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Deep Learning: A Futuristic Approach to Agriculture

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Abstract

Deep Learning (DL) techniques, mainly the methods of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), have received considerable attention and are being used in diverse fields including the agricultural sector. Most agricultural research frequently employs software frameworks without thoroughly investigating the ideas and mechanisms of a technique. The present article provides a concise summary of major DL algorithms (CNN and RNN), including concepts, implementation and applications to the scientific community to gain a holistic picture of techniques quickly. The article summarises and analyses research on DL applications in agriculture, and also focused on future opportunities which in turn help agricultural researchers in better understanding and learning of DL algorithms that facilitate data analysis, enhance research in agriculture, and thus effectively promote DL applications.

Introduction

In recent years, machine learning and artificial intelligence broadened the scopes of signal and information processing activity. Deep learning is a component of artificial neural network-based machine learning techniques (ANN). It isn't a single approach but rather a class of algorithms and topologies that can be applied to a broad spectrum of problems. The scientific fields of neural networks, artificial intelligence, graphical modelling, optimization, pattern recognition and signal processing, all intersect with deep learning. DL incorporates greater depth into the model and modifies the input using multiple functions that enable hierarchical data representation through several levels of abstraction. The enormous increases in chip processing power, the size of training data and recent developments in machine learning and signal/ information processing research are the key drivers of deep learning's current popularity. DL has gained appeal in many applications involving from natural language to image processing (raster-based data) and it is possible to apply DL in any type of data, including audio, speech, and natural language, as well as more generally to continuous or point data like meteorological data, soil chemistry, and population data. These advances have enabled the deep learning methods effectively exploit complex, compositional nonlinear functions, to learn distributed and hierarchical feature representations and make effective use of both labelled and unlabelled data. Major significant deep learning architectures includes Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN) have been successfully applied to diverse research areas, including agriculture.

Convolutional Neural Network (CNN)

CNN is composed of multiple convolutional layers, pooling layers, and fully connected layers, which has resulted in many breakthroughs in speech recognition, face recognition and natural language processing. A crucial element for the accomplishment of image processing tasks like segmentation and classification is the convolution layer. The above layer's focus is on understanding distinctive local patterns like lines, edges, and other visual components. The convolutional layer can apply a wide range of filters, producing a wide range of feature maps. The pooling layer, which gradually and spatially decreases the feature map, comes after the convolutional layers. Therefore, the pooling layer is used for minimizing the dimensions of feature maps efficiently and stays robust with the shape and position of the detected semantic features of the given image. The fully connected layers are used to combine all of the feature responses from the entire image and produce the final findings.

Applications of CNN in Agriculture

CNN is widely used in agricultural research due to its powerful image processing capabilities. When done manually, plant disease identification takes time and also needs expertise. Fortunately, with the advancement of artificial intelligence, it is now possible to detect plant diseases using image processing. Most models for identifying plant diseases are based on the classification and pattern recognition of leaves. A model for detecting plant diseases was developed using a framework created by The Berkley Vision based on DL. This model can distinguish between the leaves of different plants and their surroundings, and it can identify 13 different types of plant illnesses. The widely used CNN models for plant disease detection are InceptionV3, ResNet50V2 and DenseNet201 which are supported by the Keras framework. An improved CNN architecture *viz*., VGG19 and Regional Proposal Network (RPN) are accurate in distinguishing the different pest infestations (Gowthaman and Sankarganesh, 2022). The implications for automating agriculture made plant classification and weed identification crucial. CNN has been widely used to detect weeds or classify plants since image recognition can be employed to detect a variety of plant traits. A new method that combines CNN with K-means feature learning was developed for weed identification and control. Weak generalization capabilities and unpredictable identification outcomes in weed identification due to manual design elements. Identification accuracy was 92.89% when DL and K-means pre-training were used. AlexNet is a pre-trained CNN architecture, which is commonly employed for classifying plants. The results of using this architecture (Istanbul Technical University) show that CNN is better than other machine learning algorithms based on handcrafted features for the discrimination of phenological stages. Supervised classification with CNN helped in optical image segmentation and subsequent restoration of missing data in time-series of satellite imagery. An accuracy of 85% was achieved for this classification of major crops (wheat, maize, sunflower, soybean, and sugar beet).

