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Optimized deep learning multi-model investigation of images for ground water level detection

Santosh Walke[1], Manoj B. Mandake[2], Chetan M. Thakar[3,*], Makarand Naniwadekar[4], Ravi W. Tapre[5]

[1] *Mechanical and Industrial Engineering Department, College of Engineering, National University of Science and Technology, Muscat 620, Oman*

[2] *Department of Chemical Engineering, Bharati Vidyapeeth College of Engineering, Navi Mumbai 400614, India*

[3] *Department of Mechanical Engineering, Savitribai Phule Pune University, Pune 411007, India*

[4] *Department of Chemical Engineering, AISSMS COE, PUNE-1 411001, India*

[5] *Department of Chemical Engineering, Datta Meghe College of Engineering, Airoli, Navi Mumbai 400708, Maharashtra, India*

*** Corresponding author:** Chetan M. Thakar, cthakar12@gmail.com

ABSTRACT

When referring to groundwater in the context of the normal water cycle, the word "reservoir" is acceptable. Compared to the atmosphere or fresh surface water, groundwater has a much greater capacity to hold water. Despite the high degree of variety and complexity of the subsurface ecosystem, there is currently only a small amount of data available. People who depended on reality-based models ran into both of these challenges at some point. Statistical modeling was used in order to get a more accurate calibration of the model throughout the course of time. Because of the expansion in global population, governments in both wealthy and developing nations are increasingly looking to groundwater as an essential resource for satisfying the water requirements of their populations. Because water was preserved in such a large amount, it may be used again, even when there is a drought or other dry time. In this manuscript, a Particle Swarm Optimization (PSO) enabled Visual Geometry Group (VGG) 16 deep learning model is used in order to determine the level of ground water. Accuracy, specificity and sensitivity of PSO enabled VGG is highest among the algorithms used in the experimental study. Accuracy of PSO VGG 16 is 92.5 percent, specificity and sensitivity of PSO VGG 16 is 99 percent.

Keywords: ground water level; detection; VGG 16; accuracy; images noise removal; PSO

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1. Introduction

In the midst of the present crisis of water, it is imperative to produce estimates of the levels of groundwater that are both precise and constant. The authority in charge of water management may put this foresight to use in the future to improve the development of plans and make more informed decisions[1,2]. It is explained how artificial neural network (ANN) models perform exceptionally well in predictive research and have widespread practical applications. Furthermore, it is discussed how these models are used in a variety of scientific domains, including correlation analysis, feature extraction conversion, approximations, and decisions for input assignments. Researchers have resorted to deep learning models in order to tackle complicated difficulties that transcend numerous fields. These models have also assisted in the design of crucial scientific tools. According to the findings of this work, the use of deep learning models in the area of water research is rapidly being recognized[3].

Accurate estimates of groundwater levels are necessary in order to make decisions about the extraction of water for purposes such as irrigation, salinity, the recharging of groundwater, invasion, or contamination caused by compounds containing arsenic. There have been a number of recent research that aim to develop an early warning system for increasing groundwater levels. There is an inconsistent quality as a consequence of the heightened nature of the situation and the small data set that is necessary for prediction. Immediate action is required to enhance groundwater management in order to forestall the occurrence of water shortage[4].

It is difficult to foresee the structure of groundwater owing to its complex qualities, such as inconsistency, semi-analytical nature, and unpredictability. The many components resulting from human activity are referred to as anthropogenic components, and they are responsible for this difficulty. As a direct consequence of this, a variety of hydrogeological approaches have been created with the purpose of stimulating the groundwater system. Applications of artificial neural networks in groundwater include water level forecasts, techniques for water recovery, and study of water contamination[5,6].

Artificial neural networks, also known as ANNs, are the end result of an analytical decision-making process that was built specifically for the training phase of the process of deep learning. In order to achieve maximum performance, the process of deep learning requires hardware that is both powerful and quick. ANN is able to perform resilience in pattern identification over a broad variety of parameter values and time scales as a result of the improved nature of the system[7,8]. CNN training begins with random values for filter weights, which are then adjusted via back-propagation method utilising estimation errors of the actual output to find particular patterns. These layers are followed by max-pooling that reduces the signal size in order to maintain the most relevant properties while boosting computation performance. Convolution and max-pool layers are used to turn the two-dimensional signal into one-dimensional signals that may be utilised in ANNs.

