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Deep Learning for Smart Agriculture

[1]Dr. Harvir Singh, [2]Dr. Rudra Pratap Singh

[1]Pro-Vice Chancellor, [2]Dean

Bhagwant University

ABSTRACT

Deep Learning methods such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and Generative Adversarial Networks (GAN) have been applied in various fields including agriculture. In recent years, a massive improvement has been achieved in deep learning field. Deep learning methods have also drawn lots of attention in agriculture. One of the use cases of deep learning in smart agriculture is image recognition. The application of deep learning methods can be seen in many aspects of agriculture such as plant disease detection, weed control, and plant counting.

Keywords: Recent applications of Deep Learning in Smart Agriculture

Introduction

Most of the recent advances in agriculture are closely connected to every part of agriculture timer Ove productivity of crops, reducing and preparing for plant disease, boosting mechanized and automated modern agriculture and agro- industry. Deep learning techniques are generally used for image recognition or data classification. It is a four steps approach: data collection, data pre- processing, training of neuralne twork, model testing, and resultanalysis.

For data collection, advanced technology such as unmanned aerial vehicles (UAVs), radar, and Internet of Things (IoT) can provide high quality dataset of images and other forms. The acquired data enhance the applications of deep learning in agriculture and improve the accuracy of resulting tools.

The research and development of new deep learning models can help improve accuracy and precision. The models such as K-mean feature learning, FCNN, AlexNet can play a significant role in improving the results. The model test is required to validate the model with new data and finally the results are interpreted and analyzed for further fine tuning of the process.

Application of CNN in smart Agriculture

Convolutional Neural Network (CNN), due to its strong image processing capability, is widely used in Agriculture research. CNN can be used for plant or crop classification that is vital forest control, robotic harvesting, plant disease detection, and yield prediction.

The **Plant Disease Detection** can be done more efficiently using image processing models based on leaf image classification and pattern recognition. Berkley Vision and Learning Centre developed model that can recognize 13 different types of plant diseases out of healthy leaves. The model can also distinguish the plant leave from their surroundings. The researchers have been able to achieve the accuracy of 96.3% in detection of plant diseases.

Plant Classification and Weed Identification are important for smart agriculture. Since CNN can identify plenty of plant features, CNNs have been used to detect weed or classify plants. Deep learning CNN models combined with K-means feature learning have been able to classify plants and weeds with 92.89% accuracy.

In another study, self-organizing Korhonen maps (SOMs) were used for optical image segmentation and subsequent restoration of missing data in a time series of satellite imagery. The model could classify major crops (wheat, maize, sunflower, soybean, and sugar beet) with an accuracy of 85%.

Food Counting is important for yield prediction and robotic harvesting. Due to change in occlusion and illumination, the pre-processing of images and is challenging and use of deep learning methods is limited. However, a blob detection method with a fully convolutional network (FCN) have been successful. In this method, first, the human generated labels from fruit images is collected. A blob detection FCN method is used for image segmentation. The count convolutional network is used to generate intermediate estimate of fruit count based on image segmentation. Finally, the linear regression methods are used to map intermediate fruit count estimate to final counts. The blob detection methods improved the accuracy and efficiency of counting.

Land Classification and Area Estimation: Land classification is used for various purpose such as land use and land cover (LULC), disaster risk assessment, agriculture, and food security. Deep learning techniques have been applied in land classification and area estimation in remote sensing. The data acquired from multiple heterogeneous sources is integrated using machine learning techniques, big data, and geo-information technologies to provide data processing and visualization capabilities. Noise filtration and data clustering, classifying land cover, map post processing with filtering, and geospatial analysis are important steps of land classification. Unmanned aerial vehicles (UAV) are predominantly used to acquire high resolution images in addition to satellite images. The feature detection method based on deep CNN (DCNN) and transfer learning (DTCLE) were used. First linear features (roads and ridges etc.) were excluded based on deep Convolutional Neural Network (DCNN). Next feature extraction method learned from DCNN was used to cultivated land information extraction by introducing transfer learning mechanism. Last, cultivated land information extraction results were completed by the DTCLE and eCognition for cultivated land information extraction (ECLE). The overall precision of DCTLE and ECLE were around 90%. However, in terms of integrity and continuity DTCLE outperformed ECLE.

