# SOIL WATER FORECASTING SYSTEM USING DEEP NEURAL NETWORK REGRESSION MODEL

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**Abstract -** *With the development of mission critical sensors and sensor networks (MC-SSNs), using MC sensor for monitoring the changes of soil moisture has become convenient and real time. However, the method used to process the data obtained by the MC sensor directly affects the monitoring effect. Although the past research methods have achieved certain results, they all need to extract data features. In this paper, we propose the soil moisture retrieval algorithm with time frequency analysis and convolutional neural network (CNN) based on ultra-wideband radar echoes, which do not need to build feature database in advance. The algorithm transforms the soil echoes into time_ frequency (TF) distribution patterns and utilizes the CNN algorithm to classify soil echoes with different soil volumetric water contents (VWCs). Wigner_ Ville (WV) distribution and Choi_Williams (CW) distribution are the two methods used for time_ frequency transform; VGGNet and AlexNet are, respectively, applied to classify the TF patterns with different VWCs. We totally construct four soil moisture retrieval systems (WV-AlexNet, CW-AlexNet, WV-VGGNet, and CW-VGGNet), and the echoes of 27 soil water contents with different signal-to-noise ratios (SNRs) are studied. The simulation results with raw data show that the correct recognition rate of soil VWCs can reach 100% when the soil echoes are at 10 dB (SNR). The WV-AlexNet system has the best recognition performance among the four systems.*

***Key Words***: Security, Information, Outsourcing, Encryption, Protection etc…

## 1. INTRODUCTION

The effective soil parameter monitoring is the basis for implementing precision agriculture. The soil moisture plays an important role in soil parameters. Research on soil moisture helps farmers to grasp the growth of crops. The first key question is how to get the soil data needed for the study without destroying the soil structure. With the rapid development of MC-SSN in recent years, the use of MC radar sensor echoes to attain the data that can be used for analysis has become the main method. However, this method is more demanding on radar sensors and the radar scanning frequency is susceptible to multipath effects. The cross hole is a method of measuring the soil echoes by a ground penetrating radar proposed, but this method destroys the soil structure and requires a lot of manpower and material resources. Above all, we urgently need a simpler method of collecting soil echoes. The application of UWB radar has brought new development to soil monitoring technology due to its wide frequency band, good penetrability and strong anti-interference ability.

This method is simple in operation, high in measurement efficiency and high in accuracy. It is the most suitable technique for rapid measurement and monitoring of surface soil moisture content. Therefore, in this paper we improve and use this method to collect soil radar echoes. The above soil echoes measurement method is an important component of soil parameter retrieval, but the retrieval algorithm describing the mapping relationship between radar echoes and soil moisture is also the core of soil moisture retrieval technologies. The second key to research is how to get the soil moisture information we need from the collected echoes. At present, the existing method is to obtain a feature template by using various feature extraction methods, and then use the existing recognition method to identify the collected echoes according to the template used the fuzzy logic system to extract the feature template. However, the operation of this method is cumbersome, and the larger the amount of data, the larger the template database obtained. So we use the TFA method to preprocess soil echoes and CNN algorithm to recognize soil echoes with different VWCs. The TF image has the characteristics of time domain and frequency domain. It fully explores the characteristics of data itself, and therefore can replace the method of template. The CNN algorithm includes many powerful fitting algorithms, which can describe the high complexity and uncertainty relationship between soil echoes and soil moisture.

## 2. EXISTING SYSTEM

**•CNN**

The CNN algorithm used in this research is composed of three pairs of convolution layers and pooling layers with one fully connected layer on top, whose activation function of the top layer is changed from softmax loss layer to Euclidean loss layer.

**•ANN**

Difficulties associated with physically-based approaches have forced researchers to look for data driven forecasting tools such as Artificial Neural Networks (ANNs). Over the past several years, various attempts have been made to produce soil moisture estimates using these statistical models.

**•DNN**

Deep learning permits computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction.

This property of deep learning is useful for the classification problems with machine learning approach.

