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Applying Ai Techniques To Analyze Soil Data And Improve Foundation Design In Construction In Iraq

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Abstract: *In geotechnical engineering, building robust structures is crucial to ensure the bearing capacity of structures against external forces, so making sure soil strength and unreliable build cost and duration prediction are also very important and preliminary aspects of any construction project. Therefore, in this first-of-its-kind modern examine, the capability of various artificially intelligent (AI)-based models toward reliable forecasting and estimation of preliminary construction expenses, duration, and strength at shear is explored. First, background information about the revolutionary artificial intelligence (AI) technique along with its many distinct models ideal for geotechnical and building engineering problems is presented, The use of AI-based models in the literature for the aforementioned construction and maintenance applications is discussed in a number of current works, together with their benefits, drawbacks, and future directions. Several important input elements that significantly affect the preliminary price of construction, construction time, and soil's shear strength estimation are listed and given through analysis. Finally, some obstacles to employing AI-based models for precise forecasts in these applications are discussed, along with elements influencing the problems with cost overruns. Thus, this work can help civil engineers make effective use of artificial intelligence (AI) to solve difficult and risky tasks. It can also be used to Internet of Things (IoT) environments for self-learning applications like smart architectural health-monitoring systems*

Keywords: *Machine learning , neural network , svm , soil , Iraq ,* al Nasiriyah.

Introduction

A vast array of materials are used in civil engineering; the majority of these materials, like concrete, steel, and wood, exhibit greater homogeneity and isotropy. Some of these materials, like reinforced concrete, can be thought of almost as manufactured products with excellent quality control throughout production. Other essential elements, such as soil, are entirely natural. The field of geotechnical engineering works with materials, such as rock and soil. Because of the intricate and imprecise physical procedures involved in their production, the engineering properties of rock and soil exhibit a wide range of behavior , Geotechnical engineering materials and their properties are associated with a great deal of complexity and unpredictability. Incoherent soil composition, mistakes made during soil boring, selection, in-situ and laboratory tests for characterizing the shear strength and rigidity of soils, stress effects, time effects, building effects, and human error are a few sources of uncertainty. For instance, the inability to get undisturbed samples, such as those found in gravel or sand, might lead to uncertainty in laboratory test findings. Additionally, the same clayey soil frequently behaves inconsistently in different places[1]

Science uses mathematical models to predict, simulation, and analyze the actions of systems. These models are based on concepts from physics and mechanics. The exact solution

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in geotechnical problems is probability. Artificial Intelligence (AI) has demonstrated potential in modeling complex behavior, although traditional engineering modeling methodologies simplify difficult situations. Because AI can forecast outcomes well, geotechnical engineering uses it extensively. Unlike regression models, which are limited to handling a single response, it is capable of handling multiple outputs or responses. Soil is one example of a material that can be represented by NN process models with varying properties. Artificial neural networks (ANNs), biological programming, support vector machines, M5 network trees, evolutionary polynomial regression, and K-nearest neighbors are a few examples of AI techniques [3].

The studied area:

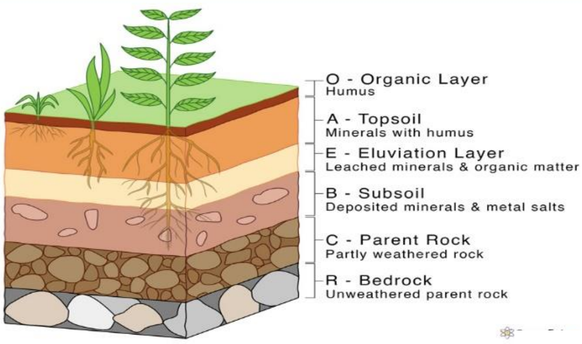


Fig.1 A section of the soil showing the yield

Iraq's varied topography, which includes deserts, floodplain plains, and mountainous areas, makes soil research there essential. These areas of Iraq have very different soil, which affects building techniques, urban growth, and agriculture [2][3].

The soil in alluvial plains of both the Euphrates and Tigris rivers is primarily clayey and silty, which is good for agriculture but makes construction difficult because of its high compressibility and low bearing capacity. Because of these features, building foundations must undergo thorough geotechnical analysis to guarantee stability and avoid problems like differential settlement , The soil in the western areas of desert is mainly composed of gravel and sand, which provides improved drainage and increased bearing capacity. Although it might necessitate taking action to solve potential problems like soil erosion, this sort of soil is better suited for building sturdy foundations.

