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Machine learning and artificial intelligence for smart agriculture

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1 Introduction

Smart agriculture mainly consists of three elements: information, knowledge, and technology. Few topics that still need investigation and debate are the main subject of this special edition. For instance, using and improving machine learning methods for plant species identification, crop disease and pest detection and identification, smart agricultural Internet of Things, food material supply chain security tracking, and other important smart agriculture-related problems.

2 Computer vision

Images processing methods were used to investigate automated separation between two disorders. Preprocessing of the obtained illness pictures included image scaling, colour image contrast stretching, and morphological opening and closure reconstruction. Then two crop leaf lesion segmentation methods based on circle fitting were proposed and implemented. Random forest models and support vector machine (SVM) models were used depending on different combinations of LBP histogram features and individual characteristics. A further need for the creation of phenotypic and genetic resources is crop classification. Using eight data types collected, Fu et al. produced the Rapeseed dataset (RSDS). Proposed was the target-dependent neural architecture search (TD-NAS). Revolutionary target-dependent search method TD-NAS is built on VGGNet.

3 Internet of things

Since computer graphics and image processing technology in artificial intelligence (AI) have advanced, visual recognition technology has been used more and more in many spheres of agricultural growth. The use of this technique in contemporary agriculture is still rather much justified (Tombe, 2020; Benos et al., 2021; Dhanya et al., 2022). The vision system has great difficulties when picking green apples or estimating yields since the target fruit must be quickly located and accurately recognised. Sun and colleagues enhanced a gradient field of depth pictures to detect and identify target fruit in a density peak cluster segmentation technique for RGB photos. In particular, the gradient field of the target picture is analysed using the image depth information.

In agricultural Internet of Things, sensor nodes gather data in the agricultural environment. Examples of these sensors include soil and air temperature and humidity sensors. Data collecting occurs via wireless transmission of data from the sensor nodes to the sink node. When the gateway gets data from the sink node, it converts the protocol into one that can be sent over the Internet (Ayaz et al., 2019; Doshi et al., 2019; Priya et al., 2021). Usually, smart agricultural IoT generates massive amounts of multidimensional time series data. But given the constraints of the scenarios, data loss and misrepresentation are common issues with smart agricultural IoTs. With the use of generative adversarial networks (GAN), Cheng et al. presented a novel anomaly detection model that can manage the multidimensional time series data generated by smart agricultural IoTs, thus resolving the previously described problems. Uyeh et al., meanwhile, used a multi-objective approach based on supervised machine learning to determine the optimal number of sensors and installation sites in a protected cultivation system. We particularly modified a tree-based model using a gradient boosting approach to observed (temperature and humidity) and calculated (dew point temperature, humidity ratio, enthalpy, and specific volume). Forecasting of time series was used to feature variables. We developed and proposed a machine learning model to choose the optimal number and positions for the sensors in a protected cultivation system. More sensors/nodes are recommended in bigger fields, including as observed in large-area agriculture, to better account for soil heterogeneity. But this (buying, labour charges for installation and removal, and upkeep) comes at a greater and often prohibitive cost to farmers. Methodologies that enable maintaining monitoring capability/intensity with fewer in-field sensors would be very beneficial to the agriculture sector. Here Through sensor data analysis across two irrigation seasons in three cotton fields from two Australian cotton-growing areas, Maia et al. found a relationship between soil matric potential and cumulative crop evapotranspiration (ETcn) calculated from satellite measurements taken in between irrigation episodes. One way to see this relationship is as a second-degree function.

4 Agricultural robots

International attention is being drawn more and more to the use of intelligent robots and technologies in agriculture (Oliveira et al., 2020). A picking robot is a kind of agricultural robot that senses the complex agricultural environment using a range of sensors and, utilising this information along with a decision-making algorithm, selects the target. By using the collected data, Ma et al. investigate the distributed averaging problems of agricultural picking multi-robot systems under directed communication topologies. Equations of algebraic graph theory and matrix theory are used to provide a distributed protocol based on nearest-neighbor information.

