

Agriculture Robots using Deep Learning

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Abstract: Agriculture is very important to the continuation of mankind, which maintains a driving factor for many world economies, especially in stunted and emerging countries. The bread and food crop mandate is increasing due to the globe's expanding population and the challenges posed by environmental issues, while reducing costs. Agricultural researchers often use software systems without an appropriate analysis of the ideas and mechanisms of a technique. Intelligence is seen as the greatest challenge for nurturing the productive capacity and accurate performance output. Throughout this paper we aim to understand the key techniques of using robots in agriculture. Deep learning was extensively studied and implemented in multiple fields of recent years, along with agriculture. Robot systems provide a stable, price-effective, flexible and modular product development system and deliver predictive results.

Keywords: Deep learning, classification, neural networks, pattern recognition, multi-robot systems, autonomous agricultural robots, identification of anomalies.

I. INTRODUCTION

Deep learning (DL) is a cohort of natural processing methodologies that use different layers to derive slowly greater-level features from the unprocessed data. It is centered on computational models with mastering how to embody. Learning can be regulated, quasi-supervised or unmonitored. It has evolved hand-in-hand with the digital era, which has produced an abundance of data in all forms and from every part of the world[1]. DL architectures is designed by using a greedy layer-by-layer approach; this includes deep neural and belief networks, recurring and convolution neural networks that are implemented to domains such as machine vision, voice recognition, web browsing, phonetic transcription, biostatistics, med chem, clinical data analysis, substance assessment and tabletop services whose outcomes are equivalent to an even exceed human analyst output. It also helps to remove abstractions and selects which features boost the output. Deep convolution neural networks are used to identify plant seedlings.

DL methods remove format optimization for controlled research activities by converting content into portable interim representations and similar to major elements and deriving stacked frameworks that reduce uncertainty in distribution. Increasing stage of DL tries to transform its input data into a somewhat further symbolic and complex model. DL algorithms can be applied to unattended learning tasks; this would be an advantage in terms as unsorted content were more prevalent to categorized content. In DL is a subfield of artificial ANN is a paradigm for cognition for computational and linguistics, prompted by the method human neural systems. intelligence that mimics a human brain's role in data processing and generates patterns for use in decision making. Deep belief networks can be combined with convolution networks to build deep belief convolution networks that leverage the benefits offered by both types of architecture based on the dataset of common fruits. The idea of neural network back propagation is the foundation of many deep learning algorithms. DL's major use in agriculture is image representation, which overcame many barriers to the rapid development of programmed and computerized agro-industry and agriculture. Some of the applications of DL includes, (1) Automatic speech recognition: The first and most compelling successful case of DL is the wide-scale automated speed recognition. LSTM overlooking gates competes with traditional speech recognition on certain objectives. (2) Image recognition: A specific evaluation system for the labeling of pictures is the collection of MNIST data bases. Profound programming-trained vehicles construe graphic overlays now at 360 degrees. (3) Bioinformatics: DL is used to forecast sleep patterns based on active data and digital medical records forecasts of medical complications. (4) Image restoration: DL has been applied effectively to reverse issues such as para-noising, ultra-resolution, outside of-painting and screen painting[4].

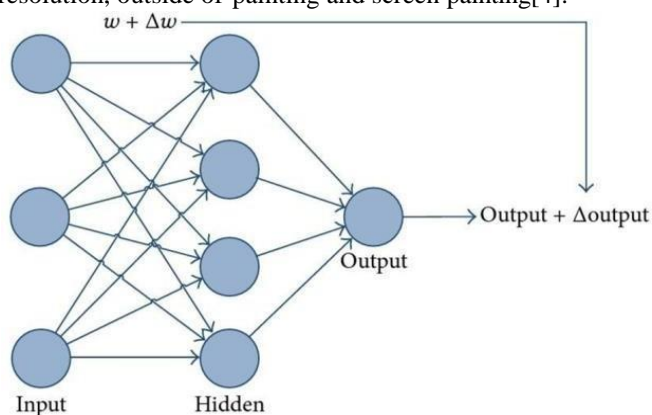


Figure 1: Simple model of ANN.

In the above figure 1, we can observe, ANN or connection systems are computational structures driven by functional neurons in organisms.

