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Classification of Layers Using Artificial Neural Networks in the Province of Kurdistan (Iran)

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Abstract: Artificial Neural Networks (ANN) is a field that combines science, technology, and ancient and modern knowledge. It has demonstrated the ability to resolve complex engineering issues beyond the computational capacity of conventional approaches and classical mathematics. ANN has applications in various fields, including computer science, engineering science, biology and medical science, and communication science. Neural networks are particularly useful in civil engineering, particularly in geotechnical problems, where soil heterogeneity and nonlinear behavior significantly impact geotechnical phenomena. Researchers have employed ANN to address various geotechnical engineering issues, including behavioral modeling, due to their potent abilities on nonlinear and multivariate problems. In this study, information from boreholes was used to collect and classify data to describe soil strata. The outputs of the neural network showed general consistency when compared to experimental borehole data, indicating its effectiveness in estimating changes in the soil layer. This was achieved by first presenting the network with information from various boreholes.

Keywords: artificial intelligence; behavioral model; behavioral modeling; geotechnical engineering; liquefaction

1 INTRODUCTION

Over the past few decades, researchers have studied the mecanical properties of soil, but soil behavior remains poorly understood. Common methods, such as mathematical and experimental methods, use simplified to solve multi-variable geotechnical problems. However, these methods cannot describe complex soil behavior. Neural networks have been used as an alternative method to solve many geotechnical engineering problems, as they have the power to solve complex problems.

The process of drilling borefloles and performing experiments to identify soil layer structures is expensive and time-consuming. Increasing reliability in interpolating soil layer structures and properties in inter-borefloles improves the quality of geotechnical evaluation, decreases costs, and facilitates proper construction planning. Artificial neural networks (ANNs) use specific capabilities of data processing in the human brain, such as learning, data generalization, and parallel processing. Many researchers have studied ANN application in geotechnical engineering, using ANN models to predict complex soil, predict landslide risk, and model soil behavior in uniaxial strain conditions.

Analog-to-digital converters are artificial neural networks that have been successfully applied in various fields of geotechnical engineering, including pile capacity prediction, foundation settlement, soil properties and behavior, liquefaction, site characteristics, retaining structures, slope stability, and tunnel and underground opening design. Known applications include predicting drive pile capacity, liquefaction, and soil properties and behavior. However, other applications, such as structure settlement, should be carefully considered until more research is conducted.

Many areas where the feasibility of artificial neural networks has not been tested include predicting bearing capacity of shallow foundations, bored piles, and the design and drainage of sheet pile walls. Mathematical models often compensate for the lack of physical understanding by simplifying problems or incorporating assumptions into the model. Artificial neural networks, on the other hand, are data-only and can be trained on input-output data pairs to determine the model's structure and parameters.

However, artificial neural networks have limitations, including a lack of theory, the success of finding a good solution, and the ability to explain solutions. As new data becomes available, the ANN can always be updated by providing new training examples for better results.

2 BACKGROUND

Artificial neural networks (ANN) are a rapidly growing field of study, with applications in various fields such as economics, industrial engineering, automation, electronics, computer technology, medicine, intelligence, and object identification. They have also been successfully used in geographical and construction engineering due to advancements in computational science and computing power. ANNs are inspired by biological neurons, which study the brain's working system. They perform operations using the learning feature of the human brain, a unique feature compared to other computational methods. Classical administrative methods, which recognize linear relationships between dependent and independent variables, struggle with complex interplay between variables in geoscience. ANNs offer alternative solutions to these problems and provide additional tools to traditional statistical methods in geographic studies.

Artificial Neural Networks (ANNs) have been successfully applied to geotechnical engineering since the early 1990s due to their ability to model the complex behavior of geotechnical materials, which exhibit great variability [1]. Classical structural modeling based on elastic and plastic theories has limited ability to accurately model the behavior of geological materials due to formulation complexity, idealization of material behavior, and a plethora of experimental parameters [2].

ANNs have been proposed as reliable and practical alternatives for simulating the homogeneous and hysteretic behavior of geological materials [3]. Geotechnical properties and soil behavior are controlled by factors such as mineralogy, which can be difficult to estimate with traditional statistical methods. ANNs have been used to estimate various soil properties, including pre-consolidation pressure, shear strength, stress history, expansion pressure, and lateral earth pressure [4].