The calcareous and stony soils of the hilly regions of northern Iraq offer sturdy natural foundations. Nevertheless, slope stability and the possibility of landslides, whether can be brought on by an earthquake or intense rain, must be taken into consideration during building in these areas [4].

In general, engineers and architects must take into account the link between Iraq's soil properties and building foundations. Given the nation's varying soil composition and seismic activity, effective soil analysis and foundation design are crucial to ensuring the lifetime and safety of structures.

Study of soil and foundations according to artificial intelligence applications:

The characteristics and behavior of soil:

Artificial neural networks (ANNs) are increasingly being employed in modeling soil properties and behavior. Studies have shown that ANNs can effectively capture nonlinear interactions between various parameters in complex civil engineering systems. For example, a simple back-propagation neural network was used to model the correlation between relative density and cone resistance from cone penetration test (CPT) for both normally consolidated and over-consolidated sands. ANNs have also been used to model the stress-strain relationship of sands with varying grain size distribution and stress history. A sequential ANN with feedback was found to be more effective than a conventional ANN without feedback. ANNs can also simulate unload-reload loops of soil stress-strain characteristics. These studies demonstrate that ANN-based soil models can be developed using proper training and learning algorithms based on a comprehensive data set [2][5].

Stack diameter:

Static loads (SLT) are commonly used to evaluate the bearing capacity of piles, although they are an expensive and time-consuming procedure. The prediction of pile axial load capacity now uses high strain dynamics pile testing (HSDPT). The ability of neural networks to estimate pile friction potential in clays has been applied. Goh (1994a, 1995b) trained a neural network to forecast pile friction capacity using empirical data [4][5].

Site description:

Prediction of soil properties at the studied site (Nasiriyah), based on a small number of tests, is known as site characterization. Analysis and interpretation of data derived from geotechnical site investigations falls into this category. The location of the granite rock head is captured using a multi-layer neural network that is trained using sample information from seismic scattering measurements. By training directly on data, a neural network model can identify patterns or relationships without having to build complex mathematical models or make assumptions about geographic changes in an area. Using the back-propagation technique, Gangopadhyay et al. He created a multi-layer visualization to define the subsurface and a Geographic Information System (GIS) to define aquifer parameters for groundwater flow modeling. In order to determine groundwater contamination in a leaking landfill and provide parameter estimates [6].

LSSVM:

The loss value of a least squares linear system is used by the statistical learning method known as the least square supported vector machine (LS-SVM) . The goal of LSSVM is to make SVM less computationally complex. In the case of LS-SVM, the equality constraints take the role of the inequality requirements for solving quadratic problems, resulting in a faster training time than SVM. Nevertheless, the robustness and sparseness of LS-SVM's solution are lacking. Particularly for industrial databases, which typically feature explosions of data, unbalanced distributions, and heteroscedasticity, this constraint results in longer training times and lower prediction accuracy . While a single LS-SVM with optimal parameters and reconstructed input samples can have outstanding predictive effectiveness in some situations, it may also have some inherent bias in other situations [4][6].

ML**:**

A branch of artificial intelligence called "machine learning" gives computers the capacity to learn from their prior experiences without explicit programming. Machine learning can be broadly divided into three categories based on the kind of training that is given to the model: unsupervised learning, reinforcement learning, and and supervised learning. Labeled data with the desired output are fed into the machine in supervised learning, also known as directed learning or learning with a teacher. However, no input labels are given to the machine in the case of unsupervised instruction, which is often known as learning with no a teacher. Rather, the machine attempts to make deductions from the dataset that includes responses without labels , Different machine-learning methods, including decision trees, regression analysis, and random forests, are available. Only the algorithms that have previously been used to estimate the pre-cost of a project and predict the shear strength of soil are included in this article [7].

Calculate and know the soil shear strength:

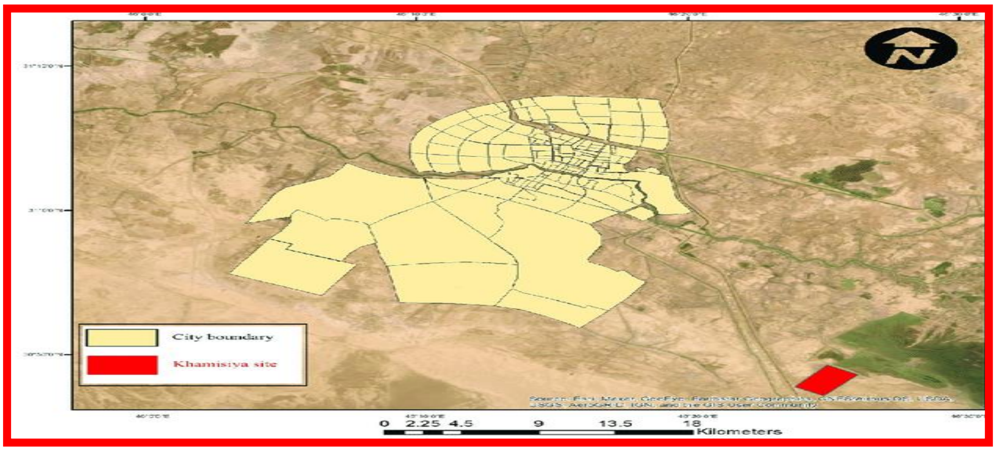


Fig.2 Nasiriyah study site

Shear strength of soil is a crucial characteristic in geotechnical and engineering disciplines that is measured and utilized when building structures like retaining walls, pavements, and dams. The two factors that determine a soil sample's shear strength are internal friction and cohesiveness. A soil's ability to withstand internal movement and slippage under load is determined by its shear strength. Thus, an infrastructure's ability to withstand is determined by its shear strength. A soil sample's shear strength can be calculated in a lab and is influenced by a number of variables, including the moisture content, plastic index, and liquid limit , However, because of challenges with managing the instruments and lengthy measurement methods to provide precise and dependable data, the process of calculating the soil breaking strength in laboratory is not only costly but also expensive. AI may therefore be used to compute soil shear strength quickly and accurately [5][7].

The following are the general procedures used to estimate soil shear strength using AI:

identification of the problem:

A- gathering information and preparing the database for use.

B- determination of important input parameters.

C- choosing a prediction model powered by AI.

D- A comparison of the developed AI models' performance.

E- Analyzing sensitivity.

F- forecast based on the most effective AI model's output.

The importance of using artificial intelligence in the principles of building construction in Iraq:

Aspect	Artificial Intelligence (AI)	Ordinary Experience
Site Analysis	Advanced geotechnical analysis using AI algorithms	Manual inspection and basic soil testing
Data Collection	Integration of satellite imagery, drones, and IoT sensors	Limited to on-site measurements
Accuracy	High precision due to data-driven models and machine learning	Depends on human expertise and tools
Time Efficiency	Faster processing through automation and real-time analysis	Time-consuming manual processes

Cost Efficiency	Reduced costs by optimizing materials and labor	Potential for higher costs due to trial and error
Risk Assessment	Predictive analytics to forecast potential issues	Based on historical data and experience
Design Optimization	AI-driven optimization for stability and cost-effectiveness	Standard design practices
Adaptability	Dynamic adjustments based on continuous data input	Limited flexibility in changing conditions
Environmental Impact	AI models can include environmental impact assessments	Traditional methods may overlook environmental factors
Regulatory Compliance	Automated compliance checks and updates with latest standards	Manual adherence to regulations
Resource Allocation	Efficient resource management using AI recommendations	Based on human judgment
Innovation	Rapid implementation of innovative solutions	Slow adoption of new techniques

table 1: achieving benefit and efficiency between old stereotypical methods and methods and applications of artificial intelligence in constructing buildings

Proposed method:

The suitability of Iraq's soil for construction is affected by regional variations in soil composition. The soil is primarily clayey and silty, with tiny particles and high flexibility, in the shallow plains of the the Euphrates and Tigris rivers. Because of its propensity to experience considerable swelling and shrinking in response to variations in moisture, this kind of soil can pose difficulties for building foundations.

Due to high evaporation rates and inadequate drainage, the soil in centre and southern Iraq is frequently saline, which can compromise the soil's structural integrity. More varied soils can be found in northern Iraq, with stony, well-drained soils found in hilly regions and fertile loams found in the foothills, Construction requires an understanding of the soil's load-bearing capacity [8]. While sandy and gravelly slopes in certain desert areas offer greater drainage and more durability, making them more suited for buildings, clay-laden soils may require substantial foundations or stabilizing measures ,at order to determine the precise characteristics and durability of the soil at a given site and to ensure safe and stable development procedures, geophysical surveys and testing of the soil are crucial [8][9].

The study's technique comprised gathering data from the disciplines and utilizing both GIS or ANNs for analysis. These technologies were used to process and analyze the data in order to draw conclusions and gain insights on the study area. As a tool to aid readers in understanding the procedure followed, Figure 3's flow chart depicts the process of this investigation. The various stages involved in combining lab analyses, ANN, and GIS can be illustrated in a flow chart, which can help readers better understand and follow the study's methodology.