Obstacle Detection: The use of highly autonomous vehicle in farming has necessitated the need of obstacle detection. In order to operate these vehicles safely, they must perform automatic real-time risk detection with high reliability. The deep learning-based image classification methods such as AlexNet and DCNN have increased the accuracy up to 99.9% in row crops and 90.8% in grass mowing.

The **Remote Sensing Images** from satellite is used for making sustainable land use planning for minimizing Carbon footprints, minimizing economic returns, and minimizing land degradation. The interpretation of the collected images is challenging. CNN and genetic algorithms have been successful in decision making especially for precision agriculture and agroindustry. CNN is used to classify plant types in a land area. The land types and other data can be added to the grid form. Aeriform model can assess objectives and a genetic algorithm produces an optimal solution. Similar concepts have been used in flower grading.

CNN have been used extensively in **weather forecasting**. Crop yield prediction is crucial for famers, consumers, the government to plan activities such as selling, purchasing, market interventions, and food shortage relief. CNN can also predict **yield** in agriculture and **animal behaviors**.

RNN application in smart Agriculture

Recurrent Neural Network (RNN) are useful to process time series data. RNN have been used in many agriculture areas such as land cover classification, phenotype recognition, crop yield estimation, leaf area index estimation, weather prediction, soil moisture estimation, animal research, and event date estimation.

Land Cover Classification (LCC) is an important and challenging task in earth observation and agriculture. The objective of the LCC is torecognizewhich class a typical piece of land is in. Many classification techniques have been deployed but they consider observation at certain point in time. They are based on mono- temporal observation and ignore time series effects in some problems. Some land cover classes, such as crops, change their spectral characteristics due to environmental influences and cannot be monitored effectively with mono- temporal approaches. Moreover, the mono-temporal approaches could also be influenced by biases such as weather. Deep Sequence Model such as long short- term memory (LSTM) neural network models can be employed for crop identification purpose. The results from various studies shows that LSTM outperform all mono-temporal models such as CNN and SVM. In some cases, the LSTM models along with Support Vector Machines (SVM) provided better results.

Plant Phenotyping is an important topic of precision agriculture. Plant phenotyping links genomics with plant ecophysiology and agronomy. The functional plant body (PHENOTYPE) is formed during plant growth and development from the dynamic interaction between the genetic background (GENOTYPE) and the physical world in which plants develop (ENVIRONMENT). The interaction determines plant performance and productivity measured as accumulated biomass and commercial yield and resource use efficiency. High resolution and high throughput genotype to phenotype studies in plants are underway to accelerate breeding of climate ready crop. In recent years, deep learning techniques such as CNN, RNN, and LSTMs have shown great success in visual data recognition, classification, and sequence learning tasks. CNNs have been used for plant classification and phenotyping, using individual static images of plants. On the other hand, dynamic behavior of the plants as well as their growth has been studied using LSTMs. The deep learning structure combines CNN with LSTM units. According to the structure, CNN extract features and its output is fed into the LSTM to build a sequence model. The sequence model improved accuracy significantly to 93%.

Crop Yield Predictions: RNN along with CNN have also been used for crop yield predictions which uses time series data to reduce biasing. Crop yield prediction is extremely challenging due to its dependency on multiple factors such as crop genotype, environmental factors, management practices, and their interactions. The convolutional neural networks (CNN) along with recurrent neural networks (RNN) can be used for crop field predictions. Other popular methods for crop yield predictions are random forest (RF), deep fully connected neural network (DFNN), and LASSO. The model based on CNN and RNN have achieved the root mean squared error (RMSE) of 9% and 8% and outperform all other methods. Three salient features of CNN-RNN are(1). The CNN-RNN model can capture time dependencies of environmental factors and genetic improvements of seeds over time without having their genotype information (2) The model has the capability to generalize the yield prediction to untested environments without significant drop in prediction accuracy (3). One of the principal limitations of deep learning models is their black box property. The feature selection can be performed based on the trained CNN-RNN model using the backpropagation method. Coupled with the backpropagation method, the model can revel the extent to which weather conditions, accuracy of weather predictions, soil conditions, and management practice were able to explain the variation in the crop yield.