ANNs have also been applied in liquefaction prediction, retaining walls, dams, explosions, mining, environmental geotechnical engineering, and rock mechanics [5]. They have been used in tunnels, underground openings, slope stability, landslides, and deep foundation pits. However, networks have limitations, such as the lack of theory to help them develop, the success of finding a good solution not always guaranteed, and the ability to explain the solution[6].

Iran, situated in the Alps-Himalayan seismic belt, faces high earthquake risk, causing significant losses. To mitigate this, measures learned from past earthquakes are implemented, including strengthening structures to resist dynamic influences and ensuring site safety to prevent geotechnical phenomena like liquefaction and landslides. Understanding soil layers below the surface is crucial for seismic response. Multiple boreholes are required to test soil layers, a time-consuming and costly process. This study uses artificial intelligence to predict soil layers and depths, and to verify network performance using common methods and available information. The output data from soil modeling is used in dynamic analysis, generating 1D, 2D, and 3D models based on soil stratification and Cartesian coordinates as input parameters. This approach reduces costs and allows for correct planning and execution of structural operations [7].

3 ARTIFICIAL NEURAL NETWORK

Smart systems, which have been around for 40 years, use models like behavior patterns, decision-making processes, brain structure, neural networks, and probabilistic reasoning to solve problems. They are intelligent within the scope of problem management rules, not performing all human brain functions. In geotechnical engineering, artificial intelligence is more efficient and economical than classical methods due to the availability of statistics. AI systems can predict phenomena by remembering their history and frequency, and if comprehensive information is used, they can predict behavior in other domains. This makes intelligent systems more efficient and economical than classical methods in handling statistical phenomena [8].

4 INTRODUCTION TO ARTIFICIAL NEURAL NETWORK PARAMETERS

Artificial neural networks (ANN) are models similar to human neural networks, consisting of nerve cell units connected by axons. The goal is to create a structure similar to the biological structure of the human brain, capable of learning and decision-making. The goal is to train the model by introducing the performance history and frequency of the dynamic system, store the system's performance in the model's memory, and use it for situations the model has not encountered before. Artificial intelligence is a vast field with roots in philosophy of linguistics, mathematics, psychology, and physiology [9].

This paper aims to link artificial intelligence with soil mechanics, specifically soil modeling through a powerful tool called artificial intelligence. The mathematical basis is considered and translated into an understandable algorithm by software, and soil modeling is performed in the software environment. The brain is well-prepared for parallel data processing, as it can hold knowledge from different sources in the brain and process it simultaneously.

Neural network computational methods estimate the strategic principles underlying brain processes to answer these questions and use them in computer systems. The brain is made up of a large number of interconnected units, and the inherently parallel structure of neural network systems makes them suitable for parallel machines, with further advantages in terms of speed and reliability.

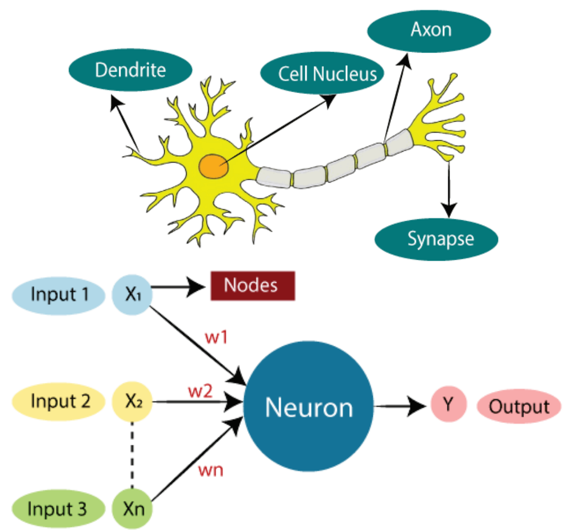


Figure 1 An illustration of the biological and artificial brain networks

Table 1 Artificial neural networks and biological neural networks' relationship

Biological Neural Network	Artificial Neural Network
Dendrites	Inputs
Cell nucleus	Nodes
Synapse	Weights
Axon	Output