**2.1 Survey**

**A. Results of, measurements, processing and modeling of GPR data showing the effect of soil moisture content on land-mine detection.**

Summary form only given. To be able to predict the performance of a ground penetrating radar system (GPR) under certain environmental conditions, one needs to relate the parameters that predominantly determine the environment, to parameters that directly govern GPR performance. Soil type and soil water content are such environmental parameters. The latter is determined by prevailing (and historic) weather conditions and has a large effect on the electrical permittivity and conductivity of the soil medium. Thus, by relating soil water content to electrical permittivity and conductivity one can gain a better understanding of GPR performance and in principle could even predict GPR performance. For the purpose of land-mine detection it is advantageous to be able to have some idea of GPR performance under given circumstances. Knowledge about the environment will influence the choice of sensor and the moment in time, the de-miner wishes to deploy the GPR as mine detection sensor. These measurements were executed under relatively dry as well as moderately wet conditions, in both sand and grassy soils. Data acquisition was done on a high-density grid with several GPR systems. The test facility contains a number of moisture conditions to GPR measurements. In this paper we will illustrate the effect of soil moisture content of different soil types, on the detection of buried land-mines, and compare this with the outcome of a numerical GPR model which takes moisture level and soil type into account.

**B. An RFID-enabled inkjet-printed soil moisture sensor on paper for “smart” agricultural applications**

In this paper, an RFID-enabled inkjet-printed passive soil moisture sensor on paper for agricultural applications is presented and the design procedure, the operation principle and benchmarking experimental results are discussed in detail. A prototype made of a passive RFID tag integrated with a capacitive sensor, which consists of a printed interdigitated capacitor (IDC), has been printed on a low-cost paper substrate. The capacitance variation of the IDC shifts the resonant frequency of the RFID tag taking advantage of the soil-moisture based load matching variations since a matching condition changes due to the capacitive sensor. The proposed sensor can be easily integrated with conventional RFID systems for practical large-scale agricultural applications.

**C. Analyzing the effects of conductive and permeable soil on the EMI response for UXO discrimination 10th International Conference on Mathematical Methods in Electromagnetic Theory, 2004.**

Unexploded ordinances (UXO) are buried typically in the top 1 m of soil. Low frequency (from tens of Hertz up to several hundreds of kHertz) electromagnetic induction (EMI) sensing has been identified as one of most promising technology for UXO detection as well for discrimination. They use the principle of EM1 in which unseen object are detected by sensing eddy current induced in metal by a primary magnetic field. It is known that the EMI sensors are sensitive to the scatters electromagnetic parameters (conductivity and permeability). Therefore, in this paper, low frequency scattering from a highly conducting and permeable metallic objects buried in geological soil are exposed and analyzed from the unexploded ordnances (UXO) detection and discrimination point of new. The method of auxiliary sources (MAS) in conjunction with thin skin approximation (TSA) is used for understanding physics of electromagnetic induction (EMI) scattering phenomena. Several numerical examples are designed to show how the geological soil's electromagnetic parameters (conductivity and permeability) affect object's EMI response.

**D. Research on new grounding technology of transmission line tower in Karst area - (2014 International Conference on Lightning Protect ion (ICLP))**

Resistivity of soil in Karst area is on the high side so that resistance of transmission line tower is difficult to fulfill the requirements of lightning protection. This paper mainly studies the calculation method of transmission line tower resistance in Karst area, and influences of Karst caves to resistance. Considering Karst topographical features, according to the similarity of constant current field and electrostatic field, the model of soil and the physical model of grounding device in frequency current are built based on current distribution, electromagnetic fields, grounding and soil stricter analysis(CDEGS), the model of soil and the physical model of grounding device in impulse current are built based on COMSOL Multi-physics, frequency resistance and impulse resistance are calculated respectively. Finally, frequency and impulse simulation experiments are carried out in high voltage test platform to verify the models, based on dimensional similarity principle. The results show that the resistances calculated by models and resistances obtained by experiments match well. What is more, factors such as cavity size, distance between cavity and grounding device, are founded to have significant influence on resistance.

**E. The Contamination Characteristic of Cadmium in Soil and Green Plant in the Downtown Area of Zhaoyuan City- 2012 International Conference on Biomedical Engineering and Biotechnology.**

In April 2010, the soil and common green plants samples in the downtown area of Zhzoyuan City were gathered to study the cadmium (Cd) pollution characteristics of plants and soils in Zhaoyuan city. The investigation area was divided into 5 zones as industrial zone, inner commercial, inner residence, Traffic Area, Park and Plaza, the soil and plants sample was collected according the Uniform distribution principle with GPS. The content of Cd in soil and plants was detected by ABS. The study showed that Cd concentration in soil was accumulated at a high level, the lowest is 3.38mg/kg and the highest is 8.32mg/kg, the soil is polluted severely, its content is more than III standard. Different area has different Cd content: industrial zone is the highest, 6.98mg/kg is at the top, Park and Plaza is at the lowest, the difference in the concentration is not very great, the city's pollution has been fairly well-distributed. The physics and chemistry characteristics of soil, such as pH, CEC and organic matter are the factors that influence the Cd concentration. The study showed that only pH has the significantly correlation with Cd concentration. Other rationalized in the Cd in the concentration is not obvious relevance. Cd concentration in plants is 0.53-0.84mg/kg. The positive relationship is significant between soil and plants about the Cd concentration.