Leaf Area Index (LAI): Leaf area index indicates the amount of leaf area in an ecosystem. LAI is an important structural property of vegetation. Because leaf surfaces are the primary sites of energy and mass exchange, important processes such as canopy interception, evapotranspiration, and gross photosynthesis are directly proportional to LAI. Compared to direct measurement method of harvesting and measuring areas of leaves, remote sensing provides an effective way to map LAI at large scale on a regular basis. Several global LAI products such as MODIS, CYCLOPES, GLOBCARBON, MISR, POLDER, VIIRS, and GLASS have been developed. All these satellite LAI products suffer from two major issues: substantial data errors and frequent missing values. Surface snow cover and high cloud frequency within the observation period are the two leading causes. Adverse atmospheric conditions, unfavorable observation geometry, instrumental failure, and NIR reflection saturation induced by dense vegetation, may also lead to missing data. To solve the problem RNN based NARX (Nonlinear Autoregressive model process with exogenous inputs) was applied. The model relates the current value of times series to both past values of same series and current and past values of driving exogenous series. For example, the series values may be air temperature at noon and exogenous series value may be the day of the year. This model took not only independent inputs into consideration but also the output of the model in the past, making it more powerful.

Weather Prediction: RNN is useful for time series and thus has been used in weather predictions. Most of the weather forecasting approaches attempted to forecast only single weather attribute at a time. They did not consider generalized weather dynamic hidden in meteorological data. There is a need to capture dynamic and chaotic behavior of weather. The RNN based model NARXnet has been able to outperform case-based reasoning model (CBR) and segmented CBR model. NARXnet has the capability to learn not only from historical data but also from the previous predictions. NARX net got the accuracy of 93.95%. LSTM model can also be used to predict 24- and 72-hours attribute of a city: temperature, humidity, and wind speed. During a study, hourly attribute data of 15 years was used to train the model and researcher got comparative results compared with other traditional methods. The deep RNN based methods have been proved as competitive alternative for weather forecasting.

Soil moisture (SM): Surface soil moisture is one of the most important factors in regional and global water cycle processes. It has played an increasingly important role in the earth sciences (e.g., meteorology, hydrology, agriculture, and biomass analysis). The estimation of soil moisture from remote sensing data is one of the most feasible ways to generate SM products at regional and global scales. Passive microwave remote sensing techniques such as Soil Moisture Active and Passive (SMAP) satellite, the Microwave Imaging Radiometer with Aperture Synthesis (MIRAS) onboard the Soil Moisture and Ocean Salinity (SMOS) satellite are available. The ongoing operation of these major satellite sensors is intended to estimate parameters that are vital for hydrological and meteorological sciences, such as surface SM. However, the data from the passive microwave sensors are not ideal for obtaining soil moisture from region characterized by extensive vegetation cover or from regions that experience severe man-made radio frequency interference (RFI) or extra-terrestrial galactic radiation. In addition, surface SM products are originally discontinuous, due to the footprints and repeat intervals of the satellite orbits, restrictions in instrument design and limitations of the inversion algorithms. Thus, the defects described above present obstacles for the application of surface SM in the study of geoscience. The neural networks can estimate complex functions and time- series input. A simplified NARX model, whose input is the current features and the prediction it had given in the last time step. When simplified NARX model is compared with Japan Aerospace Exploration Agency (JAXA), the Land Surface Parameter Model (LPRM), and Global Land Data Assimilation System (GLDAS), the simplified NARX model remained stable in both frozen and unfrozen seasons. Similarly, when the prediction of soil moisture on hourly basis were compared using the NARX model with ground measurements, the NARX model provided comparable results.

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