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MAPPING AND CLASSIFICATION OF SOIL PROPERTIES FROM TEXT DATASET USING RECURRENT CONVOLUTIONAL NEURAL NETWORK

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Abstract

Accurate and effective mapping of soil properties is regarded as a critical task in environmental and agricultural management. The evaluation of properties of soil is a daunting task while monitoring and sensing the environment. Existing sampling methods is a time-consuming and laborious job and they are limited based on the regions. However, the need of soil analysis and its properties is essential at landscape level. In this paper, we use Recurrent Convolution Neural Network (RCNN) to assess the soil properties via its classification task. The model in turn is compared with conventional geostatistical spatial interpolation methods. The utilization of Recurrent Neural Network (RNN) aims at studying the spatial and temporal variability of the properties of soil that adopts Kriging interpolation technique. The simulation is conducted to study the efficacy of the model under different soil conditions and the efficacy of RCNN is reported. The results of simulation shows that the proposed method achieves higher rate of classification accuracy than other models.

Keywords:

Regional Convolutional Neural Network, Deep Learning, Soil Properties, Prediction

1. INTRODUCTION

The texture of the soil determines the ability and fertility of the soil to store water. For agricultural applications as well as the monitoring of environmental processes, therefore, the classification of soil texture is vital. The phrase soil structure refers to the relative soil particle content of different sizes. The proportion of clay, sand and silt in the soil is determined. For the above three features, soil texture can be classed, e.g. by taxonomy KA5 [1].

The yield of crops is affected by several factors, such as crop genotype, the environment, and techniques of management. Over the years, the genotype of crop seed businesses has improved dramatically. The geographically and temporally shifting environment has a tremendous impact on year-to-year differences in crop yield and location-to-location [2]. Accurate yield predictions under these circumstances are tremendously useful for global food production. Timely decisions on imports and exports may be made on the basis of exact projections. Farmers can make informed managerial and financial decisions using the yield projection. In fresh and untested places, the performance of new hybrids can be predicted [3]. However, prediction of effective crop yields is challenging because of many complicated aspects. For example, genotype and environmental factors often interact, making the yield estimate more difficult. Environmental elements such as weather components can have challenging and precise nonlinear effects.

Monitoring soil texture is costly and is not practicable on big sites with in-situ measurements. Optical remote sensing offers an excellent alternative for covering such large areas. Hyper-spectral sensors, for example, are optical remote sensors that measure objects' solar reflectance spectra. The soil texture information obtained by a soil reflection coincides with certain soil mineral and organic soil absorption characteristics [4]. A model has to be developed to relate distinct reflection spectrums to the respective soil textures for a classification of the soil texture based on hyperspectral data.

Machine learning offers appropriate tools for learning about the link between hyper-spectral data and the structure of the soil. Machine learning can be split into superficial learning and profound learning methods. Deep learning approaches [5]-[7] in the past have been successful with hyperspectral estimation challenges. Recent studies focus on deep learning methodologies, implying multi-layered network topologies.

In this paper, we use Recurrent Convolution Neural Network (RCNN) to assess the soil properties via its classification task. The model in turn is compared with conventional geostatistical spatial interpolation methods. The utilization of Recurrent Neural Network (RNN) aims at studying the spatial and temporal variability of the properties of soil that adopts Kriging interpolation technique.

2. BACKGROUND

Many research has employed machine learning approaches for prediction of crop yield, for example, the regression tree, random forest, multivariate regression, association regulation and artificial neural networks. Performance and crop returns are dealt with in machine learning models implicitly by input factors like weather components and soil conditions, which may be quite complicated and nonlinear.

Jeong et al. [8] have used the prediction of wheat, maize, and poato for a random forest and a multiple linear regression. They showed that random forests were extremely able to forecast crop production and exceeded multiple linear regression.

In response to water availability under various irrigation systems, Fukuda et al. [9] also employed random forest to estimate mango fruit production and found random forest to be useful for mango yield prediction with a special focus on water management.

