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GROUND WATER LEVEL PREDICTION USING MACHINE LEARNING

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Abstract – ***This Paper introduces the implementation of different supervised learning techniques for producing accurate estimates of ground water, including meteorological and remotely sensed data. The models thus developed can be extended to be used by the personal remote sensing systems developed in the Center for Self-Organizing Intelligent Systems (CSOIS). To analyze these data and to extract relevant features, such as essential climate variables (ECV), specific methodologies need to be exploited.. The new algorithm enhances the temporal resolution of high spatial resolution of soil moisture observations with good quality and can benefit multiple soil moisture-based applications and research.***
Keywords – Soil Moisture, SVM, ANN, Machine Learning

Introduction

Surface soil suddenness is usually the water content inside the upper 10 cm of soil. Despite the way that such water is a little piece of the overall water content, it is on a fundamental level basic to various hydrological, biochemical, characteristic, green and various strategies. Various applications also incorporate surface soil clamminess as a key variable, including improvement building, meteorology, ecological change watching, characteristic science and country illustrating. On account of these real factors, it is basic to screen soil moistness conditions, especially to secure spatial and short lived assortments in soil clamminess. To get whatever number soil sogginess recognitions as could sensibly be normal with as high a quality as could be normal considering the present situation, much effort has been applied. Their discrete discernments measure soil suddenness exactly at express regions and are thusly insufficient to address the earth clamminess spatial transport, notwithstanding the way that they give fleetingly relentless recognitions SM is as a general rule a key state variable that impacts both overall water and essentialness spending plans by controlling the redistribution of precipitation into attack, flood, penetration in soil. SM

Over the top SM conditions that are addressed by submersion and the unchanging shrinking point (whose characteristics depend upon soil surface and structure) can propel flood events or show dry seasons. Exactness agribusiness is a developing the board technique that remembers the examination of the spatial assortments for a gather field using mechanical gadgets, for instance, Global Positioning Systems and airborne pictures. This examination can be helpful in assessing manures and other data needs by studying the close by affliction and soil conditions in a predominant way, hence hindering inflexible practices in developing. The upsides of precision cultivating are genuinely critical in agronomical, characteristic, particular and down to earth perspectives. For the meteorological strategies, SM is the "memory of precipitation" since it stores water and transmits it by methods for disappearing or overflow with some delay. On account of these credits and to the mind boggling sway externally imperativeness exchange, SM substance may emphatically influence ecological change components

DATA PROCESSING:

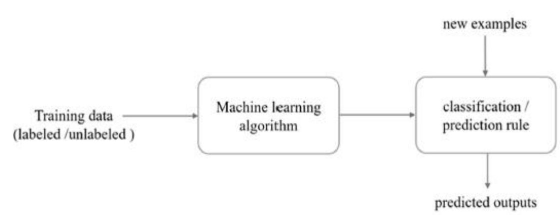

Fig.1. Data process in ML

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The performance of the ML model in a specific task is measured by a performance metric that is improved with experience over time. To calculate the performance of ML models and algorithms, various statistical and mathematical models are used. After the end of the learning process, the trained model can be used to classify, predict, or cluster new examples (testing data) using the experience obtained during the training process.

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SYSTEM ARCHITECTURE:

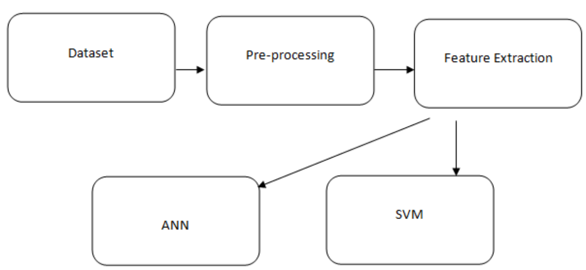

Fig.2. Types of ML algorithms

The classification capabilities of traditional SVMs can be substantially enhanced through transformation of the original feature space into a feature space of a higher dimension by using the "kernel trick". SVMs have been used for classification, regression, and clustering. Based on global optimization, SVMs deal with overfitting problems, which appear in high-dimensional spaces, making them appealing in various applications.

