AGRICULTURE AND AUTOMATION: A REVIEW

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ABSTRACT

The use of artificial intelligence has made its way into several different sectors, including medicine, education, finance, agriculture, industry, and security. Artificial intelligence implementation is highly dependent on the machine learning process. The article ends by referring to a specific AI sub-domain: machine learning. Machine learning algorithms serve as a mechanism to gather statistical data and previously acquired information for use in specific tasks. It is now possible to find many apps that do complex tasks such as analysing historical data, gathering new data, reading faces, and forecasting weather. The advancement of big data and data science is due to machine learning. In order to create intelligent machines, a mathematic approach is used.

Keywords: Artificial Intelligence, IOT, Automation.

Introduction

Agriculture automation is on the agenda of every country, but is especially important in the developing world. The population is increasing at an accelerating rate, and thus there is a rapid rise in demand for food(de Rose & Wilton, 1991; Dennett et al., 2003; Yee et al., 2008). The tried-and-true techniques that farmers use can no longer meet the increasing demand, and as a result, farmers must use more toxic pesticides. The land obtained this way is entirely barren, lacking in fertility. The study, which is titled "Using Automation Strategies to Support International IoT Security Standards," is focused on the use of internet of things (IoT)(Ampatzidis et al., 2017; Carter et al., 2008), wireless communications, machine learning, and artificial intelligence, all of which are known as deep learning. The agricultural industry is plagued by the following problems: crop diseases, lack of storage management, pesticide control, pest control, weed management, lack of irrigation, and water management. When such difficulties as the use of harmful pesticides, stringent watering restrictions, attempts to control pollution, and the effect of the environment on agricultural practises(Alvarenga et al., 2015; Ferguson et al., 2004; Flohre et al., 2011) are present, it is important that we investigate and resolve them. As well, profitability from the soil has improved because of the use of automated farming techniques. This study collates research done by various people to quickly summarise the current state of agricultural automation. It also demonstrates a novel watering method that could be used in a botanical garden.

Fig.1 shows the different use of IOT in agriculture:

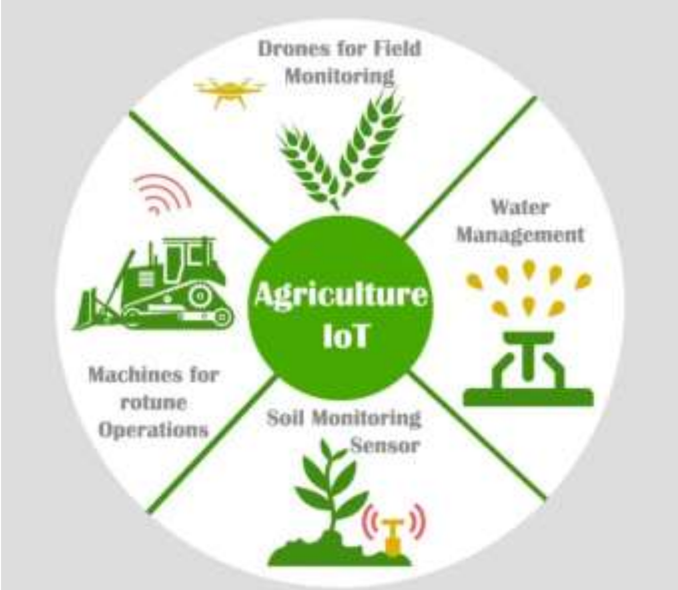

Fig.1 Use of IOT in Agriculture:
Source: : https://technofaq.org/posts/2018/05/the-impact-of-iot-on-agriculture/

Artificial intelligence falls under the purview of computer science, which is able to distinguish and recognise its surroundings, thus resulting in greater overall success. prior learning should be used in order for AI to accomplish a task. Deep learning, CNN, ANN, and machine learning are all used in the development of better machine technologies(Ampatzidis et al., 2017).

“Thing to thing” communication is called IOT (which means “the “thing to thing” type of communication”). Reducing communication costs, automating business processes, and saving money in the system are the three major goals of our three-year project. Dr. D.K. Sreekantha, from Kavya.A.M, offers in-depth explanations on how IoT could benefit society and agriculture.

Use of AI and Machine learning in Agriculture

AI and machine learning have had a profound impact on every category described above. Over the years, progress in artificial intelligence has been covered extensively in research. Beginning in 1983, computers and technology have made inroads into this industry. Agricultural progress is a long-term goal that has been the focus of a number of different database projects(Alvarenga et al., 2015; Ferguson et al., 2004; Valipour, 2015). Although the experiment was conducted in the real world, only AI-based systems proved dependable and viable. There is only one unique solution provided by the AI-based approach, and this is the limitation of the approach. The agricultural literature dating back to the early 1980s to the present day has produced significant accomplishments. This study looks at over fifty advancements in various industries, with a particular focus on agriculture, that are linked together. It covers how artificial neural networks and expert systems were used to address previously mentioned issues in the very first section of the article. Fuzzy logic and machine learning are then discussed next. In the final section, the document addresses the issues surrounding automated machinery and the Internet of Things in agriculture(Alvarenga et al., 2015; Ferguson et al., 2004; Flohre et al., 2011).