Liu et al. [10] have used artificial neural networks to roughly link maize production to the variables of input such as weather, soil, and management.

Ransom et al. [11] examined machine learning techniques employing soil and meteorological information for maize nitrogen recommending tools. Drummond et al. [12] have gradually researched multiple linear regression, the projection of

regression and the prediction of soil-based grain yield in artificial neural networks.

Shahhosseini et al. [13] predicted the maize yield and the loss of nitrate by employing algorithms like random forests and linear multiple-regression in the learning process. In order to anticipate potato yield using biomass calculated by the model, Awad created a mathematical optimization model. Jiang et al. [15] employed a multi-linear and artificial neural regression to estimate winter wheat yields based on remotely sensed and climate data, finding that the multi-linear regression was outperformed by an artificial neural model.

Prasad et al. [16] employed a piece-by-piece method to predict the yield of maize and soya based upon data from remote sensing and other surface factors. For the classification of yield components of durum wheat, Romero et al. [17] used various master learning approaches, including decision-making tree and association rules mining, and showed that association rule mining methods achieved optimum performance across all sites.

Deep learning algorithms for agricultural yield prediction have been more recently employed. The deep neural network model created by Khaki and Wang [18] was designed to estimate maize output in 2247 places from 2008 to 2016. Their model exceeds other methods like the Lasso, low-neural networks, and a regression tree. You et al. [19] applied soybean yields on the basis of a remotely sensed sequence with CNNs and RNNs. The deep neural network model for crop production forecasting by Kim et al. [20] was built between 2006 and 2015, employing optimised satellite input variables and meteorological data sets. In Wang et al. [21] a profound learning framework has been developed for the prediction of soybean crops in Argentina, which has also been successful with an approach to the transference of Brazil's soybean crops with fewer data. Yang et al. [22] examined the capability of CNN, utilising remotely sensed pictures, to estimate rice grain yield, and found that the CNN model produced a robust yield forecast for the entire maturity period. In order to estimate corner loss at 1,560 locations in the USA and Canada, Khaki and Khalilzadeh [23] used deep CNNs.

In comparison, deep learning approaches with several hidden layers tend to perform better than artificial neural network models in the literature that have one single hidden layer. But deeper models are harder to train and require more advanced technology and approaches to optimization [24]. The loss functions of deep neural networks are, for instance, exceedingly large and non-convex, making it more difficult to optimise this function because there are many local optimums and saddle points [24]. Deeper nets may also have the problem of the loss gradient, which can be mitigated with residual shortcut connections or several auxiliary heads [24]-[27]. Some other strategies for improving the performance of profound learning models have also been developed, including batch normalization [28], drop-out [29] and stochastic gradient descent [24].

3. PROPOSED RCNN CLASSIFIER

A CNN model consists of numerous convolutional and pooling layers with few completely connected (FC) layers. CNNs have certain design characteristics, including filter size, padding type, and stride number. A filter is a weight matrix with which the input data is combined. The padding procedure is the addition of zeroes to the input in order to preserve the input space dimension. The step is the amount of movement of the filter. RNNs are used to record their time-dependence for jobs using sequential data. In its hidden units, RNNs keep the history of all previous sequence elements known as a state vector and use that knowledge to process one element input sequence at a time. RNNs are extremely powerful sequence models, but training has proved quite problematic because of the disappearance and explosive problems of gradients. RNNs are improved by long short-term memory cells (LSTM) that have been carefully developed with recurrent neurons that provide greater performance in a broad range of sequence modelling applications in order to tackle this problem. LSTM cells employ a special device named a memory cell to store extended inputs and avoid the problem of gradient disappearance.

If there is data $x = \{x_1, x_2, x_3, x_4, x_5\}$, we use an auto-encoder network incorporating a hidden layer to learn some compact features from *x*, as illustrated in Fig.1. The input layer is Layer 1, the concealed layer is the input layer, and the output layer is reconstituted as Layer 3. The training method is intended to minimise errors in the reconstitution layer between the input and the output layer. In order to see the hidden layer as another kind of data representation, the key characteristics of the information are pulled out of the hidden layer.