## 3. PROPOSED SYSTEM

### 3.1 DNNR

Deep Neural Network Regression (DNNR) is a multi-hidden layer (at least two layers of hidden layers) regression neural network. Compared with the single hidden layer perception, when the same data is fitted, the increase of hidden layer depth in DNNR means the reduction of nodes in each hidden layer, which can improve data fitting capability. The advantage of the DNNR model is that it can correlate or discover feature combinations that have not appeared before, and is good at fusing hidden feature attributes, reducing the complexity of feature engineering and improving the generalization capability of the model.

The regression prediction should be clear about the correlation between each variable and the predicted feature, so that reasonable parameter characteristics can be selected for model training.

**Advantages**

- Early Announcement
- Soil Moisture Active Passive
- At best, it can only validate the behavior of global models over small number localities.

Applications ƒ (f = fertility)

- Monitoring of extreme hydrologic events ƒ
- Runoff forecasting ƒ
- Data assimilation ƒ
- Numerical Weather Prediction ƒ
- Landslide monitoring ƒ
- Vegetation monitoring ƒ
- Agricultural monitoring ƒ
- Epidemiological prediction ƒ
- GHG budget ƒ
- Climate studies ƒ
- Ground water modeling

**Dataset**

Soil Moisture Level Dataset from UCI Repository

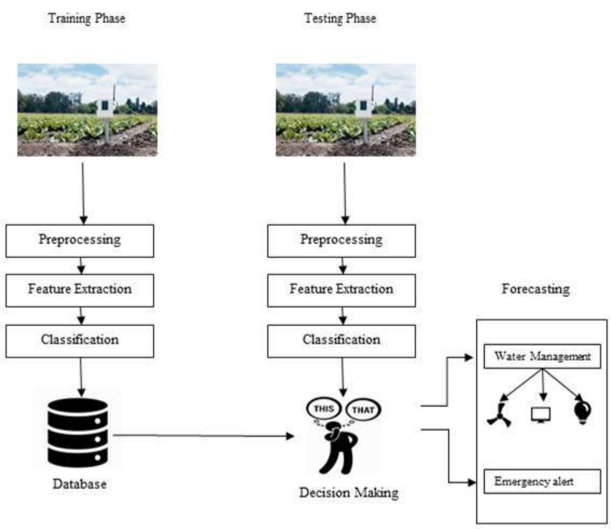


**Fig -3.1**: Architecture Diagram

### 3.2 MODULES

1. Dataset Acquisition
2. Preprocessing
3. Methodology
4. Forecasting
5. Performance Evaluation

### 3.3 MODULES DESCRIPTION Dataset Acquisition

This data set contains in-situ soil moisture profile and soil temperature data collected at 20-minute intervals at SoilSCAPE (Soil moisture Sensing Controller and oPtimal Estimator). Once an appropriate dataset has been acquired, it is transferred to the computer system and mapped to the soil data. This mapping is called registration and requires the identification of specific features or anatomical landmarks in the dataset and on the soil.

**Preprocessing**

Different sources of meteorological data and soil moisture data result in different data formats and lengths. Data integration and matching is required. The deep learning model requires a large amount of data for training purposes and a long time-span data set to ensure complete data characteristics. The method involves selecting the training set and test set according to the amount of soil moisture data. The integrated data contains missing values. If the missing value is included, and induces a large error, it will cause interference in the model training. Therefore, we chose to eliminate data with missing values. The final data set contains six meteorological features, as well as an initial moisture feature, and a pending prediction feature of soil moisture.

**Methodology**

In this module the DNNR is applied, a DNN model is used as a feature extractor and a regression model to retrieve the daily global soil moisture from the brightness temperature. deep learning is suitable for soil moisture prediction because of its data fitting capabilities. For soil temperature, the regression tree forecasts were better at nearly all the sites and depths. The regression prediction should be clear about the correlation between each variable and the predicted feature, so that reasonable parameter characteristics can be selected for model training. The first step is to analyze characteristics of the predicted variable.