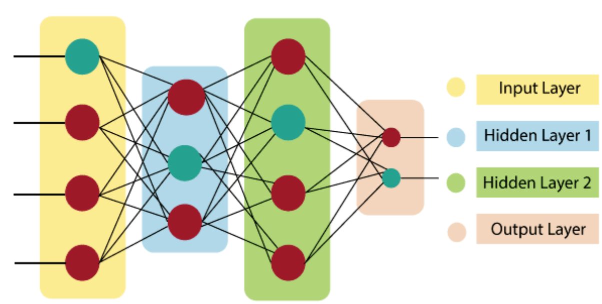


Figure 2 The three main layers of an artificial neural network

An artificial neural network (ANN) is a network of neurons, similar to biological ones in the human brain. These neurons are arranged in layers, with the strength of connection between adjacent layers represented by a 'connection strength' or 'weight'. ANNs typically consist of three layers: input, hidden, and output. In a feed-forward network, weighted connections feed activations only in the forward direction, while in a recurrent network, additional weighted connections feed previous activations back into the network. The training of the weight matrix is an essential step in developing an ANN model, where the weights are randomly initialized and updated using a specific training mechanism. Evaluation standards: Using R^2 and *RMSE* between the measured and predicted values, the accuracy of the regression equations for the development of PTFs was assessed and expressed as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{n}\left(Z_{\mathrm{s}} - Z_0\right)^2}. \quad (1)$$

The values are Z_s (observed), Z_0 (predicted), and n (number of samples).

The input layer accepts various input formats from the programmer, while the hidden layer performs calculations to identify hidden features and patterns. The output layer transforms the input through a series of transformations, resulting in the final output. The artificial neural network calculates the weighted sum of inputs, including bias, using a transfer function. This weighted total is passed to an activation function for output. Activation functions determine whether nodes should fire, with only those fired reaching the output layer. Different activation functions are available for different tasks.

$$\sum_{i=1}^{n} W_i \times X_i + b. \quad (2)$$

Artificial neural networks function as weighted directed graphs, with artificial neurons forming nodes and their outputs and inputs being represented as directed edges with weights. They receive input signals in the form of patterns and vectors, which are mathematically assigned for every n inputs. Artificial neural networks use weights to solve specific problems, representing the strength of interconnection between neurons. These weights are summarized in a computing unit. If the weighted sum is zero, bias is added to scale the output. Bias has the same input and weight as 1, with a total of weighted inputs ranging from 0 to positive infinity. To maintain the desired response, a maximum value is benchmarked, and the total weighted inputs are passed through an activation function. Activation functions can be linear or non-linear, with commonly used sets being Binary, linear, and Tan hyperbolic sigmoidal activation functions.

5 THE MAIN PARTS OF THE NEURAL NETWORK

The main parts of the neural network are:

- Structure or Architecture
- Training mechanism or learning algorithm
- Test mechanism or recall mechanism.

5.1 Structure or Architecture

When working with any neural network, its architecture or structure is what you see initially, and it depicts how the neural network is physically expressed. The appearance and internal communication of this intelligent system are determined by the neural network's topology. This part of a neural network serves as a practical way for it to store its data. More specifically, this implicitly intelligent system stores information about its mapping in its structure. Moreover, the neural network pulls the necessary data from the structure to respond to the user's query [10].

Previous studies have used the Artificial Neural Network (ANN) method to assess soil properties and classification. Ref. [11] classified soil using LL, PI, and dust content, resulting in heavy, light, hard, medium, small, and light dust soils. Ref. [12] predicted high moisture content and maximum dry thickness values using various methods, including bread, dust, golf, LL, and PL, with 126 samples. The study compared Simple-Multiple Analysis and ANN methods, revealing R^2 values ranging from 0.77-0.78 for multiple linear regression analysis, 0.74-0.82 for simple linear regression analysis, and 0.67-0.89 for ANN analysis. Refs. [13] and [14] conducted soil classification studies using Artificial Neural Networks (ANN) techniques. Hassannejad et al. found the Levenberg-Marquardt algorithm as the best for soil classification, while Tenpe and Kaur calculated OMC and MDD from LL, PL, and sieve analysis values using ANN techniques. The results showed R^2 values for OMC values were 0.85 in training, 0.76 in testing, and 0.95 in simulation. Ref. [15] used 280 data from previous studies to estimate the PI, MDD, and OMC values using ANN. The study used LL, PL, and Lime content as inputs. The R^2 value for PI was 0.91, MDD and OMC were 0.83. Reale et al. (2018) utilized CPT values to estimate soil classification using Artificial Neural Networks (ANN) on a 216-dataset dataset. They developed two ANN networks for estimating fines content (FC) and predicted for both LL and PI. The correlations showed R^2 values of 0.79 for FC, 0.85 for LL, and 0.78 for PI.

