USE OF AI IN AGRICULTURE: A QUALITATIVE EVALUATION

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ABSTRACT:

AI-powered solutions in several sectors, including agriculture, are advocated for in a discussion paper written by the Indian government agency NITI Aayog. Farming might benefit from the use of AI robots, since they might help increase soil quality, as well as information on when to use herbicide, and where pests are most likely to appear. As a consequence, AI systems may help Indian farmers take advantage of advanced farming practises, causing a nationwide agricultural revolution. This way, one must prepare for both capacity expansion and cost reduction in order to bring about such a future state. The current manuscripts attempts to evaluate the use of AI in farming in case of India.

Keywords: Artificial Intelligence, Agriculture, Smart Irrigation

INTRODUCTION

Now, let us direct our attention to how AI may make life better for regular people in the future. It is, nevertheless, possible to make more achievements in the past 15 years or so from the beginning of the 21st century than in the prior three decades(Basu et al., 2006; Bruce et al., 2006). We are surrounded by contemporary technology such as cellphones and the Internet, which allow us to enjoy options such as viewing films and listening to music online with immediate access to information through Google. Let us expand on this growing body of fresh ideas, and see how we might develop it using artificial intelligence. Artificial intelligence (AI) will wire its own reasoning in order to improve itself due to frequent repetition and practise(Bernard, 2007; Trabucco et al., 2008). Overall, artificial intelligence (AI) has both benefits and consequences. Artificial intelligence (AI) is often discussed in everyday conversations nowadays, with articles on the issue appearing in periodicals. People have spoken about climate change in the past, and that has prompted meaningful action on our part. Now, people are debating AI, and this discussion will keep on going regardless of any individual's feelings. When trying to accomplish anything, it is always a good idea to start unpleasant but crucial dialogues about AI.

Microsoft has a number of AI-related technologies that focus on such things as locating life-threatening diseases, reducing accident risks, and predicting consumer behaviour. As Artificial Intelligence (AI) advances, intelligent personal assistants like Siri from Apple, or Cortana from Microsoft, and Watson from IBM are all making great strides(Hammad et al., 1996). New products like Google Maps, ride-sharing in cabs, facial recognition in Facebook images, face unlock in mobile devices, search and suggestion in online shopping sites, and others have witnessed an increase in use in the previous few of years. In my opinion, it seems like Google is “getting ahead of the game” when it comes to implementing AI technologies. I believe that the company has recently switched to “AI first” procedures and is employing AI for a lot of applications. It was recently reported that it is now necessary to use a broad range of human ingenuity in order to produce lasting changes in the area of AI. Two of the world's foremost

AI research facilities, GoogleBrain in California and TensorFlow in Tokyo, are both operated by Google(Herbert D.A., 2000; Zhang & Benson, 2000).

Use of AI in technological revolution

Artificial intelligence has become a key technology inside the business. AI research is smart and difficult. Computers don't yet demonstrate the many cognitive capacities, including problem solving, thinking, and learning, that humans do. This topic of statistical analysis on the impact of machine learning algorithms and their capabilities is already well-known in the mathematical community. As artificial neural networks (ANN) (Barbee & Stout, 2009; DeJarnette et al., 2009; Rivera & Sulaiman, 2009; Ushada, 2008)have proliferated in machine learning, the prominence of these deep learning approaches, including convolutional neural networks (CNN), generative neural networks (GN), and variational autoencoders, has grown from previous techniques that used artificial neural networks (ANN), fuzzy systems, genetic algorithms, and their hybrid techniques (VAE). This applies, but it does not apply just to the capability to find patterns in streams of inputs (e.g. text, numbers, images, sounds, video, etc.). In regression, the items are classified into groups, while in classification, the class of group is determined. Deep learning AI boosts accuracy significantly.

Use of modern technologies in agriculture

Robotics is part of artificial intelligence-related technology, too. Robots must have intelligence with other sub-problems like localization, motion planning, and mapping in order to do things like picking up items and navigating(Chen et al., 2011; Flohre et al., 2011). Sophia, a robot developed by Hanson Robotics, is a wonderful example of how artificial intelligence may bring advantages. More importantly, once AI systems have been taught to fulfil a given objective, they are free from prejudices and biases, and this lack of prejudice enables them to contribute to society in a positive manner. The world's complicated agricultural challenges might be solved using the diverse range of AI-powered fields.

AI-powered solutions in several sectors, including agriculture, are advocated for in a discussion paper written by the Indian government agency NITI Aayog. Farming might benefit from the use of AI robots(Barrett et al., 1985; González et al., 2018), since they might help increase soil quality, as well as information on when to use herbicide, and where pests are most likely to appear. As a consequence, AI systems may help Indian farmers take advantage of advanced farming practises, causing a nationwide agricultural revolution. This way, one must prepare for both capacity expansion and cost reduction in order to bring about such a future state.

