Review Article

Applications of Convolutional Neural Network for Classification of Land Cover and Groundwater Potentiality Zones

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In the field of groundwater engineering, a convolutional neural network (CNN) has become a great role to assess the spatial groundwater potentiality zones and land use/land cover changes based on remote sensing (RS) technology. CNN can be offering a great potential to extract complex spatial features with multiple high levels of generalization. However, geometric distortion and fuzzy entity boundaries as well as a huge data preparation severance may be the main constraint and affect the spatial potential of CNN application for land cover classification. This study aims to recognize the proficiency of deep learning algorithms, i.e., CNN, for spatial assessment of groundwater potential zones and land cover. Among the groundwater influencing factors, classification of land cover (agriculture, built-up, water bodies, forests, and bare land) has been reported by several researchers for different purposes and they approved the CNN capability for the prediction of spatial groundwater potentiality zones like very high, high, moderate, poor, and very poor areas. In this study, CNN is recommended as a very essential algorithm for the identification of groundwater potential zones and classification of land use/land cover change. CNN gives a better option for scholars regarding when the limited data sets are available for validation.

1. Introduction

Identification of spatial groundwater availability and its zonation is very important for optimal utilization of groundwater resources [1] and it exemplifies as the basic reference for suitable strategies of groundwater resources management [2]. However, the spatial distribution of groundwater is dependent on the groundwater influencing factors such as land cover, soil, lithology, slope, geomorphology, rainfall, recharge, etc. [3–5]. Therefore, to evaluate groundwater potentiality, the most dominant spatial map/dataset of groundwater influencing factors should be considered prudently on the analysis of groundwater distribution and occurrence [6]. Among the influencing factors, land cover is one of the most common input parameters for the spatial assessment of groundwater potential at a given catchment. As reported by [7, 8], the land cover has an impact on the occurrence, recharge, and development of groundwater resources in an area. For example, built-up

lands can reduce the infiltration rate (has low permeable surfaces). But, forests lands facilitate infiltration rate. Therefore, the most advanced and accurate techniques are required to map groundwater potentiality zones and land cover classification. With the rise of deep learning algorithms, convolutional neural network (CNN) has emerged as a powerful and effective method [9–12] for the identification of groundwater potentiality zones and classification of land use/land cover. However, there is a major pressing problem in the field of water resources, for example, to predict the exact availability of groundwater potentiality zones as well as to classify land cover. Because of its hiddenness natural resource and with trouble detection, it is a challenging task to identify the exact water-wells location and gather geological information like aquifer thickness, as higher cost and a long time are required [13] for accuracy assessments; for example, to validate the classification of land cover and groundwater potentiality zones maps, ground truth datasets and yields of existing wells are needed, respectively. The

classification of groundwater potentiality zones and land cover output/map needed accuracy assessment, because "without accuracy assessment, the quality of output/map produced would be of lesser value to the end-user" [14]. Generally, the main problems of image classification and prediction are the lack of large datasets to validate the map of the area and the low resolution of remote sensing data to detect small coverage areas [15]. An optimal technique among deep learning algorithms (DLAs), CNN, is required to reduce some uncertainty of image recognition. Hence, convolutional neural networks (CNNs) have proven to be an efficient method for generating accurate data representations [10, 11, 16].

Recently, many researchers have used the CNN approach for the evaluation of groundwater influencing factors [16] such as land use/land cover change classification [17–22] and prediction groundwater potentiality [16, 23]. Typically, frameworks of CNN are two principal approaches, i.e., patch-based and end-to-end (pixel-to-pixel), for the classification of semantic pixel-based techniques. In the pixel-based methods, the fully convolutional network (FCN) or encoder-decoder frameworks are employed to identify acceptable facts of the input datasets. The patch-based techniques also usually utilize small images to train the process of CNN classifier and use a sliding window approach to forecast every pixel classification. This technique is commonly used for detecting a huge coverage area [24].

In addition, CNN has a great role for soil classification [25–27], hydrogeological classification [19], lithology [28], soil permeability [29], land temperature forecasting [30], flood susceptibility map [10, 21], predicting groundwater level and flow [31–33], and prediction of rainfall [34]. CNN can be applied in the recognition of waste type [11] and groundwater quality prediction.