Artificial neural networks have frequently been used in the agriculture sector due to their advantages over traditional systems. Neural networks can both predict and forecast based on parallel reasoning. For this particular instance, neural networks can be trained rather than fully programmed. The method used by (Afif et al., 1993) involved the usage of ANN for the purpose of differentiating between crop plants and weeds. to predict water resources variables in a study by (DeJarnette et al., 2009), neural networks were employed (2000).

Expert System and AI

(Diskin & Sreenan, 2000; Hens & Merckx, 2001) showed how expert systems and Artificial neural networks could be combined to provide accurate and precise information about crop nutritional levels. Because traditional expert systems systems have significant financial, infrastructural, and personal support structures when they are installed, they require extensive funding, infrastructure, and manpower to begin operation. Using ANN helps to avoid any glitches that might occur when using ES. The entire system is made up of a single-chip microcomputer. Neural networks produce the most accurate predictions over and over again. Neural networks fed with reliable variables can correctly map out complex mappings. In order to help the people of Sicily overcome the effects of frost formation in their fields, (Hou et al., 2016; Paquette et al., 2013; Wang & Yates, 1999)designed a neural network prediction model. In the beginning, obtaining raw data necessitates a lengthy process of sorting, counting, and sorting again, followed by numerous calculations (all these data were taken from 1980 to 1983). Once data was represented as a series of ones and zeros, the computation was completed. Now, two separate sets of data are created (input and output for the neural network model). Back-propagation was used as a neural network predictor. A total of ten trial sets were initially designed for the model. instead of using a single value, the success of predicting the frost was dramatically increased by using a range of values

COMAX

Two new expert systems were created to boost cotton crop production in three years. From that point onward, COMAX. It was a moderate success when the Comax Expert System was released in 1986. (COtton Management eXpert). He was the first to create artificial intelligence for agricultural use, and this was the precursor to Gossym, which is highly accessible on a small computer (DeJarnette et al., 2009; Diskin & Sreenan, 2000; Hens & Merckx, 2001; Szenci et al., 1998). For the first time, the cotton crop model was integrated with an expert system, and a computer model was created to simulate the growth of the crop. This year-round continuous-operation expert system was designed to operate in cotton crop fields, which require continuous operation year-round. Comax considers three factors derived from the field when making their decisions. Our dream would be realised if we were to design an irrigation schedule, keep the nitrogen levels constant in the field, and boost growth in the cotton crop. Stone and Toman developed a more advanced cotton crop computer system (1989). The name of the system, COTFLEX, was given to the COTFLEX system. UNIX was used to build the Pyramid 90× computer, which employed the Pyramid 90× as its operating system. Information about the cotton crop was made readily available to the farmer thanks to the integration of the farm and field databases. to provide Texas farmers with sound financial and lucrative decision-making skills, rule-based expert systems were complemented by simulation models and databases Following successful testing, COTFLEX came to IBM microcomputers, and the technology was now available for use by other companies.

In the study by (Barbee & Stout, 2009; Coulson et al., 1987; Rouchaud et al., 2000) the Soyabean crop growth model is known as SOYGRO in the article. Both the normative and positivistic approaches are based on knowledge-based reasoning, and first one approach is divided into two: the normatively-inclined methods that are intended to come to the same conclusions as the domain experts without incorporating their processes, and the empirically-oriented methods that seek to mimic the domain experts in order to arrive at conclusions. When calculating the total cost of insect-caused damage, the costs are taken into consideration. In this case, the two approaches above are ineffective because of the implementation of the approach discussed below, which is helpful in selecting insecticide and the frequency of application. Using a systematic approach does not result in an improvement in determining the insect damage rate on yield. The project's goal is to provide an estimate of soybean yield and treatment cost and damage calculation so that farmers can use the information to guide crop choices. The final result takes both of these approaches into account.

Conclusion

During an in-depth study, it was found that the ANN algorithm could be successfully applied in a variety of estimative techniques in the Dehradun Valley, India. Researchers at the Forest Research Institute in Dehradun, India, examined monthly climate data from FRI in India, and derived an estimate of when the next extreme weather event is likely to occur. The algorithm was based on Dr. Penman-method. Monteith's Levenberg-Marquardt backward propagation serves as the algorithm. The ET estimator became unstable as the number of hidden layers increased(Chen et al., 2004; Hou et al., 2016; Wang & Yates, 1999). So, for a more optimised estimate of ET, a training function should be chosen that uses the best trial and error approach. Feeding the ANN algorithms 75% of the data resulted in more precise results as well as containing the most neurons. In addition, the PM methods and ANN models were compared by way of a feed forward single layer back propagation algorithm. The Matlab software was used to develop and design the ANN model. Conducted six different simulations(Hens & Merckx, 2001).

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