**Forecasting**

Forecasting Framework will be implemented here, The importance that wet and dry events have on socioeconomic activities has motivated the development of drought monitoring and prediction tools. To further document and understand seasonal differences. This work introduces a Soil Moisture Forecasting Ensemble Model (SMFEM) by combining the features of various machine learning approaches.

**Performance Evaluation**

Four evaluation measures were selected to indicate the performance of the different models. Mean Absolute Error(MAE), Mean Squared Error(MSE), Root Mean Squared Error(RMSE) and R Squared(R2).

### 3.4 ALGORITHM DESCRIPTION DNNR ALGORITHM

With the rapid development of artificial intelligence in recent years, in 2006, Hinton proposed Deep Learning (DL), which uses a multiple hidden layer structure to increase the classification and fitting capability to big data and multi-feature data. Compared with traditional neural networks, it shows strong computing power and has been successfully applied in image recognition, search engines, stock price predictions, and other fields. Owing to the nonlinear and extremely complex nature of soil, some scholars have introduced DL into soil particle size and soil texture analysis in recent years, overcoming the problems of low prediction accuracy. Based on this, our aim is to construct and optimize a soil moisture prediction model through deep learning and its powerful data processing capabilities to achieve high-precision prediction

## 4. DATA PROCESSING AND ANALYSIS

Different sources of meteorological data and soil moisture data result in different data formats and lengths. Data integration and matching is required. The deep learning model requires a large amount of data for training purposes and a long time-span data set to ensure complete data characteristics. The method involves selecting the training set and test set according to the amount of soil moisture data from 2012 to 2016. The integrated data contains missing values. If the missing value is included, and induces a large error, it will cause interference in the model training. Therefore, we chose to eliminate data with missing values. The final data set contains six meteorological features, as well as an initial moisture feature, and a pending prediction feature of soil moisture. After processing, a total of 1,196 data samples from Yanqing area were obtained, including 954 sets of data from 2012 to 2015 to build a training set, 242 sets of data in 2016 to build a test set, and 50 data samples were randomly selected from the test set for model selection. At the same time, a total of 239 data from Shunyi area in 2016 and 235 data from Daxing area in 2016 were used to verify the extensibility of the model.

To predict the data, we must first understand the trend of the predicted features. According to Fig 1, the water timing chart of the four years from 2012 to 2016, although the moisture data fluctuates greatly, presenting a periodical status overall, generally from July to September each year represents the data peak, the maximum soil water content is up to 25.6%. From November to February of the next year indicates the period for minimum water content, which is only 7.50%. However, different years show large discrepancies because of different meteorological conditions. Facing such complex prediction features, deep learning is suitable for soil moisture prediction because of its data fitting capabilities.

The regression prediction should be clear about the correlation between each variable and the predicted feature, so that reasonable parameter characteristics can be selected for model training. The first step is to analyze characteristics of the predicted variable. It can be seen from Fig 2 that the autocorrelation graph of the predictive feature has no rapid decay to zero with increases of the delay period, so because the soil moisture characteristic is a stationary time series. Therefore, it is possible to grasp the changing trend of soil moisture characteristics according to relevant meteorological parameters.

**C. EXPERIMENTAL RESULTS AND ANALYSIS**

In order to compare the performance of the CNN and DNNR models, four classification systems, we selected the loss values generated by the two models during the training process. We use cross entropy to represent the loss of the training process.