The present work was aimed at reviewing an application of a convolutional neural network and its capability for identification of groundwater potentiality zones and classification of land use/land cover change. It is also establishing the model precision and uncertainty for the application of groundwater resources. Therefore, this paper will provide a concrete nobility about the application of CNN to identify groundwater potential and classification of land cover. To end, it gives a direction for future researchers. This paper is also structured in the following way: a brief overview of literature review, working principles, types of the convolutional neural network, land use/land cover change, groundwater potential zones, advantages, and limitation of CNN in Section 1. In Section 2, the reviewed discussion was presented, and in Section 3, a general conclusion is presented.

1.1. Literature Review

1.1.1. Convolutional Neural Network.
The CNN was initially projected and improved by Lecun et al. [35]. Spatial information from satellite images was used by layered convolution kernels to extract high-level intellectual characteristics. Several research papers have been published on deep learning algorithms (i.e., CNN) for forecasting rainfall and classification of land use/land cover, geology, soil, groundwater level [34, 36, 37], and also groundwater potentiality [16, 23, 38]. More than 146 research articles on the application of CNN and related techniques have been downloaded to perform this paper. After the inclusive and exclusive selection criteria, about 61 articles have been cited and referenced as shown in Figure 1.

Note: Springer, Elsevier, and Hindawi journal houses were the main information sources of this paper. In addition, the reviewed articles of publication dates are described as follows: 19 articles in 2021, 25 articles in 2020, 8 articles in 2019, 3 articles in 2018, 3 articles in 2016, 1 article in 2014, 1 article in 2009, and 1 article in 1998.

1.1.2. Image Segmentation.
Mean-shift segmentation was utilized to split the image into the items with uniform spectral and spatial information as a nonparametric clustering strategy. As several input dataset sources for the image segmentation, major multispectral bands (green, blue, red, and near-infrared) were combined with DSM (digital surface model). A minor oversegmentation rather than undersegmentation was used to highlight the significance of spectral similarity, and all image classifications were turned into GIS (Geographic Information Systems) polygons with distinct geometric shapefiles [39, 40].

1.1.3. Image Classification.
It is one of the most important tasks with advancement of CNN to predict the representative image, which helps to produce high classification performance [41].

1.1.4. Image Translation.
CNN is not intrinsically translation-invariant. Nevertheless, if the trained have an adequate dataset, CNN can learn translation-invariant representations. Training on the dataset with considerable quantities of variation owing to translation is the single most essential aspect in obtaining translation-invariant networks [42].

1.2. Working Principles.
Different layers existed in CNN to recognize the features images that used small squares input data:

(1) The first layer is used to extract feature maps from the input image (retaining relations between pixels) denoted as the convolution layer (CL). This layer is a mathematical setup that needs two input data functions: an image of a matrix and a kernel (filter).

(2) The second layer is an activation layer, which comes after the CL if it is nonlinear. In this layer, rectified linear unit (ReLU) function is the most common and efficient activation function. ReLU is always leveled as zeros (0) and ones (1).