5.2 Training Mechanism or Learning Algorithm

By looking at instances from the training phase, which is an estimate of the actual map of the system under consideration, the training mechanism creates a map of the neural network. In neural network nomenclature, these samples are referred to as training samples or learning patterns, and the training mechanism stores the information pertaining to this mapping that was acquired from the samples during the training phase in the neural network's structure [16].

5.3 Test Mechanism or Neural Network Call Mechanism

The testing mechanism or neural network recall mechanism is a crucial component of an intelligent system that uses information extracted from the training mechanism to answer user questions. The neural network structure acts as a memory in this system, and the testing mechanism retrieves this information. The efficiency of the neural network is determined during the testing phase or recall phase. The neural network receives expected samples representing the user's problem and outputs these, without any output to estimate. The recall mechanism uses the mapping obtained during the training phase to estimate the output of the test samples. The closer the network's answer to the test sample is to the real answer, the closer the graph formed by the neural network is to the problem system graph. Therefore, the efficiency of a neural network to solve a problem is deterministic [17].

6 RESEARCH ASSUMPTIONS (RESEARCH HYPOTHESES)

Research assumptions (research hypotheses) are:

- Soil stratification can be determined with acceptable accuracy using an artificial neural network.
- The soil of the plan is considered in layers.

7 SOIL MODELING

Artificial intelligence (AI) has become increasingly popular in various fields, with software like MATLAB and STATISTICA being particularly useful. The selection and use of boreholes is crucial for determining the exact location of the project area, allowing for accurate coordinates and utilization of borehole information. The choice of input parameters for a neural network to predict soil stratification, such as soil type and depth, is directly related to the coordinates and information of the selected borehole. Drill holes are selected based on the information in the identification table, ensuring no limit to the required information.

One of the most important steps in developing an artificial neural network is choosing the data used to train the network. After selecting the input and output variables and ensuring the accuracy and validity of the soil stratification data, the next step is selecting data for training and choosing from the available data. Control and testing the network during each step is essential to ensure the network's performance in predicting situations outside the training data.

In drilling modeling, a point is selected as the coordinate origin in the Cartesian coordinate system as the input parameter, and the classification information of the drilling is used as the input data. The chosen software chooses the most suitable network based on the input parameters, resulting in more network errors than the software raises.

8 HISTORY OF TECHNICAL DESCRIPTION IN SOIL DEFINITIONS

Many soil properties such as color, texture, density, moisture, or structure can be observed directly in the field. Most soil profiles show a series of rather well-separated layers. When this is due to soil formation or sexual reproduction, and not to changes in the parent material, it is said to be the horizon. These terms may be considered roughly synonymous herein. Often used to describe the individual soils on which soil classification and mapping are based. They are usually taken from soil profiles (Tab. 1), by digging sampling pits or coring exposed vertical transects using a soil auger.

Table 2 Common terms used in soil descriptions

Term	Description
PED	A single individual naturally occurring soil aggregate such as a granule or prism; also, a soil unit beneath the horizon level.
HORIZON	Relatively uniform material that extends laterally, continuously, or discontinuously throughout the pedo-unit; runs approximately parallel to the surface of the ground and differs from the related horizons in many chemicals, physical and biological properties.
PROFILE	A vertical section through the soil from the surface to the relatively unaltered parent material.
PEDON	The smallest classifiable soil unit, intended to be large enough to contain the root system of an average plant
PEDOUNIT	A selected column of soil containing sufficient material in each horizon for adequate field and laboratory characterization.
SOIL BODY	A representative specimen of a taxon[1] in place on the natural terrain.
POLYPEDON	A soiled area composed of many similar pedons that are all given the same soil name
PEDOTOPE	The space is occupied by a polyhedron.
SOIL SCAPE	The assemblage of soil bodies on a land surface in a particular landscape.

9 SOIL HORIZON DESIGNATIONS

With the work of Dokuchaev and later Sibirtsev on Chernozem soils in Ukraine towards the end of the nineteenth century, the scientific study of soil horizons was initiated (Buol et al., 1973; p. 174). Dokuchaev utilized the initial letters of the Latin alphabet to denote specific regions within soil and geological profiles. The letters A, B, and C were initially just designations, but over the ensuing decades, they came to have distinct meanings [18]:

1) Compared to the layers below, the A horizon (topsoil) often has a higher organic matter content and a darker hue. Eluviation, or the leaching of clay to the layers below, is another characteristic of it.
2) The subsoil, or B horizon, is often lighter in color than the topsoil and frequently exhibits clay illuviation or deposit, typically from the horizon or horizons above.
3) The parent material, or substrate, known as the "raw" soil (horizon C) is where the A and B horizons have developed.
4) A large portion of the later work on soil categorization was built around these concepts. The system changed as profile descriptions became more detailed. For example, new "master horizons" were developed (O for organic horizons, R for bedrock, and G for gley).