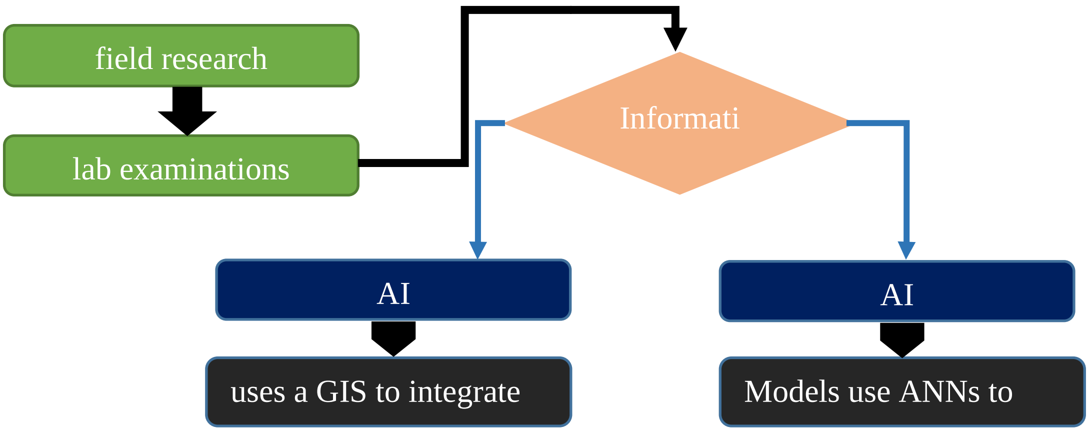


Fig .3 a flow chart that clearly illustrates the approach used in this investigation.

<u>Data gathering:</u>

The majority of the area's excavation sites provided samples for laboratory soil tests and site inspections, from which the study's results were gathered. Drilling deep wells and holes, collecting samples of both disturbed and soil that had not been at 1-meter interval from one meters to eleven meters deep, and carrying out other field tests were all part of the soil investigation process. A range of geotechnical tests were performed in the laboratory to ascertain the qualities of the soil index, screen analysis, compaction, settling, and shear strength [6][10].

The benefit of studying using neural networks:

By employing neural network techniques to analyze Nasiriyah soil, significant progress has been made in the science of soils and agricultural productivity, yielding a number of advantages. Researchers can now examine soil composition, moisture content, and levels of nutrients with unmatched precision thanks to neural networks' capacity to process large volumes of data and identify complex patterns. Precision farming relies on the ability to create extremely detailed soil maps, which is made possible by this technology. Farmers may optimize their use of fertilizer, pesticide, and water by knowing the unique requirements of the soil. This will result in more sustainable and effective agricultural operations , Neural networks also aid in the prediction of soil behavior in a variety of environmental settings, which improves budgeting and risk management. By identifying regions that are vulnerable to soil erosion and degradation, this sophisticated research has also helped to maintain the health of the soil by allowing for prompt treatments. These technologies are especially revolutionary in Nasiriyah, since agriculture plays a major role in the economy, increasing agricultural yields and guaranteeing food security. The application of neural network techniques to soil research is a major advancement that will lead to more intelligent and durable agricultural systems.

<u>Artificial intelligence and neural networks technology in the study:</u>

The program is assumed to be used in the artificial neural network creation process. The purpose of this effort is to create models using artificial neural networks. The network model that was created was created by gathering data on the geotechnical characteristics of the soils in the research area. The goal of the ANN analysis result is to estimate bearing capacity and SPT N-value using the same activation function, the Back-propagation technique, and the same algorithm. Using hidden layers and adjusting the hidden layer's neuron count, the network architecture was selected.