Manuscript received on February 10, 2020.

Revised Manuscript received on February 20, 2020.

Manuscript published on March 30, 2020.

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These systems generally glean to complete tasks without process-specific scripting by getting instances. An ANN is based on an abstract neural set of related units[5]. The primary purpose of the artificial neural model is to resolve issues in a certain manner where an organism tackles them. Each neuron connection may convey a signal to another neuron. Over time, emphasis has been centered on adapting clear mental capabilities resulting in biological derivations like back-propagation or flipping of info, and network modification to represent that information.



Figure 3: Custom stereo imaging sensor for stalks.

DL-based agriculture robots lead to greater operational efficiency, improved soil health and increase yield. An agriculture robot is an automaton used during producing food. Today the main fields of robots' intervention in production are at the cultivation phase. Nascent implementations of automatons or drones in farming usually involve herbicides, geo-engineering, seed digging up, tilling, ground evaluation and remote sensing. Factory work robots forklift/ canisters without operator and flock sheering androids was designed to accommodate mechanization. Robotanist in figure 2 is a field robot that can manage tightly spaced plant rows with cameras and sensors capable of assessing plant output[7]. Industrial farming aims at planting crops in controlled situations, along with vertical farms, which can improve plant quality or duplicate the environmental factors of specific regional areas for materials produced regionally. Intelligence was viewed as an additional enabler and a major technical critique to fostering the intellectual capital worth of all precision agriculture. The goal of automation, image processing and big data analytics is to expedite the process of farm parameters appraisal and far more specifically recognize elevated-performance variants. Robots will be used for certain permaculture activities like trimming, sorting, drenching and tracking. It could also be used in product processes such as automated feeding, laundry and catering. In figure 3, we can note that the machine is fitted with stereo image processing optics including hard-powered automotive lights to deliver great images suited for collecting durable and precise measurements of plants. Predicting exact yields lets farmers improve the quality of their crops. Robots fitted with computer vision systems offer an alternative approach. Features derived from deep CNN have been used to explain various image tasks such as object recognition and semantic segmentation. Farmland systems can be divided into domain- and process-specific automatons able to perform a particular task on a certain harvest over a

specified framework, and common frameworks trained to perform numerous activities in different disciplines. Both will likely play significant roles. Data acquisition measures produce significant possibilities in sustainability to facilitate cybernetic processes to be sovereign.

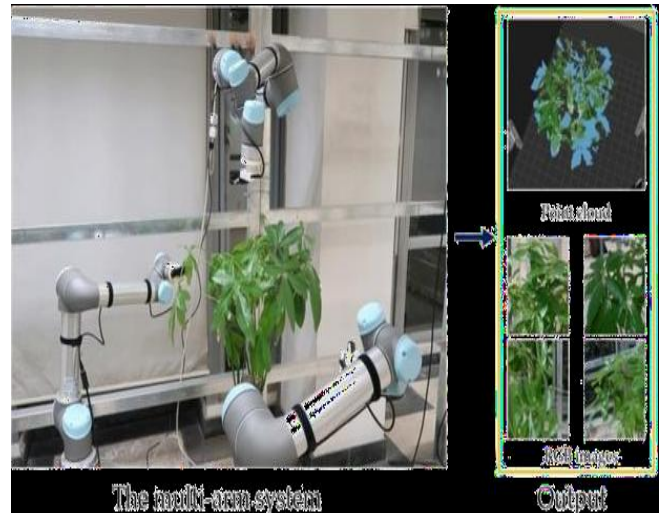


Figure 4: A breakdown of multi-robot framework for optimally performing the plant phenotyping functions.