(3) The third layer is the pooling layer, which keeps the most important information while reducing the number of parameters. In particular, this layer works
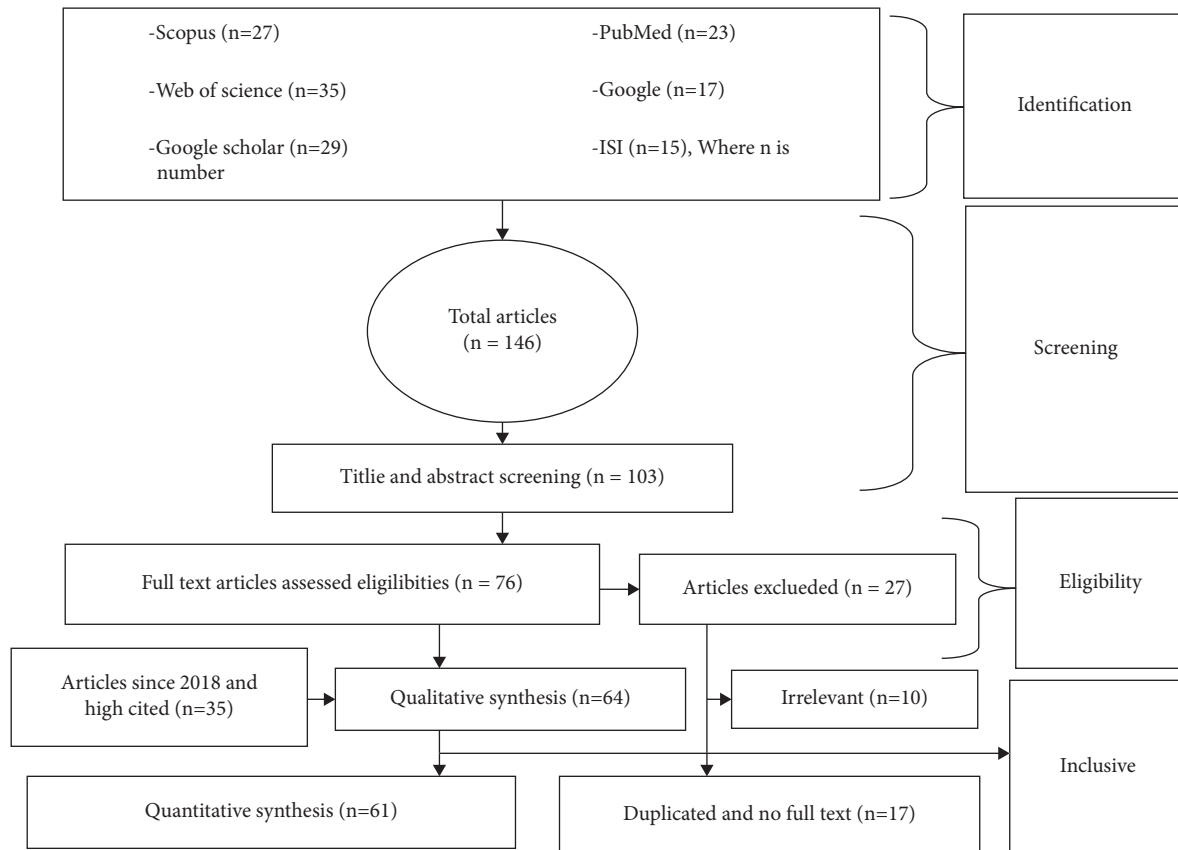
Figure 1: Flow diagram of the studies screening selection based on inclusive and exclusive criteria.

with large images effectively. Spatial pooling can be done in a variety of max, average, and sum.

(4) The final layer of a deep neural network, which performs a discriminative learning algorithm, is an actual component. This layer is a multilayer with the ability to learn weights and classify images and the general working principle has been shown in Figure 2.

Note: thematic map preparation, clipping map for the dataset, and GIS overlay techniques are the supporting tools for the successful achievement of CNN (Figure 2).

Scientists have proposed various frameworks for their research based on the type of data, images, and goals including ZFNet, Unet, SegnetLite VGGNet, VGG16, GoogleNet, ResNet, LeNet-5, and AlexNet [10].

After the overlay process, the convolutional neural network will be applied for the classification of groundwater distribution. The most common architectural approach of CNN is convolutional layers (learning convolutions and delivering the best presentation for data classification), pooling layers (it governs overfitting and underfitting, tolerates stable conversion, and improves computational performance by reducing the number of structures from convolutions), and the rectified linear unit.

Parameters of the convolutional neural network: Dahou et al. [43] optimized the following CNN parameters using a differential algorithm: kernel size, number of kernels, number of neurons in the fully connected layer, and dropout rate. The CNN model can be achieved within CNN parameters at higher accuracy and required less time than machine learning models, according to the findings of Pan et al. [20]. In terms of overall accuracy, deep learning techniques usually outclass other machine learning (shallow) techniques. On the other hand, the understanding of deep learning (i.e., convolutional neural networks) techniques is limited and more difficult for data interpretation due to the huge amount of datasets of training [44].

CNN is mainly made up of convolutional layers, which scan the input image and conduct local convolutional operations using many filters or kernels. Several filters are employed to capture the input image with spatial properties. Typically, each convolutional layer is followed by an activation function that operates on the results and outputs a value indicating whether the node is active for the given input. The rectified linear unit (ReLU) is used as the activation function in this review. The activation layer is followed by a pooling or downsampling layer, which is responsible for aggregating the output data from each layer before sending it on to the next [45].