ANNs are supervised models that are typically used for regression and classification problems.
The learning algorithms commonly used in ANNs include the radial basis function networks, perceptron algorithms, back-propagation, and resilient back-propagation. They are a relatively new area of ML research allowing computational models that are composed of multiple processing layers to learn complex data representations using multiple levels of abstraction. One of the main advantages of DL is that in some cases, the step of feature extraction is performed by the model itself. DL models have dramatically improved the state-of-the-art in many different sectors and industries, including agriculture.

LITERATURE SURVEY:

Vertessy and Elsenbeer argued that a poor understanding of soil moisture remains one of the most significant weaknesses in process-based storm flow models and the ability to predict runoff generation and erosion[1], while Grayson et al. argued that antecedent moisture is the parameter most likely to undermine model predictions[2]. Through its role in flow partitioning, antecedent soil moisture is also an important physical control on nutrient and sediment loss by overland flow (Casenave and Valentin, McDowell and Sharpley, McDowell et al) and has been demonstrated in several studies[3] (Ceballos and Schnabel, Fitzjohn et al., Karnieli and Ben-Asher)[4]. The degree to which soil moisture is a primary control on runoff generation and erosion depends on basin size and the characteristics of the precipitation event[3]. Castillo et al. It have shown that the peak discharge and runoff during high-intensity, low-frequency storms is independent of initial soil water content, but is important in controlling runoff during medium and low-intensity storms that are primarily responsible for erosion in semi-arid environments[2] (see also Merz and Bardossy, Poesen and Hooke)[6]. Soil moisture is more important where vegetation increases the spatial variability of soil characteristics and produces a range of runoff and infiltration sites (Castillo et al.)[7]. Similarly, Fitzjohn et al. have shown that spatial heterogeneity of surface moisture can reduce widespread catchment runoff and erosion by promoting discontinuity in hydrological pathways through the isolation of runoff-producing areas and the reabsorption of runoff generated upstream[8].
The role of vegetation in controlling dust emissions is most difficult to quantify because the relationships between soil moisture, vegetation cover, and turbulent shear stresses are poorly understood. Low soil moisture combined with a lack of surface cover, strong winds and low humidity is an important factor associated with dust events (Nickling and Brazel, Lee et al., Stout)[7].

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TECHNOLOGIES USED

Python

Python is high-level, interpreted, and general purpose programming language. Released first in 1991 by Guido van Rossum. Its object-oriented approach aims the programmers to write clear, logical code for large and small scale development. It is a garbage collected and dynamically typed.
This language contains a substantial body of documentation, abundant of it contributed by various authors. The markup used for the Python documentation is restructured text, developed by the docutils project, amended by custom directives and using a toolset named sphinxto post-process the Hypertext Mark-up Language (HTML) output.

Machine Learning

Support Vector Machines

The learning algorithm involved in Support Vector Machines (SVMs) comes under supervised learning. It is a widely used classification algorithm. For a simple binary classification problem, we can say that a support vector machine draws a optimal separating hyperplane between the two classes of data. The hyperplane is chosen following the fact that confidence in predictions improves when a point is far from the separating hyperplane that is the criterion is based on margin maximization of two classes in the case of a binary classification problem.

Artificial Neural Networks

An ANN as a simplified model of the structure of the biological neural network, consists of interconnected processing units organized in a specific topology. A number of nodes are arranged in multiple layers including the following:
1. An input layer where the data is fed into the system,
2. One or more hidden layers where the learning takes place, and
3. An output layer where the decision/prediction is given.

Existing System:

Groundwater level is a pointer of groundwater openness, groundwater stream, and the bodily characteristics of a spring or groundwater gadget. due to extended people and lessened groundwater restore, the intrigue augmentations and it could no longer be viable to check the draft of groundwater assets. The principle available choice is to manufacture the stimulate price to the spring via realistic strategies. Thusly it's miles imperative to quantify the ebb and drift tempo of groundwater resuscitate, screen the amendment in water desk significance and eventually envision the destiny example of water table importance earlier than any intercession.

Proposed System:

That is generally as estimation of the dimensions of a hydrological parameters. The components that impact and control the groundwater stage fluctuation had been made plans to expand a guaging display and dissect its ability in predicting groundwater stage. models for preference for water desk importance had been made reliant on synthetic Neural Networks with extraordinary blends of hydrological parameters. The excellent blend turned into asserted with component evaluation. The information parameters for groundwater degree foreseeing had been resolved the usage of Time series analysis.