The encrypted processing and recovery of foodstuffs poses a number of specific challenges relative to certain domains. The interaction poses scope from database-independent facets including adaptive prototypes, exhilarating shows and sensory responses, to quite real challenges arising from the circumstances in the subject area. Unlike robots in industries whereby human labor zones can be closed when a machine is in service, industrial systems are constrained by the lack of field security facilities and require massive, sustainable solutions. Detection of anomalies pertains to the possibility of finding motifs in records that do not conform to usual or standard behavior. The combination of background and deep learning, defining the top performance configuration known as DeepAnomaly, includes a detector of anomalies which leverages the homogeneous personality traits of the farming industry. In figure 4, we can view a realistic solution which can easily expand the existing NBV planning method for studying from a particular automation to a multirobot model which does not lose too much planning momentum. An effective, in-depth NBV planning approach that makes light of plants' systemic priorities a method of calculating the data obtained from the applicant's points of view[8]. CNN based classification systems allowed breakthroughs in many tasks. To achieve impact, farming robots need to assimilate several tools and solve important compatibility concerns. Weed detection involves the finite element analysis tracking the viewpoint and volume of distinct weed genus. Intelligent machines bearing a variety of indicators for evaluating field quality as well as condition can therefore aid to extract content expense-effectively.

II. RELATED WORK

Paper [1] The approach includes dividing of tomatoes into five categories on the basis of the correlation among preservation period and display.

Implementing a new architecture, based on profound learning to classify tomato maturity levels. t-SNE is used to check the data frame dispersal and to remove random images in order to accomplish better results of the built-in assessment paradigm.

The reports include the best forecasted results for the R&S&SN dataset. The statistical duration is less than 0.01 seconds per 100 images and the ultimate precision is 91.9%.

Paper [2] A novel method of stereo-visual identification of obstacles is proposed. This requires a barrier alert system integrating the flexibility and consistency of such a new compact decoder, and the increased efficiency of OCSVM is detection of anomalies.

Indeed, the built subscription model blends the needy attributes of deep Boltzmann machines (DBM) with the dimensional reduction capability of an auto-encoder (AE).

This involves testing the solution suggested using realistic data from two databases, MSVUD and DUSD.

Analogies of the current proposal to that of state-of-the-art designs were presented on the basis of a network of profound convictions as well as loaded instant-encoders and results reveals that the ability of the envisaged method to reliably pinpoint impediments.

Paper [3] A new approach for using deep learning methods which clearly identify and diagnose plant disorders from depictions of the leaves was explored.

The developed system became capable of detecting the prevalence of the leaves and to distinguish amongst stable leaves and 13 disorders that can be typically identified.

The complete method was defined, from the collection of pictures for use in learning and validation to the preprocessing and expansion of images as well as subsequently the training protocol for profound CNN and refinements. The experimental results achieved precision of different class assessments around 91% and 98%. The qualified model's final overall accuracy was 96.3%.

Paper [4] This summarizes the principles, methods, drawbacks and DL algorithms. It could be noted that DL is extensively seen in various fields such as crop disorder prevention, crop evaluation and weed verification, vegetable racking up, farm specification, barrier countermeasures, illustration interpretation, remote sensing, volatility estimation and delineation of human biology.

DP can be used directly as a data-driven design framework to relate plant determinants, external factors and cell growth progress. The creation of an optimal control strategy renders use of significant-time crop biochemical prestige measurement as well as statistical data through using DP to pattern food production technologies.

Paper [5] A neural-convolution approach is used to recognize as well as interpret banana ailments. This current proposal may fulfill as more of a tactic designed to detect the banana plant sickness.

The main contribution is the use of optimization techniques to simulate two famous banana ailments, banana sigatoka and banana speckle in reality and under hostile conditions such

as lighting, intricate context, specific image resolution scale, location and orientation.

In particular, there is use of the LeNet architecture to classify image datasets as a convolution neural network. The initial findings indicate the efficacy of the approach suggested, only under difficult circumstances.

Paper [6] The introduction of a new, high-quality, fruit-containing image collection also presents the results of a numerical experiment to train a neural network for fruit detection. The images were obtained filming the fruits while motorized and then extracting frames. This article is streamlined as defies: in the first portion, there is addressing of some outstanding achievements achieved by natural language processing of fruit notoriety, preceded by an assessment of the DL principle. In the second the discussion of the system known as TensorFlow and the reasons why it is chosen is done. We can also find the outlined training and test data used and the results obtained. Finally, concluded with a few suggestions on how to boost project outcomes.

Paper [7] A new pipeline is being built which collects precisely only sensed objects with sparse semantic aggregation for stalk count and speed spacing extraction.

The field machine is used for an elevated-resolution projector spectrometer capturing a sparse view of interdisciplinary plotlines of sorghum plants. This approach for counting stalks was found to be 30 times better and 270 times larger for measuring stalk widths.