2. Literature survey

Sugeno and Yasukawa[9] hypothesized the existence of a gated neural network (GRU) for the purpose of modeling groundwater level prediction. Their major objective was to improve the accuracy of regional characteristics found in the central and eastern parts of the United States. Principal component analysis, often known as PCA, was used in order to construct an accurate model of GRU based on a wide number of input variables. The findings of groundwater level predictions have been replicated using the GRU model, and they have been done so in 78 different catchment basins. In places where there is a high average temperature, a high average rainfall, and a low average snowfall, people tend to have better results. The results of this research demonstrate how machine learning may be used effectively and appropriately in a non-linear environment.

Bárdossy and Disse[10] examine the accuracy of various different AI modeling strategies for the purpose of forecasting the quality of groundwater in. During the process of forecasting the quality of groundwater, the efficacy, strategy, and accuracy of the results of four different computer systems were each investigated. Adaptive network-based fuzzy inference systems, evolutionary algorithms, artificial neural networks, and support vector machines were the types of computational models that were used in this research. According to the research that was carried out, it was discovered that the processing capacity of these algorithms, when combined, performs much better than when used individually. In addition, the findings demonstrate that artificial intelligence models are always useful for groundwater management and forecasting.

Panigrahi and Mujumdar[11] used several machine learning techniques, including multivariate linear regression (MLR), multilayer perceptron (MLP), random forest (RF), eXtreme gradient boosting (XGB), and support vector machine (SVM). The MLR method was used to establish a correlation between the predicted and actual output. Using MLP, patterns may be categorized, and non-linear alterations to the refining process can be discovered using MLP. Both RF and XGB are examples of ensemble approaches that may be used in the process of analyzing regression trees. One type of machine learning known as supervised learning, which may be implemented in the form of support vector machines (SVMs), can be used to address problems relating to both classification and regression. These approaches were used in order to provide predictions of groundwater for terrestrial water storage (TWS) using the GRACE dataset.

Awasthi et al.[12] produce accurate forecasts regarding the groundwater level in Ijebu-Jesa, which is located in Southwest Nigeria, by using geoelectric features. Both the practice of predicting water levels using geoelectric features and the establishment of a relationship between the two have never been attempted previously. This research, on the other hand, demonstrates the competence of artificial neural networks on non-linear structures for existing wells and demonstrates how they might be used. The model correctly anticipated the future, as shown by the high value of the regression coefficient (R) and the low value of the mean square error (MSE). This demonstrated that yearly variations had very little effect on the amount of water that was contained in the well.

The Alvisi et al.[13] demonstrates the data- or input-driven approaches that are applied in machine learning for groundwater level modeling. They do this by examining the large resolution groundwater level variation in Illinois using two degrees of access to machine learning. The flow or trend of water resources, as well as the availability of those resources, are highly essential to forecast, and they are threatened by the unending or ongoing dangers posed by climate change, humanistic impact, and data sets with high resolution. The gravity recovery and climate experiment (GRACE) provided the raw data that was used to simulate the high-resolution discrepancy that was investigated in this work.

Affandi and Watanabe[14] attempted to improve prediction on limited basins in the paper, which demonstrated that contemporary machine learning algorithms are more effective and have the potential to find important dataset layout for multi-basins. A comprehensive deep learning model has the potential to acquire hydrological properties that are consistent all over a region as well as those that are specific to a single site. Even for a single catchment area, training an artificial neural network needs a vast amount of data to be input. The key objectives of this research are to (1) determine the seasonal trend of the rainfall runoff model, and (2) elaborate on the exploitation of large-scale data that is available for the purpose of hydrological study.