The International Society of Soil Science (ISSS) published a "Proposal for a uniform system of soil horizon designations" that forms the basis for most of today's soil classification systems. Subdivisions of these major horizons were introduced, first by the use of numeral subscripts, and later by subscript letters (e.g. b for buried or h for hummus). The emphasis of the description shifted from the (assumed) processes which had formed the soil to the actual morphology of the profile [19].

10 SOIL CLASSIFICATION SYSTEMS

As an alternative to the soil hierarchy classification, the first soil classification system was created in Russia (Buol et al., 1973; Duchaufour, 1982). The parent material of the central high plains of Russia is rather consistent, loess-like, and exhibits a steady increase in temperature from north to south as well as a gradual increase in precipitation from east to west. Three types of soil classification systems have been developed: non-zonal, intrazonal, and zonal. Interrazonal soils are influenced locally by things like parent materials; zonal soils are immature soils like those found on recently eroded slopes; and zonal soils are soils generated mostly by vegetation and climate. Two issues need to be addressed by soil classification:

1) It should categorize higher units by assembling the primary soil types found worldwide based on the prevalence of their basic characteristics, so offering a structure that serves as the foundation for soil research.
2) The tool ought to facilitate the creation of expansive maps for pragmatic uses, like farming, where precise details of marginal significance are frequently needed for unit designation and definition.

10.1 German Bodensystematik

Developed the German soil categorization system known as the "Bodensystematik", which is a genetic system based on the idea of soil kinds (German: Typen), or what he refers to as the "characteristic stages of soil development" (op. cit.).The distinct features of such vistas as well as their distinctive arrangement characterize types. Higher categories 5 are divided into two suborders (G.: Klassen) and an order (G.: Abteilungen). The direction and extent of infiltration—the movement of materials through the soil by water—determine the top layer division primarily. Soils classified as terrestrial, semi-terrestrial (groundwater and flood), and submerged (underwater) are the basic categories. Soils are categorized at the sub-level based on comparable horizon configurations. Based on qualitative characteristics like the presence of calcium carbonate, types can be further classified into subtypes (G.: Subtype). Specifying transitions or changes between types is a crucial application of subtypes. The following primary horizons are identified by BS: F, H, L, P, T, S, M, E, and Y [12]. Only three appear in the following areas: M (colluvium, from L.: migrate), S (stagnant water-affected deposit, G.: Stauwasser), and H (peat, from humus). Subscript letters in lowercase are used to indicate horizontal scale subdivisions; genetic trait-related letters come after the primary symbol, while all other letters come before it.The German method allows for some flexibility with regard to slope; for example, strata that demonstrate the effect of many soil formation processes can be described by combining up to three primary symbols. Likewise, combinations of up to three different kinds of symbols can be used to define variations. Moreover, soil surveyors have some leeway to interpret soil profiles genetically because the BS classification system considers the complete profile. The most significant distinction is seen in the USDA's "soil taxonomy", whose "diagnostic" scope is mostly determined by physical or chemical measures [20].

10.2 Soil Classification

Fine-grained soils are defined as those with a grain size of less than 0.075 mm, and more than 50% of their dry weight should be finer than 0.075 mm. These soils are a mixture of clay and silt grains, with the clay fraction being the size limit between the two. The plasticity properties of silt and clay are better separators than particle size [21] initially defined six 'Limits of consistency' to classify fine-grained soils, but in present engineering applications, only three of these limits are used: liquid (LL), plastic (PL), and shrinkage (SL). These limits are used to understand soil mechanics and physical properties, such as swelling and shrinkage potentials, shear strength, and compressibility.

