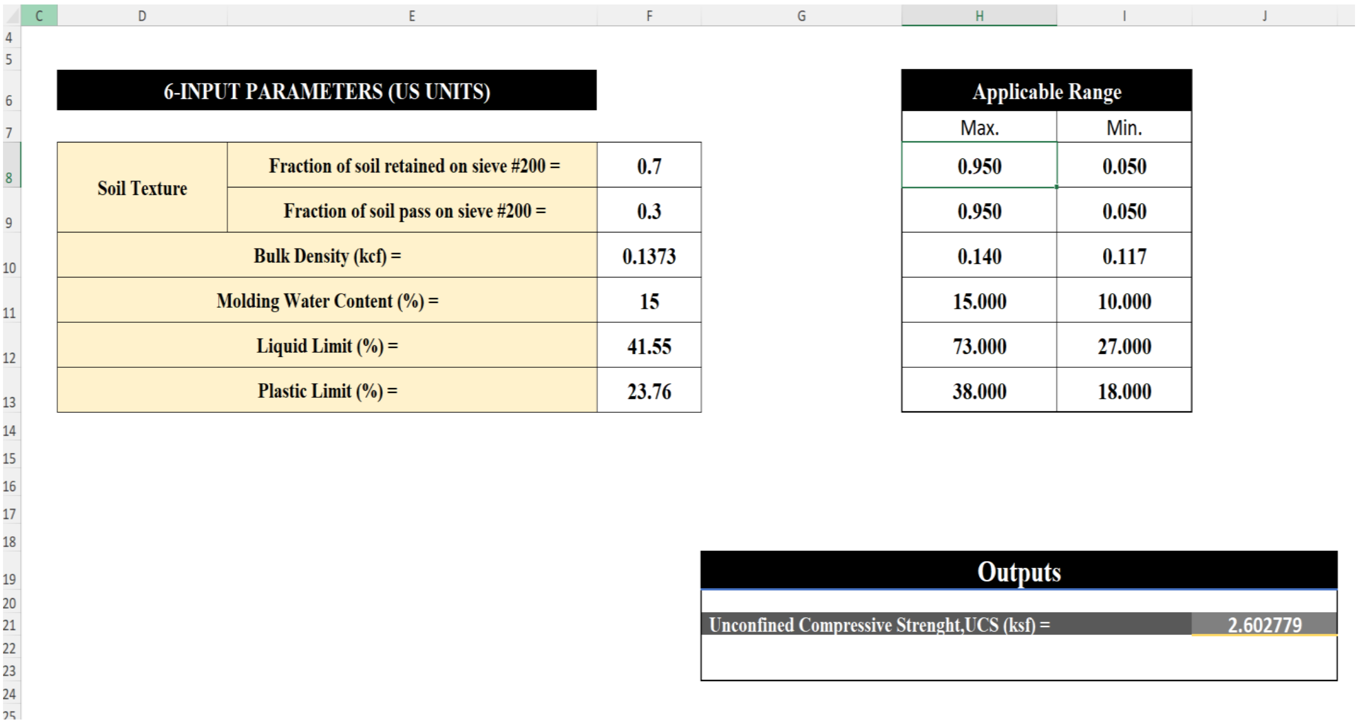


**Figure 7.** ANN-based graphical user interface (GUI).

## 4. Concluding

UCS is a widely used soil shear parameter in most geotechnical engineering projects. This study aimed to introduce a prediction model for UCS values based on soil basic parameters. The database was first processed by conventional regression models MLR and MNLR using Excel Data ToolPak. Key findings include:

- The MLR and MNLR models showed a moderate predictive accuracy of $R^2$ = 44.5% and ASE of 3.63, and $R^2$ = 49.2% and ASE of 3.92, consecutively.
- Twenty ANN models were trained, and the optimal ANN was achieved at 16 HN and 20,000 iterations. The optimal ANN model yields a high accuracy of $R^2$= 84% and ASE = 0.002869.
- The developed GUI will help geotechnical engineers estimate UCS values in designing and analyzing projects, which will reduce reliance on extensive laboratory testing.

Future studies will focus on integrating UCS values with soil hydraulic characteristics such as erosion and shear strength; an expanded database is available.

**Author contributions:** Conceptualization, YN and HY; methodology, YN and HY; software, MA; validation, YN, MA and HS; formal analysis, MA and YN;

investigation, MA and HS; resources, YN and AAO; data curation, MA and HS; writing—original draft preparation, MA and YN; writing—review and editing, MA and YN; visualization, MA; supervision, YN and AAO; project administration, AAO and YN; funding acquisition, AAO and YN. All authors have read and agreed to the published version of the manuscript.

**Conflict of interest:** The authors declare no conflict of interest.

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