Paper [8] Manual phenotyping is sluggish and error prone. In this approach usage of deep learning methods is done to present and automatic robot to measure accurately and quickly.

This approach has two steps, the first step is to estimate a set of candidate voxels to determine optimal points of view using deep neural networks and then use these voxels to determine optimal points of view. Later usage of simulations and robotic tests with up to three mechanical arms is done. The main objective is to calculate the next-best viewpoint.

Paper [9] The main aim of this article was to promote the classification and identification of food crops using DL. The CropDeep dataset is composed of 31,147 illustrations and 49,000 abridged occurrences from 31 multiple classes.

The first step is to implement the datasets of CropDeep and then compare the reliability of different categorization and tracking systems. The current method has 99% and 92% accuracy respectively for classification and detection. The advantages of this system are - the dataset is unbiased and includes 31 crops in common greenhouses.

Paper [10] The principal task of marketing and product management is to estimate crop yields. This helps farmers enhance the quality and outcome-making of the crops. Manual approach is workers counting the fruits at chosen sampling locations.

This is costly process, and requires manual power. The estimation of crop yields using computer vision is commonly divided into two categories 1) area or region based 2) counting based.

Attributes derived from DL were implemented to many aspects of comprehension of images. This publication proposes a strategy to evaluate tomato counts from the perspective of the whole image. This helps to reduce overhead for localization and identification of artifacts.

Paper [11] This paper uses a deep anomaly neural network pairing DL and anomaly detection to leverage homogeneous agricultural traits. CNN-based systems have problems not detecting distant, heavily occluded and unknown objects and unusual scenarios.

Deep anomaly is compared with RCNN- the real object detection network with regional proposal. The shots were taken from a turntable display and mounted on a sensor

platform.

The heuristic employs thumbnails from the left display, while the right camera info is used to estimate the range to impediments. Paper [12] In this paper, there is implementation of a two-class classifier that takes images of plant seedlings with 12 different species and creates a model using deep convolution neural network. This model predicts the type of image of plant seedling.

The training model achieved an accuracy of 99.48%. The first four layers of convolution layers with weights from the dataset are initialized in this process. The fifth and final block is initialized with weights saved from the corresponding layer and loaded.

III. LITERATURE REVIEW

Table I: Comparative analysis of distinct agricultural robots using techniques based on deep learning.

Reference No	Approach	Method	Parameter	Result	Advantage
1	Deep learning derived rubric which enhances the consistency and interoperability of tomato maturity with a tiny amount of test data.	CNN (Convolutional neural network), Image Annotation and verification, Augmentation methods.	t-SNE (t-Distributed Stochastic Neighborhood Embedding), Pooling, Classifier.	The final accuracy is 91.9 percent, and the predictive time is less than 0.01 seconds per 100 images.	It has less feature, calculation and high precision compared to other classical architectures.
2	The creation of a groundbreaking hybrid encoder that combines deep Boltzmann machines (DBM) and auto-encoders (AE) to detect obstacles reliably.	Estimating the location of obstacles and tracking their positions with the proposed hybrid model with OCSVM via scene densities.	V-Disperity, U-Disperity, One-class support vector machines (OCSVM), Malaga Stereovision urban dataset (MSUD), Daimler urban segmentation dataset (DUSD).	The use of both models achieves high precision; A simple approach is developed to estimate obstacle positions by monitoring changes to the density map using the three-sigma rule.	The detection efficiency of OCSVM is improved to that of SVDD.
3	Design of a model for the identification of plant diseases, based on the classification of the leaf images.	Deep convolutional networks, Image processing and Labeling, Augmentation process, Neural Network Training.	Graphics Processing Unit (GPU), CaffeNet, OpenCV framework.	The built model precision for separate class tests between 91% and 98%, on average 96.3%	A beneficial effect on sustainable development that will affect crop quality for upcoming generations.
4	Requirements, principles, methods, drawbacks, deep-learning algorithms in agriculture are reviewed.	Feedforward neural network and backpropagation (BP), CNN, Recurrent neural networks (RNN), Generative adversarial networks (GAN).	Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), NARX model, TensorFlow.	Deep learning work is gathering steam in broad, DL analysis is very divergent for agriculture according to metadata analysis.	Agricultural information processing was the basic basis of modern technology-based agriculture.