Researchers have used these limits to investigate the fundamental properties of soils, with studies showing significant relationships between clay rate, LL, PL, and PI values. Studies in Canada and Nigeria have reported significant relationships with clay rate, LL, PL, and PI values. Additionally, clay content, montmorillonite ratio, and organic matter ratio have a weighty effect on LL and PI. In conclusion, fine-grained soils are classified using Atterberg limits, which can be used to understand soil mechanics and physical properties. Since early 1990, Artificial Neural Networks (ANN) have been widely used in civil engineering and geotechnical engineering studies. ANN is commonly used to estimate the compaction and uplift of pile foundations, axial and lateral load capacities, drilled poles, foundation settlements, and anchors embedment. One study by Goh et al. (1995) used 93 data for training and 74 data for testing, obtaining a nonlinear relationship with a correlation coefficient of 0.97 for training and 0.91 for testing. The prediction of settlements in foundations is affected by uncertainties, similar to other complex issues in geotechnics. Researchers tested settlement prediction using ANN, using 79 data sets for training and 10 datasets for testing. Five parameters were used as input values: net pressure, average standard penetration test (SPT) values, foundation width, foundation form, and foundation depth [22].

ANN is applied to various earth sciences applications such as retaining walls, dams, earthquakes, geographical information systems, mining, geoenvironmental engineering, petroleum engineering, and rock mechanics. Traditional statistical methods may be insufficient due to interactions between variables, and predicting physical properties of soil like mineralogy, porosity, water content, grain size, etc. with statistical methods is difficult. ANN algorithms can estimate or determine various soil characteristics, including soil classification.

10.3 USDA Soil Classification

Before the release of the (relatively) comprehensive "Soil Taxonomy" (ST) (Soil Surveyors, 1975; most recent revision 1995), the United States Department of Agriculture (USDA) soil classification system 6 underwent a number of "approximations". Rather than particular characteristics of any pathogenic process, families—the taxonomic layers beneath subgroups—differ substantially according to useful standards. Take soil temperature, parent material, or texture, for instance. Because it is primarily functional in nature, the definition of soil series is comparable to that of house. In order to provide more specific information, the series level—which is the lowest level of "soil taxonomy"—can nevertheless be further broken down into stages according to factors like slope or stoniness. The fact that ST prohibits soil classes at the series level from crossing any hierarchical boundaries with classes above them is crucial to understand. Among all soil classification systems, the USDA Soil Taxonomy is distinct in that it specifies a whole new set of terms for the upper classes. Despite seeming odd at first, these phrases encode the large group, suborder, and order they represent directly. They also avoid the confusion-causing issue of giving terms that are already in use new meanings. From ancient tropical soils disturbed by millennia of earthworm activity to Arctic permafrost, the USDA's Soil Taxonomy system is made to function with soils from all over the world. By dividing categories using diagnostic ranges, it also aims for objectivity. Still, there are many who disagree with the system. Thus, comparatively uniform natural soil bodies that are dispersed throughout several soil series cannot be shown on a soil map as a single plot unit. Consequently, Nettleton et al. It is advised to lift this limitation. He proposes looking into non-hierarchical classification systems because, in contrast to Nettleton et al., he does not see a way out of this predicament. Fitzpatrick, who created his classification of non-hierarchical soils because he was so against any kind of soil hierarchy, made a similar argument with great vigor. Most likely the most intricate and sophisticated soil classification system is the USDA "Soil Classification" utilized in the United States. It makes the claim to be broadly applicable and acts as a benchmark for contrasting with other systems. In addition to containing water, air, and living things, soil is the end result of the transformation of minerals and organic materials on the surface of the Earth. It exhibits its morphological organization and has grown and is still growing as a result of environmental influences. Higher plants develop in soil, which also provides the foundation for animal and human survival. Given that soil expands both in space and time, it is a four-dimensional system. Everyone has a general notion of what soil is, yet soil experts' opinions can frequently differ greatly from ours.Experts view soil as a complicated system with a distinct structure, while laypeople typically think of the "earth," the black surface layer that aids in plant growth in fields and gardens [23].

10.4 French Référentiel Pédologique

"Référentiel Pédologique" (RP) is a type system as opposed to a rank system, like the USDA's "Soil Classification" and the German "Bodensystematik" [24]. The system's goal is to achieve a distinct division between the conceptual domain and the actual reality. In RP language, the solum, or vertical section of soil visible in a trench or pit, represents the reality soil mantle. The reference horizon and the conceptual solum or reference are the two key ideas connected to this reality. In contrast to USDA diagnostic ranges, reference ranges are conceptual ranges that are defined in morphogenetic typology, allowing for educational interpretations. In stark contrast to the USDA system, the RP places more weight on pedagogical judgments and less on exact definitions. The USDA's "soil taxonomy" is a prime example of an unstable system since minor variations can have a significant effect. For example, the diagnostic ranges used to classify soils as hiatus require that a specific percentage of topsoil organic carbon be present. One comparable soil beyond that limit and one below it will wind up in entirely different regions of the USDA system. One more way that RP differs from other systems is that it may be made to adjust to the specific needs of local classification by simply adding (local) references.