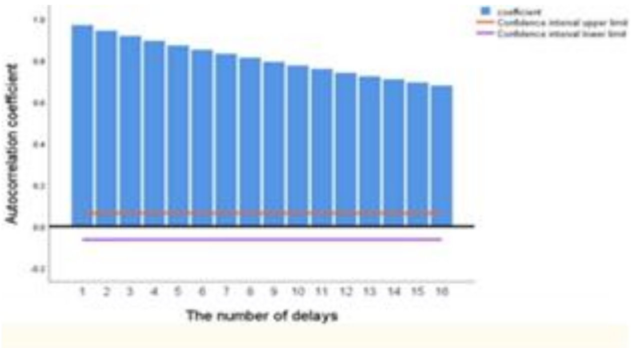


Fig 4.1 Data Process and Analysis Bar Chart Representation

Fig 4.1 explains the results of the correlation analysis between the features of the data set and soil moisture are shown in. The reference variable of the Taylor map is the soil moisture feature (the REF point of the X- axis), and other features standard deviation divided by the standard deviation of the soil moisture are used to obtain the standard deviation ratio, which can be used to evaluate the similarity between the fluctuation range of other features and the moisture feature, and is then added into the correlation to participate in the analysis. There are seven variables to be analyzed, where points 3 and 4 (average humidity and average wind speed) are outside the standard deviation range. The data fluctuation range of these two points is more than 1.5 times the soil moisture, and exhibit data jump phenomena. Point 2 (average pressure) has a standard deviation ratio of less than 0.25 (the data fluctuation is much smaller than the moisture fluctuation range), but the correlation is the lowest. The data fluctuations of the three variables of points 1, 5, and 6 (average temperature, daily precipitation, and surface temperature) are close to the REF data. The standard deviation ratio is approximately 1.5, and the correlation is between 0.1 and 0.3. Point 7 (initial moisture) is the closest to the standard deviation ratio of the soil moisture prediction data, almost coincides with the REF line, and the correlation is close to 0.99, which indicates strong correlation characteristics. Thus, it is an essential training feature to provide maximum weight for soil moisture prediction to improve regression accuracy.

Table 4.1 Soil Characteristics of different days

| Date | Temp | Humidity | Moisture | Result |
|---|---|---|---|---|
| 20-08-2019 | 10.53 | 11.76 | 11.91 | **Normal** |
| 21-08-19 | 2.38 | 3.21 | 4.59 | **Low Level** |
| 22-08-19 | 32.47 | 29.65 | 24.53 | **Overfull** |
| 23-08-19 | 2.05 | 1.09 | 1.16 | **Low Level** |
| 24-08-19 | 29.52 | 33.04 | 28.09 | **Overfull** |
| 25-08-19 | 20.67 | 21.41 | 22.53 | **Normal** |

Normal - Fertilty of the soil is more than the required fertility rate of a crop.

Low Level - Fertilty of the soil is less than the required fertility rate of a crop.

Overfull - Fertilty of the soil is fit for the crop

Table 4.1 show that the four soil moisture classification systems have high probability of correct recognition. Under the influence of different noise levels, the WV-AlexNet system maintains the highest correct recognition probability, and as the noise increases, the correct recognition probabilitydecreases the least.

During the training process, the two CNN models have a sudden increase in individual loss values, away from the cluster point, indicating that the adjusted parameters are not optimal for all situations, but the final results are optimal, indicating that CNN is unstable in the training process due to too many parameters and layers, and it is prone to fluctuations. At the same time the DNNR provides the accurate results and provides the detailed information of the uploaded data or the given input.

The ability of two CNN models to classify soil echoes with different VWC is similar. However, the execution time is four times that of DNNR, and the different SNRs do notice influence the running time.

As of the previous results the DNNR specifies the perfect values by deep learning techniques and provides the exact scenario of each and every level of the data that has been inbuilt and uploaded by the users involved in the system. Due to deep learning technique the entire data and datasets are completely analyzed and classified for extraction to get an enhanced result that has been provided by the DNNR.

## 4. CONCLUSIONS

This paper proposes a soil water content classification algorithm based on TFA images and CNN under MC radar sensor condition. Time-frequency transform technology is used to convert soil signals with different VWCs into time-frequency analysis images, and input into deep learning model to achieve the purpose of classification and identification of water content corresponding to soil signals. In this paper, Wigner- Ville time-frequency transform and Choi-Williams time-frequency transform are used respectively, and two deep learning frameworks, ALexNet and VGGNet, are used in the classification process to construct four recognition systems. Four system performances were verified using 27 categories with different soil VWCs measurements.

The results show that the four soil moisture classification systems have high probability of correct recognition. Under the influence of different noise levels, the WV-AlexNet system maintains the highest correct recognition probability, and as the noise increases, the correct recognition probability decreases the least.

At the same time, CW-Alex Net has a classification ability close to WV-Alex Net with a faster training process, which is more suitable for the identification of soil echoes with different VWCs. Though CW-VGG Net also has a high CRR, it is not suitable for big data sets' classification due to its long execution time.

This system is helpful to the farmers by providing realistic information about the soil moisture statistics in future and the changes to be incorporated in the cropping pattern. In future, this work can be extended to the real deployment of soil moisture sensor nodes in the field of interest to collect the measurements and the performance of the proposed approach is to be investigated.

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