The approach using CNN with blob detection improved the accuracy and the efficiency of fruit counting, which is important for yield prediction and robotic harvesting. DL approaches have been used in remote sensing and other agricultural imaging for land classification and area estimation. The fundamental idea behind this strategy is to fuse or integrate data from numerous heterogeneous sources by leveraging machine learning techniques and new big data and geo-information technologies to give data processing and visualization capabilities. Weed identification is crucial for farmers in agricultural lands, especially with the rise in popularity of highly autonomous machines. These machines must execute automatic real-time risk detection with great reliability to run safely without supervision. The Deep Convolutional Neural Network (DCNN) were employed to detect items which improved the performances of machines and achieved a row crop accuracy of 99.9% and grass cutting accuracy of 90.8% (Magomadov, 2019).

Recurrent Neural Network (RNN)

RNNs are specially designed for mining temporal information and semantic information. They have been successfully used in fields such as time series analysis, speech recognition, machine translation and image captioning. One of the basic network architectures on which other deep learning architectures are based is the RNN. A recurrent network may feature connections that feed back into earlier layers in addition to purely feed-forward connections, which is the main distinction between a standard multilayer network and a recurrent network (or into the same layer). RNNs can retain track of earlier inputs and model problems over time. RNN processes sequence data by elements and preserves a state to represent the information at time steps. A traditional neural network assumes that all units of the input vectors are independent. Consequently, the traditional neural network is ineffective for predicting using sequential data.

Applications of RNN in Agriculture

RNN has been utilized in numerous agricultural fields, including land cover classification, phenotypic recognition, crop yield estimation, leaf area index estimation, weather prediction, soil moisture estimation, animal research, and event date estimation. RNN, in addition to CNN, has been used for crop yield estimation, which employs time series data to reduce bias. Two RNN-based classifiers, an LSTM network and a Gated Recurrent Unit (GRU) network were used in conjunction with mono-temporal models to map winter vegetation quality coverage. The GRU model surpassed all other models, with an accuracy of 99.05% on a 5-fold cross validation dataset. The employment of techniques and technologies that make the management of climate-related factors in greenhouses is a highly important topic since it is still difficult to accurately forecast behaviour and control the variables of many parts. Thus, the RNN model as a DL algorithm is used for the prediction of the greenhouse microclimate. RNN has also been applied to the macro and microcosmic scales of animal research.

With the development of deep learning, RNN-based models combined with the particle swarm optimization (PSO) algorithm can be used to predict the locations of animals with a low level of errors, which is very useful for the identification of endangered species. RNN models can also be used for the estimation of animal growth, especially in size and body mass. A crucial hydrological parameter for climate change, meteorology, and precision agriculture is soil moisture (SM). The difficulty in making an accurate calculation arises from the fact that SM in farmlands depends on numerous variables and can change greatly over time and geography.

Neural networks are applied to this task because they can estimate complex functions and time-series input efficiently and precisely. Leaf Area Index (LAI) and its dynamics are widely used for estimations of environment, vegetation status, carbon cycle, *etc*. The traditional LAI estimation methods results may suffer from spatial or temporal discontinuities, which limit their applications in climate simulation and weaken their robustness. To solve this problem, an RNN-based model named NARX (Nonlinear Autoregressive model process with exogenous input) was applied. This model was more potent since it took into account both independent inputs and the model's previous output.

Conclusion

Deep learning is the modern data analysis technique have been widely used in different fields of agriculture *viz*., plant disease detection, weed identification, fruit counting, land classification, obstacle detection, image translation, weather forecasting, yield prediction and animal behaviour classification and so on. DL encourages its continued usage in different areas and it is possible to be exploited fully to achieve sustainable agriculture goals.

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