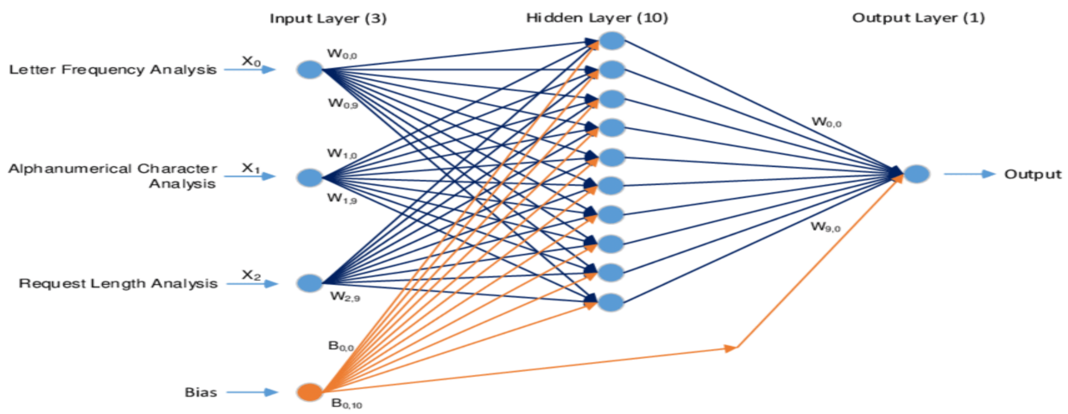


Fig.4 Artificial intelligence and neural networks technology in the study

Previous studies have indicated that there are approximately {14-19} neurons in the buried layer. For data predictions, the network performance with the lowest error and its correlation coefficient value closest to 1 is best. An evaluation metric for ANN models that is frequently used is the root mean squared error (RM-SE). The root mean square error (RM-SE), which is expressed in the identical units as the target variable, calculates the variation between the expected and actual values. The predictions are shown to be near to the real values when the RM-SE value is low, and to be far from what is real when the RMSE value is high. RM-SE is utilized in ANN models to assess model performance and ascertain the caliber of The forecasts.

Into the Hidden Layer:

The soil shear force (Fshear) can be predicted by a feedforward neural network using input parameters including soil qualities, loading circumstances, and other pertinent information , $X = [x1.x2.\dots.xn]$ be the input vector, with xix i representing various features (such as density, normal stress, soil moisture content, etc.). The buried layer's input can be shown as follows:

$$\mathbf{H = f(W1 \cdot X + b1)}$$

The weight matrices for the input to connections in the hidden layer is W 1.

The slant vector for the layer that is concealed is b 1 b 1.

The activation function, such as ReLU, sigmoid, or tanh, is denoted by $f(\cdot)$.

H is the hidden layer's output [7][10].

From Secret Layer to Display Layer

The output layer can be expressed as follows, providing the projected soil shear force:

$$\mathbf{Fshear = W2 \cdot H + b2} \qquad \mathbf{2}$$

The weight tensor for the connections from the hidden to the output layer is W 2.

The biased value for the result of the layer is b 2. Z=MAE

$$\boldsymbol{R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_{mea} - y_p\right)^2}{\sum_{i=1}^{N}(y_{mea} - y_m)^2}} \qquad \mathbf{3}$$

$$\boldsymbol{RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_{mea} - y_p)^\wedge 2}{N}}} \qquad \mathbf{4}$$

$$\mathbf{Z = \frac{1}{N}\sum_{i=1}^{N}|y_{mea} - y_p|} \qquad \mathbf{5}$$

The value that is observed at i-th time is y i,measured.

yi, forecast

The model's ii-th anticipated value is represented by the value y i,predicted.

The measured value of y

The average of the the values seen is measured.

The maximum amount of observations is N.

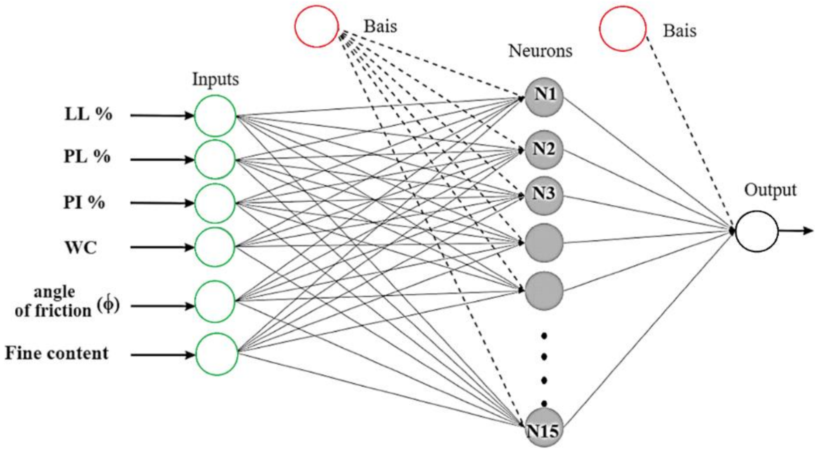


Fig.4 Neural network system architecture using artificial intelligence

We will include an attached practical part, which is a Python code that shows the application of artificial intelligence algorithms and neural networks in order to study the soil, classify the soil, and create a database of its own, giving a set of results that will be placed in the results section of this study [11][13].