Solaimani[15] provided predictions on urban water levels as well as water flows. It is possible to anticipate future water flow and water level using the features of the Shannon River, which is located in Ireland. We used data spanning thirty years, beginning in 1983 and ending in 2013. The framework is comprised of three distinct parts: analytics at the city size, fusion of different types of data, and domain knowledge that is specialized to data analytics. These three main stages serve as the cornerstone upon which the work that has been done on deep convolutional neural networks (DCNNs) is built. The projections of the water level in the Shannon River at its three different sites or stations were generated using a total of four different time-series models. Previous efforts to predict water level and flow from 2013 to 2080 have been surpassed by the model that has been developed. The water authority board utilized the results to develop choices and plans for the distribution of water to different sectors, including but not limited to families, farms, companies, and power plants, amongst others.

According to the findings of research conducted by Mayilvaganan and Naidu[16], current trends indicate the use of a wide variety of AI models, the majority of which are ANN, as well as the most often used tools and models in the scientific and technical sectors. When ANN models are altered or enhanced, it is much simpler to make predictions about the quality and amount of groundwater.

3. Proposed methodology

This section contains optimized deep learning multi-model investigation of ground water level prediction. Images are enhanced using CLAHE algorithm. Features are selected using the particle swarm optimization algorithm. Machine learning algorithms like VGG 16, SVM and random forest are used for classifying images. This framework is shown below in **Figure 1**.

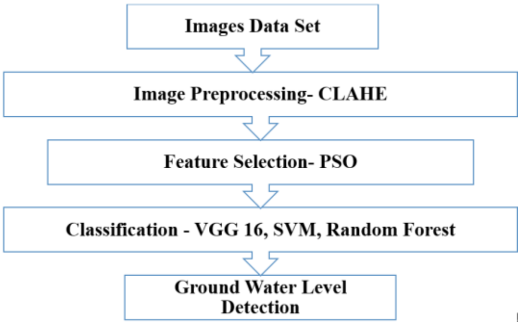

Figure 1. Optimized deep learning multi-model investigation of images for ground water level detection.

When formulating a strategy for the extraction of the background, it is very necessary to take into consideration the unique qualities and composition of the picture. Only pixels that are directly next to the histogram itself are used to produce the histogram that CLAHE[17] generates. As a result of this, CLAHE places limitations on the maximum "clip level" that may be used to boost the height of the local histogram in order to avoid producing an excessive amount of contrast enhancement. Because of this, there is noticeably less noise in the final product. Contrasted against a white background, lesions are easily noticeable. Even while using this method makes, it simpler to differentiate between signal and noise, the photographs still have a significant amount of graininess.

The PSO[18] algorithm will take use of the fact that many organisms, such as fish and birds, operate in a swarm-like manner, and it will do so by using this behaviour to its advantage. Within the parameters of the search, every particle has a different position and velocity, and they are free to go in whatever direction they like. Even yet, the velocity and mobility of the particle continue to be constrained, and the particle is guided in the direction of any particles that have been successful in the past. In addition to this, the particle is led to the location of any other particles that have previously been able to effectively complete their tasks without causing any problems. Because of the use of a set of criteria that have been outlined for the purpose of this particular method, it is now possible to precisely characterise particles at any and all points in time.

CNN is a sort of neural network. Artificial neural networks (ANN) operate with one-dimensional vectors, while these use two-dimensional pictures as input. The input 2-D signal is convolved through a given number of filters in each layer of CNN. Initial layers detect edges and corners, while in deeper layers they are taught to identify increasingly complicated characteristics of the picture. The convolutional neural network (CNN or ConvNet) is a subtype of neural networks that is mainly used for applications in image and speech recognition. Its built-in convolutional layer reduces the high dimensionality of images without losing its information. That is why CNNs are especially suited for this use case.

CNN training begins with random values for filter weights, which are then adjusted via back-propagation method utilising estimation errors of the actual output to find particular patterns. These layers are followed by max-pooling that reduces the signal size in order to maintain the most relevant properties while boosting computation performance. Convolution and max-pool layers are used to turn the two-dimensional signal into one-dimensional signals that may be utilised in ANNs. Finally, the model contains a softmaxlayer with the number of output classes as its nodes. Using this layer, you can see how likely each of the classes is. The highest probability node receives a value of 1, while the other nodes get a value of 0.

There are just two values in the output: 0 and 1. The input image's class is represented by the node with value 1.

