Minireview Article

Application of Artificial Neural Networks in Soil Science research

ABSTRACT

Soil Science research plays a vital role in understanding and managing the complex processes occurring within the soil environment. Due to the increasing accessibility of innovative computing techniques, Artificial Neural Networks (ANNs) have developed into useful tools for modeling and forecasting soil-related activities. The numerous applications of ANNs in soil science research, with a focus on how well they can classify soils, assess soil fertility, forecast soil erosion, and estimate soil moisture. By training on vast datasets that contain the chemical, biological, and physical properties of soil, ANNs are able to accurately predict different soil types and enable land-use planning, precision farming, and environmental management. An effective and flexible tool for addressing a variety of problems associated with soil science research is provided by ANNs. They are vital tools for identifying soil types, evaluating fertility levels, predicting erosion, and soil moisture estimation. Due to their capacity to simulate intricate interactions and provide accurate forecasts about soil moisture. By improving ANN methodology and getting through related challenges, ANN approaches possess the potential to increase our understanding of soil science and encourage informed decisions for soil management and conservation.

Keywords: ANN, input-output, Prediction, Accuracy, soil properties

1. INTRODUCTION

The main focus of soil mechanics challenges is on a few soil types that exhibit unpredictable behaviors in the natural environment. It can be challenging and occasionally difficult to model soil behavior utilizing the majority of traditional physically-based engineering techniques. Artificial neural networks (ANN) are used to predict the complex characteristics of the soil since they have shown to be more accurate predictors than conventional methods. An enormous amount of attention has been generated by ANN as effective tools for modeling and forecasting intricate soil dynamics [13].

An enhanced learning algorithm known as a "Artificial neural network" (ANN) was developed in response to the study of biotic neural networks in humanoid brains. Here, the human brain is attempted to be mimicked. Even though they are referred to as artificial intelligence, artificial neural networks can only be employed with structured and numeric data as input. They are made up of a network of artificial neurons that can identify patterns in data, learn from it, and provide classifications or predictions. It is a potent technique for predicting and categorizing many physical, chemical, and biological traits of soil types. By training on large collections of data that contain samples of soil and related properties, ANNs are effectively able to capture the intricate spatial and temporal changes of soil parameters. ANN assists in understanding the characteristics of soil, producing precise forecasts, and applying this knowledge to guide decisions about land use, agriculture, and environmental preservation [28].

2. ANN: AN EFFECTIVE TOOL FOR AGRICULTURE

ANN generated models can be used to categorize soils, assisting with planning land use, managing soils, monitoring the environment, irrigation management, water resource planning, and estimation of soil moisture content. It can produce real-time predictions of soil moisture levels by taking into account inputs including precipitation, temperature, vegetation indices, and soil parameters. This makes it possible for farmers and managers of water resources to optimize irrigation methods, save water, and increase the effectiveness of water use in agriculture.

ANN provides a strong and adaptable method for tackling numerous difficulties in soil science research. Their promise to revolutionize soil management practices, boost agricultural output, and encourage sustainable land use is based on their capacity to model complicated interactions, anticipate soil attributes, and support informed decision-making. Researchers can gain new insights into soil science and help to improve soil conservation and environmental stewardship by investigating and improving ANN techniques.

2.1. Architecture of an artificial neural network

A neural network consists of a large number of artificial neurons, which are termed units arranged in a sequence of layers. Artificial Neural Network primarily consists of three layers namely Input, Hidden and Output Layers. Input Layer accepts inputs in several different formats provided by the programmer. It serves as the network's primary source of raw data. The hidden layer presents in-between input and output layers. It performs all the calculations to find hidden features and patterns and acts on the input and weights from the layer before it by applying a non-linearity before sending the results to the output layer. Output layer collects and transmits the information in a planned manner. The input goes through a series of transformations using the hidden layer, which finally results in output.

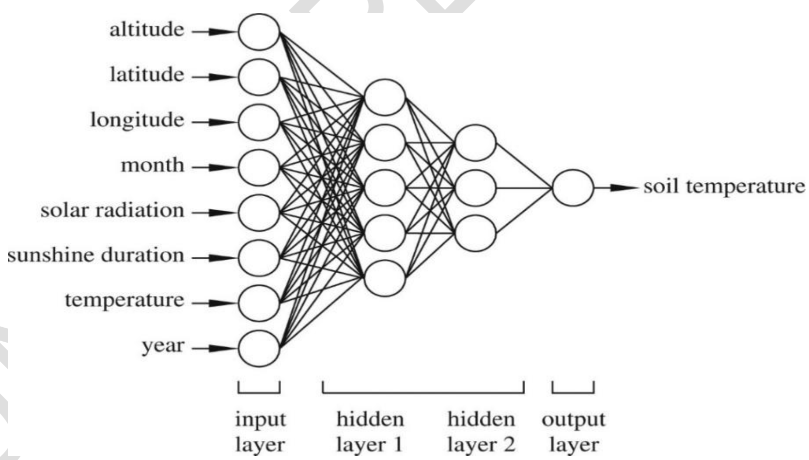

Fig.1 ANN model used for estimating monthly mean soil temperature at various depth
(Source :Ozturk Murat et al., 2011)