The results:

The fines content of the soil is one of the most significant elements affecting its qualities, such as its shear strength, compressibility, and plasticity, and, indirectly, its ability to support a foundation. The findings show that the majority of the examined area in AL Nasiriyah city center has a higher level of fines concentration. According to the data, a significant proportion of soil particles with a diameter of smaller than 0.08 mm are present in the bulk of the region, with a fines content of more than 84%. It is anticipated that the soil's high fine content will significantly affect its mechanical qualities, such as its plasticity, shear strength, and compressible qualities. Future construction and development initiatives in the region must carefully analyze how the characteristics of the soil impact its ability to support loads, transfer loads, and resist deformations. Information highlighting the need of considering soil fines when making judgments about development projects will be very helpful to planners and engineers working in the AL Nasiriyah city center.

The level of soil compression becomes significant when large particles are replaced by small particles, and the effect of the fines' amount becomes more apparent when the soil is nearly saturated. This has been noted by other authorities in the field. Due to their connection, it is impossible to evaluate the natural water fulfilled and fines content separately ,Increasing natural water content can occasionally diminish the influence of penalties included on soil shear strength because fines are sensitive to variations in natural water content. When conditions are dry, particles have minimal influence over the behavior of the soil due to suction [15].

GIS software was used to map the soil properties of the research region. These maps displayed the distribution of the following metrics at three different levels: cohesiveness, compressing coefficient, rebounding index, fluid limit, plasticity limitation, cohesiveness from the earth content, and foundation capacity for bearing. Within the survey region, soil attributes had been interpolated at different depths to illustrate the geographical distribution of these values. Typically, all soil characteristics are categorized into six main categories, each of which is represented on the map by a distinct color.

the relationship between the SPT values in the soils in the study region and the final capacity for bearing was determined by Meyerhof's equation. This graph shows a strong relationship with the SPT values and the foundations' final bearing capability. the relationship between soil cohesiveness (shear strength parameter) and ultimate bearing capacity as determined by the SPT values for the soil layers in the research area. Figure 5 shows the findings of a correlation between the final load bearing capacity determined by Meyerhof's calculation and the ultimate bending capacity determined by the SPT metrics for the soil layers within the research region [17].

The discipline of geotechnical engineering has made extensive use of the estimation of ultimate load capacity from SPT values, which is based on experimental correlations. Although this method's simplicity is an advantage, it might not precisely reflect the actual conditions of the soil due to a variety of factors, including soil type, stratigraphy, or and loading circumstances [18].

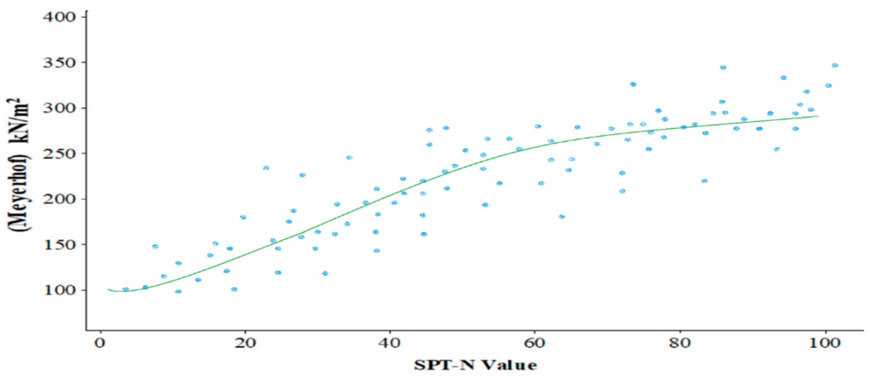


Fig.5 ultimate carrying capacity and soil cohesiveness in the research region are correlated.

In the following figure, we show the results of applying the artificial intelligence algorithm to extract properties and study soil according to deep learning algorithms and neural networks [19].