Soil Management:

ML application on prediction-identification of agricultural soil properties, such as the estimation of soil drying, condition, temperature, and moisture content. Soil is a heterogeneous natural resource, with complex processes and mechanisms that are difficult to understand. Soil properties allow researchers to understand the dynamics of ecosystems and the impingement in agriculture. The accurate estimation of soil conditions can lead to improved soil management. Soil temperature alone plays a significant role for the accurate analysis of the climate change effects of a region and eco-environmental conditions. It is a significant meteorological parameter controlling the interactive processes between ground and atmosphere. In addition, soil moisture has an important role for crop yield variability. However, soil measurements are generally time-consuming and expensive, so a low cost and reliable solution for the accurate estimation of soil can be achieved with the usage of computational analysis based on ML techniques. More specifically, this study presented a method for the evaluation of soil drying for agricultural planning. The method accurately evaluates the soil drying, with precipitation data.

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The goal of this method was the provision of remote agricultural management decisions. The second study was developed for the prediction of soil condition. In particular, the study presented the comparison of four regression models for the prediction of soil organic carbon (OC), moisture content (MC), and total nitrogen (TN). More specifically, the authors used a visible-near infrared (VIS-NIR) spectrophotometer to collect soil spectra from 140 unprocessed and wet samples of the top layer of Luvisol soil types. The samples were collected from an arable field in Premslin, Germany in August 2013, after the harvest of wheat crops. They concluded that the accurate prediction of soil properties can optimize soil management. In a third study, the authors developed a new method based on a self adaptive evolutionary-extreme learning machine (SaE-ELM) model and daily weather data for the estimation of daily soil temperature at six different depths of 5, 10, 20, 30, 50, and 100 cm in two different in climate conditions regions of Iran; Bandar Abbas and Kerman. The aim was the accurate estimation of soil temperature for agricultural management.

In this we have used some modules for soil moisture using ml to determine the groundlevel.

1. **Field survey**

   Subject audit changed into finished to set up the statement nicely territories practical for the assessment region. The wells had been picked so districts of various statures are fittingly made positive about. The groundwater stage become recorded from time to time

2. **Factor analysis**

   In issue examination the relationship between's information parameters ability evapotranspiration, temperature, sogginess and precipitation were destitute down the usage of Statistical package for Social Sciences (SPSS) for hurricane and non-rainstorm season. Any issue having segment regard five was isolated as it's miles less fundamental for the records mixture.

3. **Time series analysis (TSA)**

   In this level the statistics parameters required for the desire for groundwater stage have been assessed. The characteristics had been guage concern to as of late watched facts. on this examination, time sport plan evaluation challenge to transferring normal system turned into gotten.

4. **Prediction using ANN**

   An ANN includes data, hid and yield layers and each layer fuses an assortment of planning segments. An Neural framework is depicted by means of its plan that addresses the case of dating among center factors, its technique for selecting the association hundreds, and the inception work.

RESULTS AND DISCUSSIONS:

Count plot :

Analysis of Situation Attribute

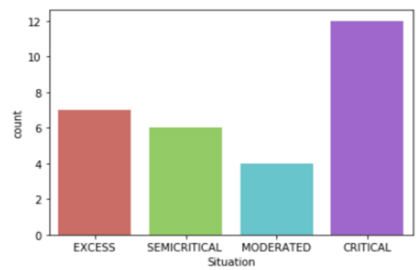

Fig.1.**It spectacle the situation attribute results**

In the above section, we are going to count the values of each method or situation which is determined by the variable are going to give the prediction.

Analysis of Excess Attribute:

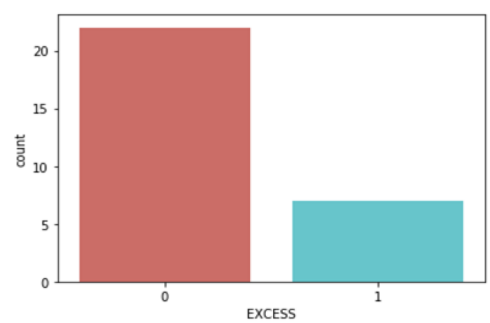

Fig.2. **It spectacle the excess attribute results**

In the above section, we are going to count the values of all method to analyze the

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excess attribute which is determined by the variable which are going to give the prediction.