5	A profound learning approach which streamlines the pathway of classification of banana leaves ailments.	The LeNet architecture is used to classify imagedata sets as a convolution neural network.	Scale invariant feature transform (SIFT), Color Layout Descriptor (CLD), Color Structure Descriptor (CSD).	The proposed method greatly facilitates accurate identification of leaf diseases with little computational effort.	Outbreak monitoring lets farmers determine how to intervene to stop the outbreak.
6	The approach includes a new, high quality, fruit-containing image dataset.	Faster Region-based Convolutional Network, Multi-column deep neuralnetwork, MNIST dataset, Fruits-360 dataset.	RGB and NIR models, Pooling layer, Rectified Linear Unit (ReLU) layer.	Obtained a Software which can recognize images.	Fruit identification from the images is easy to recognize, with less consumption of time.
7	Deep learning pipelines for calculating plant stalk number and stalk width at a high bandwidth.	A ground robot with cameras and sensors is used to detect visual data of observational plotlines.	Machine vision stereo camera, RCNN, SGBM.	This stance is 30 times and 270 times slightly quicker for stalks count and stalk width measurement respectively.	Rapid and accurate estimation of plant properties.
8	Plant phenotyping by deep learning multirobots operator.	Next-best view is the method most general in robotics that collects information of unknown objects based on information entropy model.	RGB-D sensor, VR5 robotic arms, Intel Real sense SR-300	A deep learning based NBV planner that computes next-best viewpoints.	It can be applied quickly to a multirobot device.
9	CropDeep, a crop division database for labeling and diagnosis in strategic agriculture focused on deep learning.	Various statistics are obtained in greenhouse by different filters and appliances.	Autonomous robots, greenhouse, images, datasets.	99% accuracy in classification and 92% accuracy in detection.	CropDeep is unbiased.
10	Extrapolation of real-time produce based on DL.	Uses deep learning convolution neural network for deeper understanding of image.	Synthetic images.	The accuracy for 100 randomly sampled actual pictures was found to be 91%	Under appalling conditions the statistical model is rigorous.
11	Fusing background subtraction and deep learning for monitoring hindrances and aberrations in an agriculture sector.	Exploits homogeneous characteristics of agriculture field using deep anomaly.	RCNN, Deep anomaly.	High accuracy and low computation time.	Can be extended to also detect secluded, highly unobserved and unexplored obstructions.
12	Plant seedlings classification using deep learning.	Uses CNN to predict the type of image and plant seedling.	Datasets, data augmentation.	Accuracy of 99.48% was achieved on the training model.	Improve crop yields and boost productivity.

IV. CONCLUSION

Deep learning with its high-precision algorithms aims to increase the quantity and quality of goods by note using much manual input and reduced time. Industrial automatons optimize the farmers’ repetitive, low and dull activities by

allowing them to focus further on achieving better consumption. From identified research articles focusing on the specific area, specifications of the prototypes employed, data points in use, pre-processing operations and data enhancement techniques adopted, and overall performance metrics within each article.



Various authors try to find ways to increase the precision rate. Several methods provide data sets that help in classification and detection. These datasets are usually camera-captured images. This paper proposes a survey on various methodologies used to improve the agricultural sector by integrating robots for agriculture using deep learning. Our intention is to encourage further scientists to explore with deep learning, to apply it to solving various farming issues like identification or estimation, image processing and data analysis, and perhaps more wide analytics. Recent results show how DL delivers better consistency and surpasses certain common processing frameworks. The possible benefits of DL are promising for its sustained need for informed, faster sustainable practices and healthier crop production.

V. RESULT

Agriculture suffers from certain major problems which diminish production and yield quality. This can be overcome by using sophisticated deep-learning diagnostic tools. This paper provides various deep learning techniques such as neural networks, automations, DL based algorithms etc which enhances the solution to be feasible. The efficiency of using DL techniques in agriculture is high compared to other machinery languages based methods. Around 90% of accuracy is gained by DL techniques. DL and its tools is considered as flexible solution for both simple and complex problems.

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