1.2.1. Convolutional Layer. The convolutional layer is the heart of a CNN model, which employs convolution kernels to extract features from input images. This operation can transform the pixels of the next layer into a local receptive
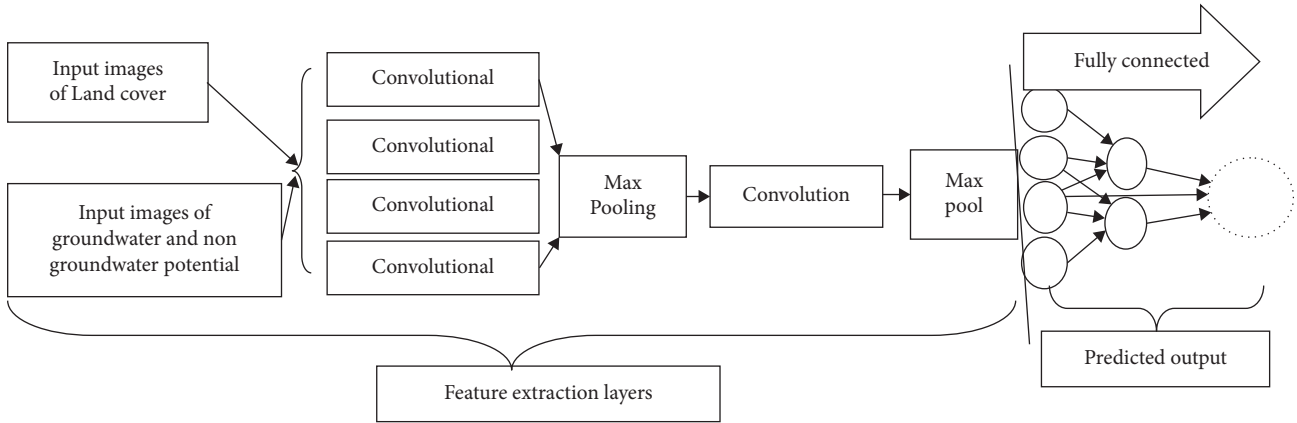
FIGURE 2: The general working principles of CNN [10, 23, 43].

field (the connected region of any convolution kernel on the input image) [46].

The convolutional kernel is multiplied by each position of the source pixel. It has multiple convolution kernels, invariant convolution, multichannel convolution, and so on. The formula for calculating the convolution layer is as follows [46]:

$$xL_j = \left(xL - l_j K_{ij} + bL_j\right), \qquad (1)$$

where xL_j is the layer output, f is the activation function, K is the convolution kernel, l is the number of convolution layers, MJ is the sensory field of the input layer, and b is the bias value of each input graph.

1.2.2. Pooling Layer. This layer performs downsampling to reduce the dimension of feature maps and improve feature extraction images. The pooling layer integrates a local receptive field into a single neuron to minimize the dimension. Pooling has three common types (maximum pooling, mean pooling, and random pooling) for the application of groundwater and land cover. When the size of the feature graphs becomes smaller the effect of computational complexity always reduces. The calculation formula of the pooling layer is [46]

$$xL = f\left(\beta L_j \text{down}\left(xL - l_j\right) + bL_j\right), \qquad (2)$$

where xL is the layer output, down $(xL-lj)$ is the subsampling function, β is the subsampling coefficient, b is the bias, and f is the excitatory function which is used to reduce the input by subsampling the input.

1.2.3. Fully Connected Layer. This layer mainly serves as an integrator (means that the fully connected layer integrates the image features in the feature maps through multiple convolutional layers and pooling layers), which is to obtain a high-level sense of the attributes. The classifier implies that the convolutional layers' feature image is mapped to a fixed-length feature vector, which is used to measure the score of the class to which it belongs and the error between the output and actual values. The data from the convolutional layer and pooling layer finally enter the fully connected layer. In this layer, each neuron is connected with all the neurons in the previous layer, but there is no connection between neurons in the same layer. The function of the fully connected layer can enhance the ability of nonlinear mapping [46].

1.2.4. Batch Normalization Layer. The batch normalization normalizes previous layer activations in each batch to maintain the mean activation value close to 0 and the standard deviation activation value close to 1. It can greatly improve convergence speed, reduce overfitting, reduce initial weight insensitivity, and enable us to use a higher learning rate.

1.2.5. Flatten Layer. The flattening layer is typically used to convert from a convolutional layer to a fully connected layer by converting the input from multidimensional space to one-dimensional space.