AI Driven Agriculture

AI-driven solutions are working to help farmers, suppliers, and consumers do everything from soil and crop monitoring to weather forecasting, as well as analysing market trends and simplifying delivery. With cloud computing infrastructures such as data ecosystems, Internet of Things (IoT), and artificial intelligence, farmers may use digital agriculture to increase their productivity while decreasing expenses. They may do this by using smart farming practises including smart irrigation, fertiliser application, disease/pest diagnosis/detection, and spraying(Alvarenga et al., 2015; Ferguson et al., 2004; Flohre et al., 2011; Szenci et al., 1998; Thies et al., 2011). The widespread use of machine learning and soft computing technologies with pattern recognition can be seen in nations with satellite pictures and drone cameras (which may be used to gather photos and video) processing. Activities related to farming, predicting diseases and pests, weather forecasts, application time, harvest, etc. Neural networks are artificial neural networks that are built around the concept of how the brain operates and how it is constructed, such as (ANNs). Deep learning provides massive parallelization since increasingly complex models are used. In segmentation, deep learning has shown to have great accuracy when it comes to detecting various diseases and varieties, as well as crop output predictions and forecasts.

AI and Precision farming

Using artificial intelligence in agriculture is certain to be mind-boggling. AI may be used to machine-integrated systems to create intelligent machines that function quicker and more precisely than humans while yet emulating human behaviour. As a result of advancements in artificial intelligence, the Internet of Things (IoT)(Ampatzidis et al., 2017; Carter et al., 2008), and sensor technologies, we believe precision agriculture will see more innovation. AI can considerably increase the distribution of Climate Smart Agriculture across a vast region, especially with remote sensing technology. Agricultural breakthroughs such as high-yielding or disease-resistant cultivars that may help farmers to boost their earnings might be possible with the use of mobile-based recommender systems and expert systems like these(Afif et al., 1993; McQuiston et al., 2005; Murphy et al., 2013; Rivera & Sulaiman, 2009). Counsel for farmers all around the country will become a reality thanks to artificial intelligence, which can combine location-based advisory services with context-specific advice. Innovative services offered by entrepreneurs as services to farmers are now available, due to automation, sensors, drones, the Internet of Things, and solar power, and the addition of artificial intelligence. When using AI, we can both benefit from it and help farmers put it to good use by providing them with extensive information on several crop kinds, weather patterns, and ideal planting times. We can focus our time and effort on things where we can be more creative and effective if artificial intelligence aids with the drudgery and monotony in a broad variety of agricultural procedures.

Previously, machines have been used to grade and sort vegetables and fruits with the purpose of developing a worldwide agricultural commodities standard in order to facilitate worldwide commerce. Digitization of food quality is assisted by using advanced image processing algorithms and deep learning to analyse food images(Ampatzidis et al., 2017; Cao et al., 2010). To give the same service to numerous things and locations, we will have to develop millions of more images. Even though this seem somewhat far-fetched, collecting, digitising, and labelling images might provide some actual results. The majority of agricultural data remains with governmental organisations, therefore the onus is entirely on them to annotate and make the data usable. The amount and quality of deep learning results in an unavoidable influence on performance. To accurately anticipate solar or energy generation, long-term data is required. Students are aided by AI-powered adaptive e-learning and decision support tools that help them identify knowledge gaps and then target content in order to get new concepts. The introduction of these technologies may lead to the creation of new issues. Content and assessment created via web-based tools are superior than classroom-based teaching and learning.

Reliability of AI

When it comes to AI applications, reliability, security, and an up-to-date database are necessities. Without intelligence, an AI-based system will not be able to judge intelligently on the basis of the underlying database(Ferguson et al., 2004; Frary et al., 2004; Thies et al., 2011; Turner et al., 2003). The idea that AI systems are data-hungry machines that draw on an enormous quantity of previous data to arrive at conclusions is known as the data hunger theory. To envision AI solutions powering agriculture, we need execute our data collecting and data digitization efforts more methodically. We should question more into the data's use, where to store it, and how we'll create intelligence from it. Only fresh data from non-AI (human) sources is able to sustain this new generation of AI-enabled systems as they learn and improve. Knowledge engineering must be included into AI research because of this(DeJarnette et al., 2009; Diskin & Sreenan, 2000; Short & Colborn, 1999).

Conclusion

The amount of relevant data machines have is what makes it possible for them to do jobs comparable to those of humans(Doets et al., 2008; Frary et al., 2004; Johnson, 2000). AI systems must have access to all the objects, categories, characteristics, and relations that exist within them in order to do knowledge engineering. If they don't have an ordered database, it is hard and time-consuming to supply robots common sense, reasoning, and problem-solving skills(Ehsan et al., 2015). When it comes to AI, there are a lot of chances. We must support agricultural output by being proactive, creating new systems, and devising ways to improve crop yield. This is well known, but it is important to remember that although AI will almost always be something or something “artificial”, it allows the possibility of humanity in the humans stepping in to interfere if they are not interested in letting AI systems affect their lives. Our ideas and excitement will help in the development of AI-powered agricultural solutions in the future. Non-biological and human features are both present inside artificial intelligence. Obviously, AI will play a significant role in every business, requiring a radical change in R&D methodologies. New knowledge must be continually provided to computers employing artificial intelligence (AI) and more information must be supplied to the databases they use in order to carry out their responsibilities with practically zero error, such as discovering a new location. When it comes to AI, this theory suggests that AI systems will not only evolve and improve, but also have more options for customization than human systems do.

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