Table 3 Classification of the desired test soil

Clay	C	CL	CH	-
Silt	M	ML	MH	-
Sand	SM	SC	SW	SP

Table 4 Details of a typical borehole in the Saqqez zone

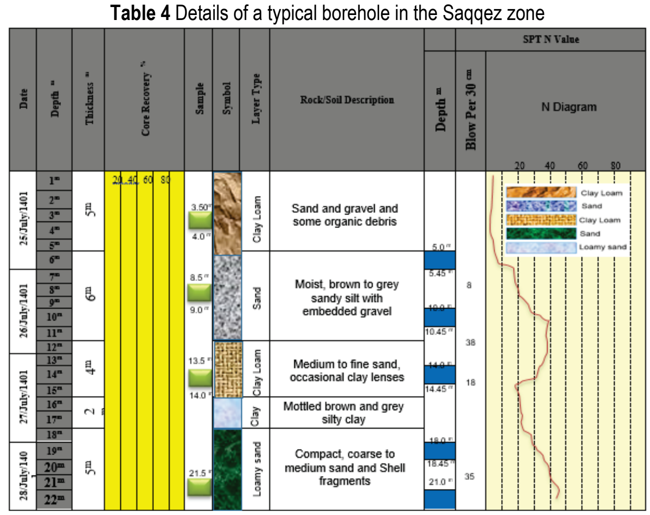
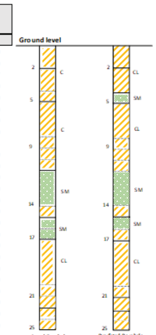


Table 5 A example of the record from the site inspection for the borehole

Depth	USCS	SPT	Ground water level 2m LL	PL	PI	W%	Yd	Direct shear C	Φ	Consolidation Cc	Cs	Pc
1	CL	9.2	43.3	34.8	9.3	34.1	2.5	0.0	0.0	0.0	0.0	0.0
2		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	CL	9.2	49.5	35.0	15.3	36.6	2.5	0.0	41.4	0.2	0.0	1.7
4		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	CH	17.3	63.1	37.4	26.5	36.1	2.5	0.0	0.0	0.0	0.0	0.0
6		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	CL	8.1	53.0	30.1	23.7	32.4	1.7	0.0	0.0	0.2	0.0	2.3
10		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11	ML	20.7	31.8	31.8	0.8	33.6	2.4	0.0	0.0	0.0	0.0	0.0
12		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
13		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
15	CL	12.7	49.6	31.6	18.8	42.2	2.3	0.0	0.0	0.0	0.0	0.0
16		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	ML	12.7	45.7	27.9	18.6	28.3	2.5	0.0	0.0	0.0	0.0	0.0
18		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
19		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
22	ML	25.3	49.1	29.6	18.0	40.0	2.5	0.0	0.0	0.0	0.0	0.0
23		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
24	MH	34.5	52.6	38.8	20.0	29.7	2.6	0.0	0.0	0.0	0.0	0.0
25	ML	35.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0



A few soil parameters, including bulk density, water saturation percentage, sand, silt, and clay, were included in the input data for the prediction of FC and PWP. However, the cation exchange capacity projection used organic carbon and clay as inputs. found a substantial relationship between CEC and these inputs. shows the RMSE plot for every one of the many neurons in the buried layer. The best model for every soil attribute was produced using two neurons, as these data showed. For cation exchange capacity, correlation coefficients of 0.86 and 6.43 were found; for water percentage at permanent wilting point, 0.82 and 4.58; and for water % at field capacity, 0.86 and 6.1. Using MATLAB software, multi regression was calculated for three soil train data sets.

11 PREDICTION OF A BOREHOLE AND COMPARISON WITH ACTUAL BOREHOLE INFORMATION

Ultimately, the following graphically illustrated result was generated by running the application at a point where the layering information is available. When it comes to accurately predicting the type of soil, the shape is perfect, and its association with depth accuracy is also rather good. Naturally, modeling cannot adequately convey the presence of local lenses, which are the shape of the SM layer seen at a depth of six meters. It is not very significant in light of the objectives of this study.