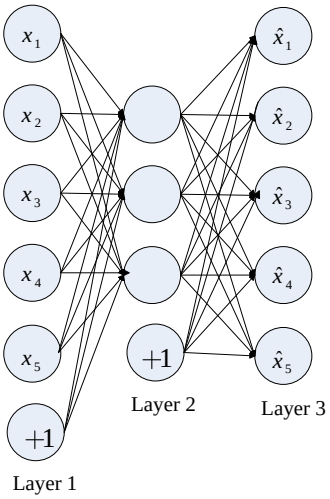

Fig.1. Schematic diagram of RCNN

The network is actually aimed at auto-encoding that learns $h_{W,b}(x) \approx x$. By restricting the number of neurons in the hidden layer, the structure might minimise the hidden functions of the data. For example, 1024 neurons can handle a 32×32 image. Auto-encoding networks with a 50-neuron hidden layer can train the image in a compact way. Neurons in the buried layer are nevertheless relatively tiny. In fact, if the number of neurons in the oversized layer is large, we can also find the intrinsic properties of the data with sparse constraints. Assume the activation value of the j^{th} neuron at the hidden level a_j is added, by applying the following limit, a network can become sparse.

$$\rho_j = \frac{1}{m}\sum_{i=1}^{m} a_j x_i \quad (1)$$

where,

m – total neurons in input layer.

ρ_j - sparse constraint parameter and it is not a variable and is supposed to be close to the sparse constant ρ (like 0.05).

When solving the hidden layer, we can optimize ρ_j using the KL distance function.

$$\mathrm{KL}(\rho\|\rho_j)=\rho\log\frac{\rho}{\rho_j}+(1-\rho)\log\frac{1-\rho}{1-\rho_j} \quad (2)$$

In the conversion layer, the input of each feature map is simply specified by the time-space conversion kernel. The human setup of the strategy, however, limits the network automatic capacity to learn the crucial elements. A sparse auto-combination approach is used to further increase the functional learning capacity, such that the input feature maps can be automatically learned as a combination in the convolution layer.

For the l^{th} sub-sampling layer, if there are N_{in} input feature maps, to calculate each output feature map of the sub-sampling layer, each feature map has only two parameters, which are the convolution kernel W_{ij}^{ℓ} and the bias term b_j^{ℓ}. We introduce a sparse constraint parameter α_{ij}, which represents the weight or the contribution of the i^{th} input feature map $X_j^{\ell-1}$ when determining the j^{th} output feature map X_j^{ℓ}. Thus the j^{th} output feature map X_j^{ℓ} can be expressed as the following formula:

$$X_j^{\ell}=f\left(\sum_{i=1}^{N_{\text{in}}}\alpha_{ij}(X_i^{\ell-1}*W_{ij}^{\ell})+b_j^{\ell}\right) \quad (3)$$

The following requirements must be fulfilled:

$$\sum_i\alpha_{ij}=1,\ \text{ and }\ 0\le\alpha_{ij}\le 1 \quad (4)$$

The corresponding connection relation between the sub-sampling layer and the next convolution layer is to be established first for the backpropagation process of the last sub-sample layer.

Thus, the remaining layer of the next layer can be reversed. Thus the residual $\delta^{\ell+1}$ of the next layer can be conducted backward. We can use the gradient descent to calculate the residual δ_j^{ℓ} of the j^{th} feature map.

Suppose the derivative $f'\left(z_j^{\ell}\right)$ of the activation function f for the input z_j^{ℓ} of the l^{th} layer. The calculation process is the following formula:

$$\delta_j^{\ell}=f'\left(z_j^{\ell}\right)\cdot conv2\left(\delta_j^{\ell+1},rot180\left(W_j^{\ell+1}\right)\right) \quad (5)$$

In the above calculation process, we need to rotate the convolution kernel, so that the convolution function $conv2(\cdot)$ can be performed cross-correlation calculation.