1.2.6. Dropout Layer. In each training batch, the dropout operation sets the neuron value to 0 at random with a probability of 50%. The CNN becomes less responsive to particular sets of neurons as a result of this process, which helps to minimize the interaction between hidden layer neurons, prevents the overfitting phenomenon, and improves the model's generalization ability [20].

1.3. Types of Convolutional Neural Network

1.3.1. 1D Convolutional Neural Network. A one-dimensional input grid cell containing different attribute features must be transformed into a two-dimensional matrix to initialize the map. The photos generated are very broad since none of the data is labeled and is constant [10].

1.3.2. 2D Convolutional Neural Network. CNN-2D has been used by geoscience researchers to obtain and publish noteworthy results, so it was used in this analysis. Furthermore, since CNN input data must be in the form of

photographs, and since the input data is one-dimensional, the primary data must be converted into images [10].

1.3.3. 3D Convolutional Neural Network.

CNN-3D applies filters that are smaller than the input raster images, which extracted and expressed information in the domain almost proficiently. By loading fully connected convolutional layers, the CNN extracts feature maps at different levels. The convolutional layers are fair to conversion, which means that output will be shifted by an unchanged amount if the input feature is shifted [31]. Currently, CNN has attained remarkable achievements in the 2D raster image recognition task, it has been prolonged into 3D remote sensing image analyzing training [29].

1.4. Land Use/Land Cover.

Commonly, there are two types of remote sensing data classification: unsupervised and supervised approaches. The unsupervised technique includes the assembling method for classification (e.g., kernel fuzzy C-mean clustering). Also, supervised classification groups include the neural network, the Random Forest [47], the support vector machine [48], and the sparsely represented classifier [49]. As suggested by Rai et al. [22] supervised classifier approach is more appropriate for land cover image recognition when the ground truth dataset is available for accuracy assessments. Hasmadi et al. [14] also showed that the overall efficiency of supervised classification was better than unsupervised classification. Recently, the land use/land cover change has been classified using deep learning algorithms (convolutional neural networks, CNN). As improved by several researchers [17–22, 50] the result is also impressive for input parameters for groundwater potentiality prediction. As reported by Calderon-Loor et al. [51] land cover can be classified as follows: cropland (rainfed and irrigated cropping area (permanent and annual)), forest (includes open, closed, scattered, and sparse trees), grassland (rainfed and irrigated managed and native pastures, tussock, chenopods, and hummock grasses), built-up (human-made surfaces areas inside urban centers and buffer zones), water (permanent water bodies), and other areas (includes mines, wetlands, bare lands, and salt lakes).

1.5. Groundwater Potential Zones.

Lately, some scholars have studied the efficiency of convolutional neural networks under DLAs in spatial groundwater resource mapping [28] and they figure out its performance capacity over the other approaches. Panahi et al. [21] used convolutional neural networks effectively in subsurface water potentiality mapping in South Korea. So this scholar proofed its prediction performance, which was 84.4% (for example, as it was compared, the detection capability of CNN is better than support vector machine). Xu et al. [46] also used convolutional neural networks and effectively investigated subsurface water potentiality mapping in China with a prediction performance of 85.4%. To review, several scientists are striving to simplify problems based on different modeling approaches. For the matter, the application of a convolutional neural network for groundwater has got great credit among the family of deep learning algorithms since 2020. Pradhan et al. (2020) also verified the capability of CNN to capture groundwater potentiality zones in the Nepal Himalaya mountainous terrain areas and the spring inventory map of 145 groundwater potential locations was arranged in the field survey technique. The efficiency of the technique was about 82%. Therefore, the prediction ability of the CNN is very good and it has a great contribution to minimizing some ambiguity of results.

1.6. Related Works

1.6.1. Soil Mapping.

As reported by Li et al. [38] different soil types have been classified successfully by deep learning, i.e., convolutional neural network, and its performance was better than that of machine learning, i.e., support vector machine. In addition, as suggested by Wadoux et al. [52] CNN has the benefit of utilizing the spatial information contained in the vicinity of a sampling location by relying on the local 30 representations of variables.

1.6.2. Lithological Mapping.

The arithmetical results have verified the effectiveness of the classification of CNNs, which showed that the deep learning algorithm can obtain acceptable results. CNN demonstrated that the 3D CNN and 2D CNN systems improve the classification of lithological type remote sensing images [53].