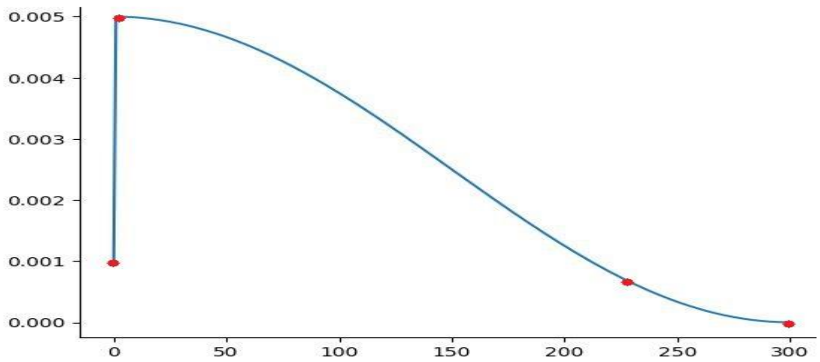


Fig.6 The code resulting from the study came out

Regarding the lines, a percentage of error represents the variation between the expected and actual values based on the analysis of two models. It is a gauge of how well the model predicts the future. A model is more accurate when its error percentage is smaller; conversely, a higher error percentage denotes a less accurate model. The admissible error level for that particular field and the particular application will determine the acceptable error rate. A lower mistake rate, like 3%, might be reasonable in some circumstances, but if the cost of one fewer error is too great in another, a larger error rate might be reasonable [23].

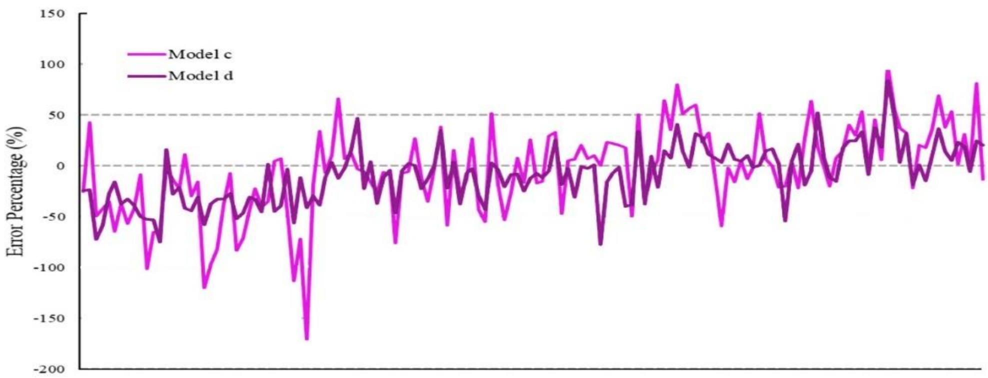
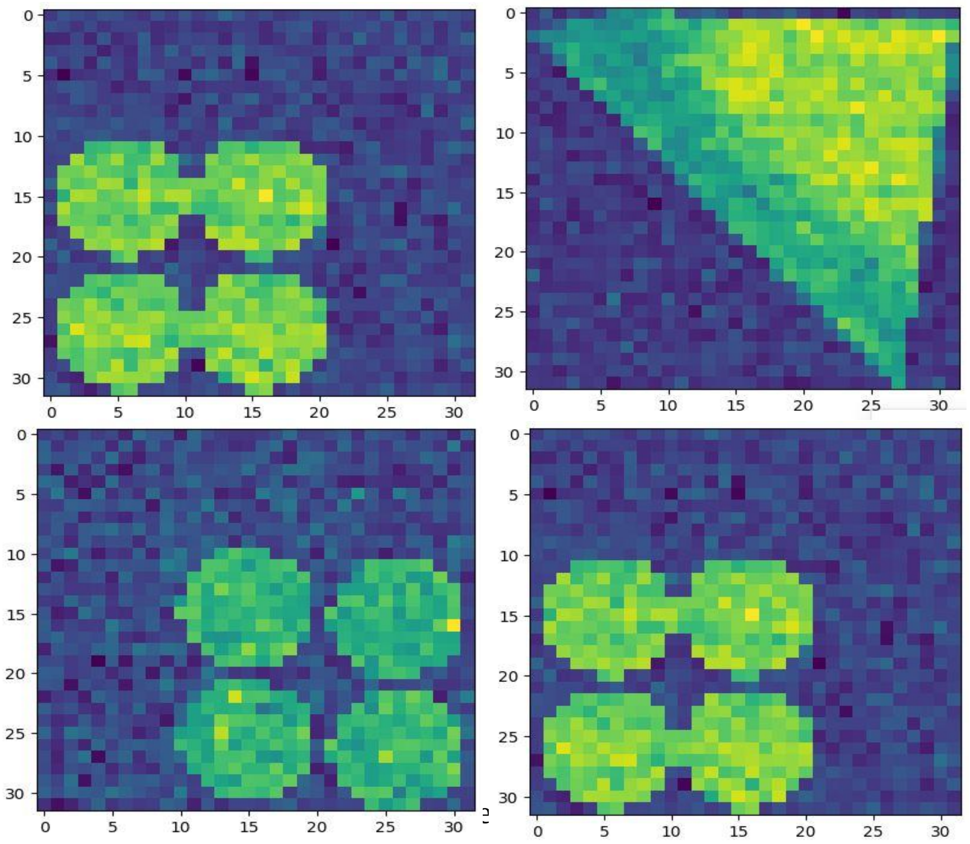