The sparse restriction of the output is applied to the sparse auto-encoder neural network. We impose a limited restriction on the contribution here, however. Both modalities work differently, but the functions are identical. It can extract low-level features from input data in a sparse automotive neural network. A limited number of neurons in the output layer are engaged when the sparse constraints are used on the output side. For this study, we shall limit only a few inputs to the activation of a neuron in the output layer so that the most compact representation of the data may be found to obtain a compact presentation of input data, i.e. extract advanced characteristics from data.

The main modification in this framework is that all the feature maps of the previous layer are taken as inputs for each output feature map during the spatio-temporal convolution. However, because of the sparse limits, the number of feature maps added to the feature map is highly limited.

3.1 RECURRENT NEURAL NETWORK

The RNN model has been developed over several years to capture the interval dependence of agricultural output. Two contrasting observations have motivated the use of the RNN model. In the last four decades, on the one hand, maize yield and soybean production have shown increasing trends, which, thanks to considerable research and development expenditure on breast and agricultural technologies, may be linked to an ongoing improvement in the fields of genetics and management practices. For this prediction study, however, genetic data was not publicly available.

The effect of the genotype should therefore be indirectly reflected by the data available in the model. An RNN is an artificial neural network type that reflects time-node dependencies in a graph. Through genetic enhancement, we constructed a specified RNN model to capture the temporal dynamic behaviour of crop yield. These RNNs have been strengthened by LSTM cells, which have been carefully built to capture time dependencies. The LSTM networks do not need to describe the non-linear functions to be evaluated compared to other time series models, and in a large number of sequence modelling applications they have shown superior performance.

The RNN model consists of LSTM cells (k), which during year t_k to t have predicted the crop yield in the country. The cell input contains average cell outputs, management data, and output of the FC layer (across all counties in the same year, etc) which retrieves essential features processed using weather and soil data by the RCNN models. The exception is that the RCNN and FC models were developed to transmit soil data recorded directly to LSTM cells at the ground surface.

Although the soil data is normally static, RNN permits soil data to be subscribed over time to change soil conditions. The RNN model can predict crop yield by employing previous trends in cultivation yields even without weather and soil figures by utilising historical means. Suppose t is the target year of a yield prediction, then the average yield in Y_t, and then it may be replaced by Y_{t1}, and the unnoticed portion of the weather in W_t may be replaced by the projected data of the weather. However, in the training phase, such replacement is not required because all the data is available.

4. DATASET

In this paper, the data analysed included four kinds of data: yield performance, management, weather and soil; there was no genetic data available to the public to supplement the four sets of data.

- The performance data set included averaging observed returns on maize and soybeans in 1,176 maize counties and 1,115 soybean counties between 1980 and 2018.
- Every month from April of every year, the management data comprises the cumulative weekly share of the planted fields in each state.
- Daily record of six weather variables, including precipitation, solar radiation, equivalent snow, temperature maximum, temperature minimum, and vapour pressure were included.
- The weather data includes weather data was 1 km^2 spatial resolution.
- Soil data covered wet soil bulk density, dry bulk density, clay %, plant content limits available, low plant water content limits available, hydraulic conductivity, percentage of organic matter, pH, sand and variegated volumetric water content, measured at different depths.
- Four soil variables, including the field slope in percentage, the national maize productivity index, the average national productivity index for all plant species, and the crop root depth were recorded at the soil surface only. The solar data was 1 km^2 spatial resolution.

Based on the approach to the Grid Map, we have selected several weather and soil samples from each county and have taken the average of those samples for weather and soil representative samples. For several areas, soil data lacked 6.7%, which we said was based on the mean of the same soil variable for other counties. For some places, the management data had a lack of 6.3%, which we claimed was the same management variable for other jurisdictions in the same year. We investigated several strategies of imputation, such as medium and frequent, and found that average results were obtained with the highest precision.

There were no missing values in the weather data, but we observed that daily data was more granular than necessary for the information to be revealed. This led to a 365×52 dimension reduction ratio in the weekly average. The number of trained parameters of the first layer of the neural network model decreased significantly during pre-processing of weather data.