5 Pest control

Long a major problem in agricultural production, crop diseases and pests have a detrimental effect on farmers' income, contemporary agricultural progress, and agricultural output. Early disease and pest identification, monitoring, and management are critical for avoiding the large-scale spread of diseases and pests, protecting the quality of crops, and decreasing environmental contamination brought on by pesticide residues (Buja et al., 2021; Liu and Wang, 2021). A piercing-sucking bug known as the brown planthopper (BPH), Nilaparvata lugens (Stl; Hemiptera: Delphacidae), badly damages rice plants by suckng out their phloem sap and disseminating viruses. A physical control mechanism based on BPH courtship disruption is a workable solution to lower mating rates and hence lower environmental pollution. In order to compile successful signs of courting disruption. Feng and associates developed a method for BPH vibration signal capture, monitoring, and replay. Male competitiveness and BPH courtship signals were gathered and assessed using this technique to ascertain their frequency spectra. The mean pulse rate and mean primary vibration frequency of female courting signals are found to be 23 Hz and 234 Hz, respectively. Mean main vibration and pulse frequencies of male courtship signals were 255 Hz and 82 Hz, respectively. Moreover, three species of migratory pests—Nilaparvata lugens, Sogatella furcifera, and Cnaphalocrocis medinalis—severely lower rice output and cause yearly economic losses. Sun and colleagues develop a machine vision and searchlight trap-based intelligent surveillance system for migrating pests to replace human identification. Within the system are comprising a machine vision-based searchlight trap, a cloud server, a Web client, and an automated identification model for migratory pests. Nighttime illuminations from the searchlight trap attract insects moving at high altitudes. Rotating brushes and multi-layer insect conveyor belts are used to disseminate all caught insects. The three migratory pests may be automatically tracked by the intelligent monitoring system in due course.

6 Food security

Food traceability is critical for the safety and quality of agricultural goods (Ivar et al., 2020). In Jing and Li, a red jujube traceability system is constructed using a hybrid manner of block-chain and IoT. With features like tamper-proof, decentralisation, and distributed storage, block-chain and Internet of Things technologies are integrated to solve the problem of date and quality traceability. Within the block is documentation of the whole red jujube growing, processing, and sales process. To ensure that the red jujube quality traceability is realised in the framework throughout the whole big data processing process, and the important data collected at each step is stored in the database.

References

Mansour, A., Aggoune, E.-H. M., Sharif, Z., Ammad-Uddin, M. (2019). Internet of Things (IoT) based smart agriculture: Towards enabling field communication. IEEE Access 7, 129551–129583. doi:10.1109/ACCESS.2019.2932609.

Benos, L., Berruto, R., Kateris, D., Dolias, G., Tagarakis, A. C., and Bochtis, D. Agric. machine learning: An extensive revised review. Sensors, 21: 3758; doi: 10.3390/s21113758

Buja, I.; Sabella, E.; Monteduro, A. G.; Chiriacò, M. S.; De Bellis, L.; Luvisi, A.; and others. Progress in the identification and monitoring of plant diseases: from conventional tests to in-field diagnosis. 10.3390/s21062129. Sensors 21, 2129.

Dhanya, V. G., Ritika, G., Kushwaha, N. L., Subeesh, A., Vishwakarma, D. K., and others. Deep learning based computer vision methods for smart agriculture applications. 10.1016/j.aiia.2022.09.007. Artif. Intell. Agric. 6, 211–229

Doshi, J.; Bharti, S. K.; Patel, T. (2019). Smart farming using Internet of Things, a way to best monitor agricultural conditions. 10.1016/j.procs.2019.11.016 Proc. Comput. Sci. 160, 746–751.

Shah, A. N., Solovya, B., and Ivar, V. (2020). Getting the trade-offs right between food security, safety, and sustainability. Sustain. Front. Food Syst. 4. doi: 10.3389/fsufs.2020.00016

Liu, J., and Xiao, X. Review of deep learning-based plant disease and pest detection. Plant Methods 17, 22. DOI: 10.1186/s13007-021-00722-9

Morteira, A., Silva, M., and Oliveira, L. F. (2020). Agricultural robotics: An overview of current developments. The 23rd international conference series on mobile machine assistance technologies and climbing and walking robotsMoscow, Russian Federation doi 10.13180/clawar.2020.24-26.08.44 279–286

Ramanujam, S. and Priya, O.V. (2021). Internet of things (IoT) effect on smart agriculture. Current Developments in Intensive Computing doi: 10.3233/APC210176

Tombe, Roger (2020). In computer vision for sustainable agriculture and smart farming. IST-Africa Conference (ISTAfrica) proceedings, 2020 May 18–22; IEEE: Piscataway, NJ, USA.