1.6.3. Vegetation Mapping.

Mapping and classification of vegetation types are the most crucial tasks in ecological resources management. However, it is not an easy task to apply conventional methods because of field surveys (highly labor-intensive). Recently, deep learning and convolutional neural networks CNNs can be applied for the classification and mapping of soil to reduce the costs and labor for vegetation mapping [54]. Crop types have been classified by applying convolutional neural networks (VGG16 and GoogLeNet, which are pretrained) [55].

1.7. Advantages of Convolutional Neural Network

(i) CNN appears to be a good fit for multidimensional imagery processing for classification and regression.

(ii) can have rough arbitrary functions with a spatial context [56].

(iii) It is particularly good at learning spatial relationships from image data, allowing the model to learn positions and scales in a variety of structures [57].

(iv) can be fed high-dimensional pattern images as inputs and extract sophisticated features from the imagery data, improving the neural network's explanatory and predictive power.

(v) When images are available at a high temporal frequency, CNN's applicability to prediction tasks can be extended [58].

(vi) CNN differs from traditional multilayer vision neural networks in its ability to learn multiscale spatial patterns from multisource gridded data. CNN searches the input image in each dimension using a convolution operation as a kernel [59].

(vii) The rectified linear unit (ReLU) function is a popular activation function for hidden CNN layers because it is less expensive than other nonlinear functions and has previously been shown to significantly increase CNN training speed [59].

(viii) Local pattern sin images are used to create sparse connections.

(ix) Weights are shared across an entire input image by using the same filter (resulting in translation of equivariant).

(x) Pooling operation leads to local shift invariance [45].

1.8. Limitation of Convolutional Neural Network. The limitation of CNN has been underlined, due to the prerequisite of the high amount of data [46]. It may be a waste of time to interpret the data processing in a given large watershed area.

2. Discussion

As shown by many researchers, several approaches have been established to avoid overfitting. The first approach is to verify the accuracy of the methods after training by using a collection of data validation (10% of train data), which not only adjusts network parameters but also helps to prevent overfitting by comparing network accuracy of data and training data. The second method involves using a dropout layer after each convolutional layer, which removes half of the input layers after each iteration, allowing the network to train all aspects of the dataset while avoiding overfitting. Another option is to use a small network, which would protect the network from being overfitted [10].

Convolution neural network (CNN) is a deep learning network structure that has a good effect on picture categorization, making the CNN approach widely employed in many fields. CNN is a new, nondestructive approach for monitoring the quality of agricultural products, which involves the detection and grading of fruits, vegetables, and other produce, and has shown promising results. For classification modeling with a large sample size, CNN is commonly utilized [38].

On the basis of geological, geophysical, geochemical, and remote sensing data, various approaches to geological mapping have been used to aid in the detection of groundwater resources. Through multilayer network learning, deep learning algorithms are dominating in dealing with high-dimensional datasets for classification and prediction. A convolutional neural network (CNN) is a sort of feedforward neural network with convolution processing

and a depth structure, for example [60]. Generally, as reported by many scholars the performance CNN was more than 80% for classification of soil, lithology, groundwater, and land cover.

3. Conclusions

This study presents the application convolutional neural network for the classification of land cover and spatial groundwater potentiality zones. As reviewed in this paper, the following three conclusions were drawn: (i) Deep learning (i.e., CNN) techniques have a better performance than machine learning algorithms for image pattern recognition. CNN provides high-level prediction performance and is multidisciplinary in the areas of limited recorded data availability. (ii) In the working principles, one (1) was considered as groundwater potential areas and zero (0) was considered as nongroundwater potential for assessment of accuracy and the precision level, and (iii) image classification with accurate overlay techniques is vital in the field of water resources.

The map of spatial groundwater potential can be zoned into four main groups with relative distribution of groundwater such as very high (excellent), high (very good), moderate (good), low (poor), and very low (very poor). Land cover also can be classified into five/six major categories: cropland, forest, grassland, built-up, water, and other areas [61].

In future research directions, scholars include applying hybrid deep learning techniques with the CNN model for groundwater predictions. The author will study the application of CNN in the field of groundwater engineering (i.e., geology, groundwater depth forecasting, aquifer thickness or lithological layers, soil, land cover, and groundwater potentiality).

Data Availability

No data were used to support this study.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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