It was created by visual geometry group (VGG)[19] at the University of Oxford, and is based on the VGG 16 CNN architecture. The default input picture size for this model is 224 × 224, however it may be set to as little as 48 × 48 if necessary. The 3 × 3 filter size is standard. Starting with the input layer, it contains 13 convolution layers with 64, 64, 128, 128, 256, 256, 256, 512, 512, 512, 512, 512 and 512 filters in various convolution layers starting from the input layer. It also has 3 Dense layers with nodes equal to 4096, 4096 and 1000 nodes. In all levels, the activation function is ReLU. It contains imagenet weights trained on ILSVRC that have been pre-defined. Its pictorial representation is given in **Figure 2**.

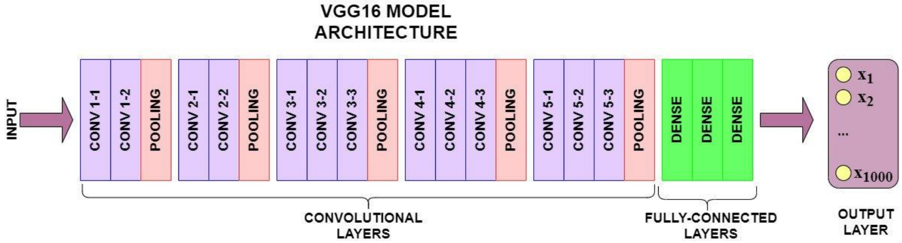

Figure 2. Architecture of VGG 16.

Support vector machines (SVMs)[20] are supervised models that assess data and may be used for classification and regression analysis. These models share common evaluation methodologies. Given a set of training examples, the SVM training technique creates a model that assigns new instances to one of two categories, turning it into a non-probabilistic binary linear classifier. This classifier can only assign instances to one of the two categories. Example locations in space that have been mapped are used to demonstrate SVM models, which divide cases into different categories by a distance that is as great as is practically possible. Because of this, it is easy to make an educated guess as to which category a new sample belongs to based on where it falls in the gap. SVMs are able to do non-linear classification of what is known as the trick because they implicitly translate their inputs into high-dimensional feature spaces. This allows them to do so.

The RF method is a technique to ensemble learning that may be used for classification and regression. This approach constructs a collection of decision trees with controlled variance by combining Breiman's bagging algorithm with a random selection of features. It is feasible to construct an ensemble of decision trees by taking a random sample of the data used to train each tree and then combining those samples. According to the statistics, around 64 percent of instances should be included in the sample. Cases that occurred outside of the bag made up 37 percent of the total sample, while those that occurred within the bag made up just 36 percent[21].

Each tree in the ensemble is utilised as a basis classifier when attempting to assign a label to an unlabeled instance. In order to classify an instance, a majority vote is used, during which each classifier votes for the class label it believes should be assigned to the instance. The usage of the class label is determined by which one obtains the most votes.

4. Result and discussion

In the course of our analysis, we made use of a database that included 174 satellite images illustrating monthly groundwater levels from[22,23]. A color-coded system is used in each photo that is 360 pixels wide and 180 pixels tall to show the TWS of the world's landmass. The National Aeronautics and Space Administration (NASA) of the United States of America, specifically through the agency's GRACE investigation, is acknowledged as the source of these photos. The Physical Oceanography Distributed Active Archive Centre (PO. DAAC), whose online database is accessible to the public, provided the fundamental data set. The vegetation indexes (VI) (normalized difference vegetation index (NDVI), normalized difference snow index (NDSI), infrared index (IRI), radar vegetation index (RVI)), and statistical features (entropy, root mean square (RMS), skewness, and kurtosis) were extracted from the preprocessed remote sensing images.

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN)$$

$$\text{Sensitivity} = TP/(TP + FN)$$

$$\text{Specificity} = TN/(TN + FP)$$

where, TP = True Positive; TN = True Negative; FP = False Positive; FN = False Negative.

Figures 3–5 depicts the performance metrics of our groundwater level forecasting model.