2.2 Applications of ANN in soil science research

2.2.1. Predicting engineering properties of soil

Predicting soil engineering properties, viz. maximum dry density (MDD), optimum moisture content (OMC), permeability, unconfined compressive strength (UCS), and shear strength parameters is a difficult task. These engineering properties depend on water content, dry density, and bulk density, mineralogy present in the soil, liquid limit, plastic limit, plasticity index, linear shrinkage, grain size distribution, particle shape, and lots of other parameters.ANN algorithm is favorably used for predicting the engineering properties of soil depend on the input parameters [31] [10].

2.2.2. Compaction parameters

ANN was applied to estimate maximum dry density (MDD) and unconfined compressive strength (UCS) of stabilized soil where ANN was a more accurate prediction method [1] [8]. As inputs, soil plasticity (LL, PI), clay content (C), sand content (S), gravel content (G), moisture content (MC), and cement content (CC) were utilized to estimate the MDD and UCS of cement stabilized soil [9] [29].

2.2.3. Permeability

A soil's ability to allow water to travel through it is referred to as permeability. Given that groundwater conditions are regularly encountered during construction projects, permeability is a crucial soil engineering attribute that the designer must be aware [27]. ANN is used as a tool to predict the soil permeability coefficient ‘k’ allowing the reduction of the costs and time needed to conduct laboratory or field tests to determine this parameter. They presented a method that can be extended to more types of non-cohesive and cohesive soils [14].

2.2.4. Shear Strength Parameters

The shear strength of the soil determines its capacity to support a slope in equilibrium, assist in the stacking of a structure, or support its overburden [2]. Shear strength criteria are utilized for foundation design, slope stability, earth and rock fill dam design, earth pressure issues, and highway and airfield design [22]. Shear strength of soil (expressed in terms of cohesion and friction angle) is significant in designing of civil engineering structures and for solving many geotechnical problems. The compaction characteristics, permeability, and soil shear strength were related to soil index properties [31]. The potential of ANN and regression tree technique has been used for the indirect estimation of shear strength parameters [17].

2.3. Predicting the geotechnical aspects of expansive soil

Artificial neural networks are used to forecast the complexity of the soil and more efficient. Geotechnical engineering can be used to predict a number of expansive soil parameters, including free swell index, unconfined compressive strength, soil shear strength, swelling pressure, swell percent, and plasticity index.

2.3.1. Free Swell Index

Plasticity index and shrinkage index were given as input factors, with free swell index as the output factor. Back propagation and multiple regression models were used to investigate the ANN model. The free swell index of the soil was precisely estimated using the suggested neural network architecture [12].

2.3.2. Unconfined Compressive Strength

By using artificial neural networks and regression analysis [26]. The prediction of unconfined compressive strength (UGC) of a treated expansive clay soil was done. The soil sample's curing time, the doses of bottom ash and eco sand used as stabilizers, the liquid limit (LL), the plasticity index (IP), and the free swell index are just a few of the elements that go into creating a model.

2.3.3. Swelling Pressure and Swell Percent

Artificial neural networks are used to estimate the swelling pressures of expansive soils. A model with two different transmitted pressures, such as horizontal swelling pressure and perpendicular swelling pressure, was created using the ANN technique. These pressures were used to train an artificial neural network (ANN) to predict transferred lateral and vertical swelling pressure [16].

2.4. To estimate soil temperature

ANN has the ability to recognize complex online correlations between environmental variables and soil temperature [23]. In terms of predicting soil temperature; ANN models performed better than traditional regression models and showed positive outcomes [20]. ANN models performed better than Support Vector Machine models in terms of accuracy and had fewer errors. Due to their accuracy in estimating soil temperature, ANN models can be useful in agricultural and environmental studies [36] [32]. ANN models can successfully be used to estimate soil temperature with high accuracy, especially when trained on big datasets [21] [30].