Table 6 Statistical information for the FC and PWP test data sets

Neurons in hidden layers		Clay	Silt	Sand	SP	OC	Bd	FC	PWP
Training set	Min	13.8	19.7	4.7	29.9	0.0	1.4	18.9	6.0
	Max	89.4	86.6	55.0	102.6	39.1	2.0	55.4	32.1
	Mean	47.4	51.6	19.5	60.6	1.3	1.7	36.4	18.7
	Std	18.3	13.9	10.9	15.1	4.1	0.1	7.5	6.2
RMSE (%)		17.8	19.9	18.1	19.7	17.4	17.6	17.8	17.5

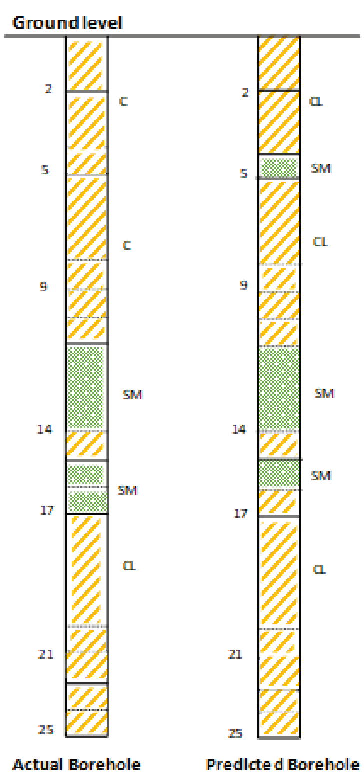


Figure 3 Borehole and comparison with actual information

The proposed neural network is designed to predict soil layers in boreholes at a site. The network uses coordination (x, y, z) to recognize the class of layer. The results show a high level of accuracy in predicting soil layers. Three performance measurements are used to evaluate the classification strategy: correctly classified instances for total accuracy, true positive rate (TPR) and false positive rate (FPR). The confusion matrix is used to assess the classification strategy. The precision of the network is indicated by the main diagonal, where higher values correspond to more accuracy. Soil layer depth and class are predicted using a multi-layer perceptron (MLP). The training approach uses supervised learning and is based on back propagation. The accuracy of the ANN model Soil layer depth and class are predicted using a multi-layer perceptron (MLP). The training approach uses supervised learning and is based on back propagation. The accuracy of the ANN model in predicting soil layers was up to 86%. The actual data and the ANN's forecast are compared to determine the accuracy values.

According to the shape in the forecast in the soil type is perfectly correct and in the case of depth is accompanied by good accuracy. The SM layer, which is at a depth of 5.5 meters, is in the form of a vertical lens.

12 CONCLUSION

The researchers created a model using Artificial Neural Networks (ANNs) to forecast the soil composition of Saqez City, Iran. Saqez City's 100 square kilometers of data were gathered, and the data was then trained to classify various soil strata at various depths. At a given depth, the model could calculate each layer's thickness. In the initial stage of geotechnical projects, site research was made possible by the model's 85% prediction accuracy. When input examples fall inside the trained range, the accuracy of the model is enhanced. Subsequent studies will concentrate on the accuracy of ANN models in data set extrapolation. Because of the precision of the model, fewer boreholes need to be drilled, potentially saving time and money.

1) According to the results obtained, the information obtained from the artificial neural network in the investigation of geotechnical phenomena such as estimating the thickness of the earth's layers, compiling the field operation plan. Interpretation of land conditions and soil classification using its characteristics has acceptable accuracy.
2) Using a closed environment instead of using data dispersion is associated with better results.
3) With the increase of boreholes during network training, the forecasting accuracy also increases.
4) Placing local lenses in the training data category increases the overall error and is recommended to be removed in the modeling.
5) When we have the concentration of boreholes in one area and the point where we want to determine the layering of the soil is also located in the same area, it is recommended to do modeling around this area in a closed environment and from boreholes far away from this area. Do not use it in modeling.
6) In cases where the boreholes are almost uniformly

distributed if we have a concentration of boreholes at a certain point and the point where we want to determine the soil stratification is far from the location of the local concentration, it is recommended to have one borehole from the concentration point in the modeling. Should be used, otherwise, the changes made in the weight function will increase the error.

7) Local lenses are not seen in the software forecast.

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