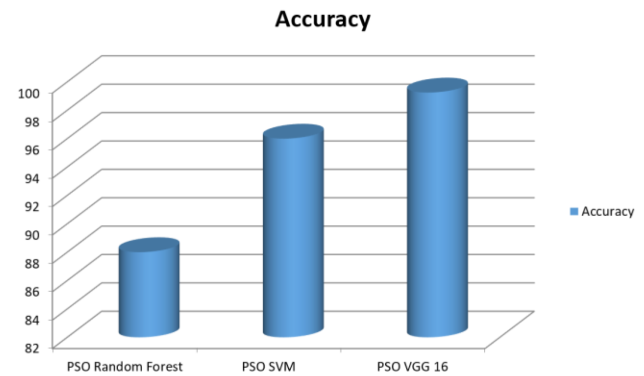

Figure 3. Accuracy of model for detection of ground water level.

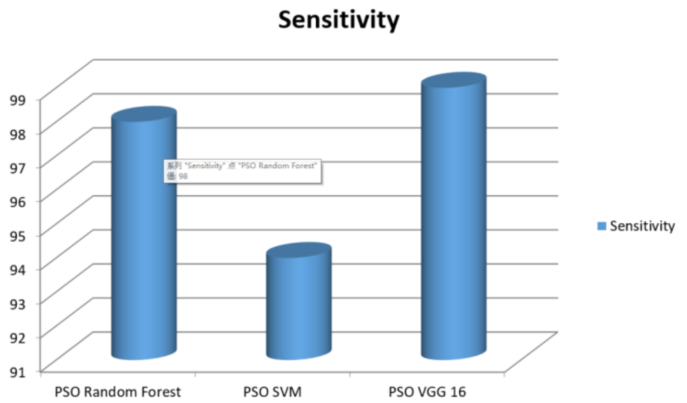

Figure 4. Sensitivity of model for detection of ground water level.

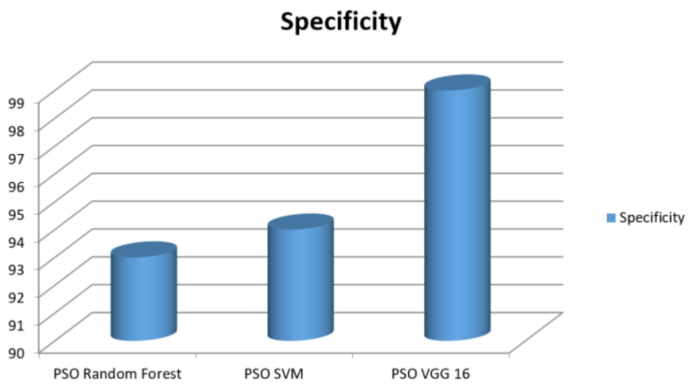

Figure 5. Specificity of model for detection of ground water level.

5. Conclusion

The hydrological cycle, which occurs naturally, includes groundwater as a reservoir of water that is located at depths greater than atmospheric and surface waters. Groundwater is known for its limited ability to store water in the short term. It is worth noting that subterranean habitats exhibit a high level of diversity and complexity. However, there is a noticeable lack of field data available, which presents a significant difficulty. The lack of available data disproportionately affects practitioners who heavily rely on empirically grounded models. The utilization of statistical modelling over a period of time has resulted in improved accuracy in the calibration of these models. The importance of groundwater has increased significantly as a crucial resource to address the growing water needs of a rapidly expanding worldwide population, encompassing both economically developed and developing areas. The reservoir's significant storage capacity allows for strategic utilization, particularly during periods of aridity or drought. This article presents a groundwater level forecasting model based on deep convolutional neural networks. Groundwater plays a crucial part in the hydrological cycle by virtue of its substantial storage capacity. Despite the limitations imposed by data constraints, the utilization of statistical modelling techniques has been found to gradually improve the accuracy of model calibration. The significance of this resource extends beyond geographical and economic limitations, as it functions as a reliable water supply during times of water scarcity. The article's primary contribution is the introduction of a novel forecasting model based on deep convolutional neural networks. This approach enables more accurate predictions of groundwater levels.

Author contributions

Conceptualization, CMT; methodology, CMT; software, SW; validation, SW; formal analysis, MBM; investigation, MBM; resources, MBM; data curation, MN; writing—original draft preparation, MN; writing—reviewing and editing, MN; visualization, RWT; supervision, RWT; project administration, MN. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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