2.5. To estimate soil water retention

The potential of ANN models to forecast the properties of soil water retention was highlighted [25]. It highlighted the extent to which ANNs represent complex non-linear relationships between soil properties and water retention. When estimating soil water retention, ANN models are frequently more accurate than traditional regression models [4]. The performance of ANN and multiple linear regression (MLR) models to estimate soil water retention. In terms of accuracy and precision, ANN models excelled MLR models. The ANN models were able to capture the nonlinear nature of the relationships between soil properties and water retention, which improved predictions [5] [20].

2.6. Estimation of soil properties by using ANN

ANN’s capacity to manage intricate connections between soil qualities and environmental conditions. ANN models were effective at predicting soil characteristics like pH, organic carbon concentration, and clay content [19]. To estimate soil parameters, the effectiveness of ANN models with regression models. The outcomes demonstrated that ANN models performed better than regression models in terms of precision and accuracy. ANN models are useful for forecasting soil characteristics and can offer insightful information for soil management and land-use planning [15]. The benefit of ANNs in managing complicated, non linear interactions and capturing spatial variability was emphasized [34]. ANN models have shown promise in predicting soil parameters like soil moisture content and soil texture [24].

2.6.1. To predict soil hydraulic conductivity

The effectiveness of using ANN models to forecast soil hydraulic parameters, such as hydraulic conductivity [35]. It demonstrated how effective ANNs are at capturing intricate connections between soil properties and hydraulic conductivity. ANN models out perform conventional regression models and can offer precise estimates of hydraulic conductivity. In order to estimate soil hydraulic conductivity the effectiveness of pedo-transfer functions (PTFs) and ANN models [3]. ANN models outperformed PTFs in terms of accuracy and had fewer errors. ANN models can be useful for hydrological modeling and can be good in estimating soil hydraulic conductivity.

2.7. ANN in predicting crop yield

ANN is currently a preferred technique for crop yield prediction, forecasting, and classification in biological science domains. Regression models take more time to design, but an ANN model can forecast crop yields more accurately than regression models. There are many variables that affect agricultural productivity, and it will be shown how to utilize ANN to predict crop yield utilizing both direct and indirect variables [7].

2.7.1. FACTORS IN ANN

- ANN in environmental factors.
- ANN in soil and soil-plant hydrology.
- ANN in sensing technologies.
- ANN in biomass factor.
- ANN in controlled environment.

2.7.1.1. ANN in environmental factors.

The yield at the end of the growing season is strongly influenced by the environment for agricultural plants including wheat, corn, soybean, and paddy. The most crucial environmental elements that affect plant development, growth, and production include temperature, photoperiod, and water stress [33].

2.7.1.2. ANN in soil and soil-plant hydrology

In order to evaluate the nonlinear relationship between soil characteristics and crop yield used a feed forward neural network. The estimated yield maps produced by the neural network method tended to be fairly close to the real yield map, despite the fact that the model tended to overestimate low yielding sites while underestimating the higher yielding ones [11].

2.7.1.3. ANN in sensing technologies.

For site-specific management in agriculture, sensing technologies have grown in significance. Many different types of sensors and instruments, including field-based electronic sensors, spectro radiometers, machine vision, air borne multispectral and satellite imagery, thermal imaging, etc., have been used in the development of sensing systems for various applications, including yield mapping and prediction, irrigation control, etc. These technologies have a wide range of applications in monitoring a wide range of variables, including crop nutrients, water content, and soil characteristics [18].

2.7.1.4. ANN in biomass factor

In order to forecast leaf moisture, created a generalized regression neural network (GRNN), which they later compared to multiple linear regression (MLR). Based on temperature, relative humidity, wind speed, solar radiation, and prediction, leaf wetness is forecast in order to forewarn of disease in agricultural crops that would sooner or later damage crop yield production [6].

2.7.1.5. ANN in controlled environment

In controlled environments like green houses and glass houses, ANN models have also been used. In a green house, environmental elements include temperature, humidity, radiation intensity, and carbon-dioxide concentration a real ways taken into consideration in order to optimize plant development and production [33].

3. CONCLUSION

Artificial neural network (ANN) use in soil science research has considerable promise for overcoming major obstacles and improving our comprehension of phenomena relating to soil. An effective tool for increasing soil science research is ANN. They have the potential to revolutionize soil management techniques, increase agricultural output, and encourage sustainable land use due to their capacity to model complicated soil processes, anticipate soil attributes, and support decision-making processes. Researchers can gain new insights into soil science and help to improve soil conservation and environmental stewardship by further investigating and improving ANN techniques. The continued use of ANNs in soil science research will open the door to a greater comprehension of the soil environment and the creation of methods for sustainable soil management.

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