Analysis of Moderate Attribute:

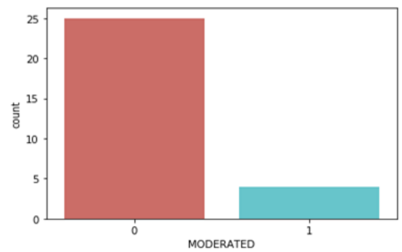
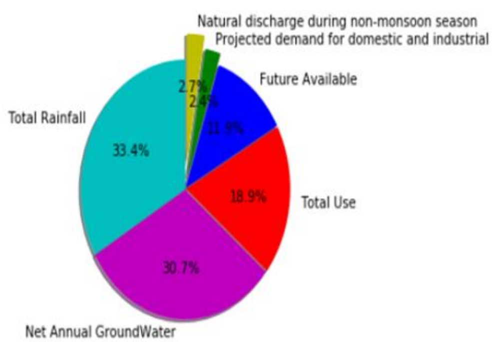


Fig.3. .It spectacle the moderate attribute results

In the above section, we are going to count the values of all method to analyze the moderate attribute which is determined by the variable which are going to give the prediction.

Representation of Pie Chart for Net Annum Ground Water



Display In Between Total Rainfall,

Groundwater, Recharge In Mansoon Season:

Display lets you show a histogram with a line on it. A distplot plots a univariate distribution of observations. The distplot() function combines the matplotlib hist function with the seaborn kdistplot() and rugplot() functions.

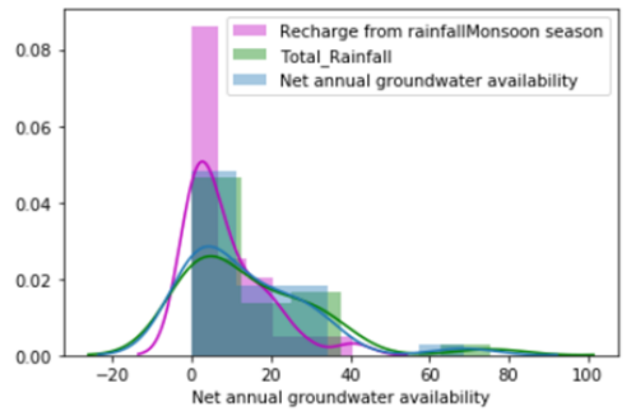


Fig.4 .It spectacle the plotting between net rainfall and total rainfall

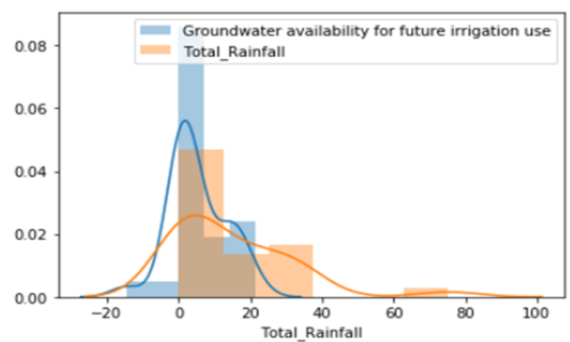


Fig.5. shows the plotting of availability in ground water and total rainfall

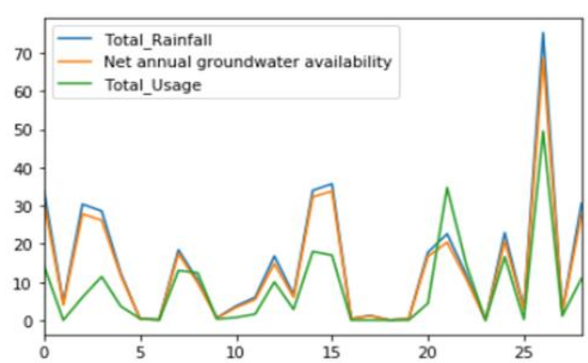


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Fig.6. .It spectacle the usage of rainfall and plotting graph between total rainfall and total usage

CONCLUSION

One of the main goals of developing all these models is to produce reliably good estimates of Soil Moisture. This information is very helpful to farmers and water researchers to understand the approximate conditions of the fields and guides them to decide more efficiently about farming practices such as irrigation and application of fertilizers. The present work has also given a chance to explore different kinds of empirical modelling techniques The results obtained are quite satisfactory and encouraging. This paper introduces diverse device getting monthly set of rules before which we have collected climate statistics.

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