5. PERFORMANCE EVALUATION

The principle component of our important analysis is temporal resolution, which allows for a fuller understanding of the workings of the complex agricultural system at critical moments. Of the six factors tested here, the most sensitive factor in maize production was sun radiation and the least sensitive element was snow. This is fair from an agronomic point of view, because radiation drives photosynthesis and then the generation of biomass and the yield of grain. On the other hand, soil water and precipitation and steam shortages have more significant effects than snow as they stay longer, especially during the summertime. Snow-water has an impact on soil water balance. Before and after the growth season, snow is rather crucial and was well described in the current investigation.

There were two choices of radiation: one at week 15 before planting and one at week 30, coinciding with the most important time for maize. Around silking time, it is decided the kernel number by plant and it can be seen from the literature that it is very strongly linked to the growth rate of the kernel and the plant via photosynthesis. In the yield forecast around week 20, which often coincided with maize planting, the maximum temperature was identified as the most sensitive. From the agronomic point of view, temperature is extremely essential at that time as it impacts the germination and emergence of seeds and typically results in a fast and consistent appearance at high temperatures, while slow and uniform low temperatures affect plant growth yield. Around weeks 22 and 35, the minimum temperature was particularly sensitive. Week 22 has the same value as the maximum seed temperature. It is interesting to note that during the grain fill period, the model has identified the impact of the minimum temperature, which is well known to affect maize production. The same applies to soybeans too, and the model caught that. The rising importance of precipitation during grain filling periods, also supported by experimental research, is another notable result of this analysis.

Our investigation has shown that several components are sensitive to both forecasts of output in terms of soil variables. All these parameters are outside the focus of this research, but all of these factors are known to affect the provision of soil water, nitrogen and crop output.

From April 20 to May 15, a time which was considered to be the optimal planting date in the Corn Belt region, was the least responsive in terms of planting dates. From an agricultural point of view, the maize yield declines beyond that ideal range, and by raising the sensitivity to the date, the model might reflect this fact. Opposite results for soya were found, although the models from 15 May to the end of May were more sensitive and are seen as the optimal soybean planting timing.

We have acquired prediction findings based on a subdivision of features to evaluate the performance of the selection approach. The RCNN model has been trained on the 1980-2021 data and utilises the 2019-2021 data for functional selection. Finally, on the 2022 yield prediction, we evaluated the efficiency of the function selection approach. We have sorted all characteristics based on the estimated effects and selected the 50% and 75% most important characteristics.

The Table.1 displays the RCNN model's output prediction performance utilising these functions. The RCNN model has not decreased much in prediction accuracy compared to the RCNN model employing all the features, which suggests that the selection process can locate the key characteristics correctly.

The Table.2 compares the achievement of the above four models in maize and soybean yield prediction. RCNN has shown similar performance to existing corn and soya yield prediction methods, and their precision prediction is considerably higher than that of existing approaches. The results showed that weather and soil play a similar role in the yield forecast, and more than managing techniques, explained the difference in yields. The findings also showed that the dates of planting have more effect on soybeans than on maize.

Table.1. Validation Error Crop prediction with soil properties

Model	Training Error	Validation Error
CRNN	13.25	16.51

CNN	15.33	19.52
RNN	17.84	22.83
DNN	19.84	26.24
ANN	20.15	31.45

Table.2. Accuracy on Crop prediction with soil properties

Model	Training Accuracy	Validation Accuracy
CRNN	96.26	93
CNN	94.18	89.99
RNN	91.67	86.68
DNN	89.67	83.27
ANN	89.36	78.06

6. CONCLUSION

In this paper, we use RCNN to assess the soil properties via its classification task. The model in turn is compared with conventional geostatistical spatial interpolation methods. The utilization of RNN aims at studying the spatial and temporal variability of the properties of soil. The simulation reports the efficacy of RCNN under different soil conditions. The results of simulation shows that the proposed method achieves higher rate of classification accuracy than other models.

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