Fig. 7 System (c) and system (d) percentages of errors lines for predicting Q

Through the practical section and our attached software code, we delved into one of the methods of artificial intelligence, which is neural networks, in order to study the nature of the soil in Iraq for the purposes of establishing constructional foundations for buildings and other buildings above the aforementioned soil. According to studies, the neural network in this case carries out the process of studying and examining samples entered from the soil in order to give their properties and analyze them for the experts to know the ability to build constructional foundations on them. Below, and from the attached software code, we attach a group of soil samples entered into the aforementioned system (neural networks) in order to investigate them. And examine the sample



Below is a comparison table of the different artificial intelligence methods used in studying soil in Iraq. Considering the different artificial intelligence techniques and their applications in soil analysis. Below is a table summarizing the comparison:

AI Method	Example in Iraq	Disadvantages	Advantages	Applications in Soil Study	Description
Machine Learning (ML)	Predicting soil fertility using historical data	Requires large amounts of labeled data, may overfit	High accuracy, ability to handle large datasets	Soil classification, nutrient prediction, yield prediction	Algorithms that learn from data to make predictions or decisions
Deep Learning (DL)	Analyzing satellite images for soil moisture content	Computationally intensive, requires large datasets	Handles complex patterns, high accuracy in image analysis	Image recognition, soil texture analysis	Subset of ML using neural networks with many layers

Geostatistical Methods	Mapping soil properties using geostatistical models	Requires spatial data, complex computations	Accounts for spatial relationships, precise mapping	Soil mapping, spatial variability analysis	Statistical techniques that incorporate spatial coordinates
Support Vector Machines	Classifying soil types based on spectral data	Less effective on noisy data, complex tuning required	Effective in high-dimensional spaces, robust	Soil type classification, land cover mapping	Supervised learning models for classification and regression
Random Forests	Predicting soil erosion risks	Can be less interpretable, requires parameter tuning	Handles large datasets well, reduces overfitting	Soil quality assessment, erosion risk prediction	Ensemble learning method using multiple decision trees
K-Nearest Neighbors	Classifying soil textures based on sample data	Computationally intensive, sensitive to irrelevant features	Simple to implement, no training period	Soil texture classification, soil moisture prediction	Simple algorithm that classifies based on the nearest data points
Artificial Neural Networks (ANNs)	Predicting soil salinity levels	Requires large datasets, prone to overfitting	Can model non-linear relationships, adaptable	Soil property prediction, modeling soil processes	Computing systems inspired by biological neural networks
Fuzzy Logic	Assessing soil suitability for different crops	May be less precise, complex rule-based systems	Handles uncertainty well, intuitive	Soil suitability analysis, irrigation scheduling	Logic system that handles reasoning with uncertain or imprecise data

Table 2: Comparison of different artificial intelligence methods

We notice from the set of samples that the system, according to the software code attached to the file, is given primitive default weights to the neural network system for artificial intelligence in order to start the deep analysis process (the primitive weights are shown in the attached software file).

Conclusion:

This project focuses on producing maps for soil topographical attributes utilized by geotechnical specialists in foundation structure capacity. An artificial neural network (NN) algorithm was constructed for calculating SPT-N value and ultimate load bearing capacity using soil characteristics and borehole coordinates. GIS analysis was utilized to examine early exploration of technical problems in iraq The results demonstrated that the soil includes a large amount of fine-grained minerals, especially clay and silt, which can effect its physical and technical capabilities. The study also indicated that the parameters of Atterberg in most of iraq are within 39% and 50%, with low–plasticity clay and clayey silt prevalent , Digital location of shear strength characteristics revealed modest soil strength in superficial strata, with increased values at deeper levels indicating greater soil strength features. However, the soil in iraq is not capable of holding huge loads without modification or additional design procedures. The ultimate bearing capacity is a measure of the utmost weight or load a soil may bear without failure. Strengthening the soil through compacted or stabilisation and employing particular footing designs can boost the soil's load bearing capacity and assure the safety and security of structures placed on the soil.The created ANN model showed accurate forecasts performance based on productivity indices, indicating the utility of neural networks for predictive purposes in earth sciences projects. However, it must be utilized in concert with other methodologies and confirmed with separate information to provide accurate predictions.

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