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Review JoAIRA

Hybrid Authentication Scheme Based on Cyber Physical System Use in Agriculture

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Abstract

Recently, the agriculture industry has seen the application of artificial intelligence (AI). To maximize yield, the industry must overcome a number of obstacles, including poor soil management, infection by pests and pathogens, the need for huge information, low output, and a technological lack of clarity among farm owners. The core principles of intelligence in farmland are expense, precision, good speed, and scalability. This study reviews the various applications of artificial intelligence for the management of weeds, disease, crop production, and land. Application's advantages and disadvantages are highlighted, as well as how to use expert systems to increase productivity using hybrid authentication as a substitute for traditional authentication. Combining text and pictures, it was discovered that there was increased security at efficiency of an authentication system over time. A follow-up study with bigger sample sizes might be interesting, which pointed out that limited sample sizes have been employed in graphic password studies in the past (2005).

Keywords: User authentication, graphic passwords, workable security, cyber physical systems (CPS), artificial intelligence in agriculture, crop management, disease management, weed control

INTRODUCTION

According to data from the National office of Economic inquiry, agriculture and farming accounted for more than half of all companies worldwide in 1880. According to new Bureau of Labour Statistics data, the number of employments lost by farming enterprises worldwide in 2015 was less than 2%. There is a system for harvest planning that links crop assignment with vehicle route. With the development of artificial intelligence (AI), our senses and capacity to shape our surroundings have grown significantly. The workforce, which was formerly limited to a small industrial sector, is now contributing to several industries thanks to these rising technologies. Intelligence is based on a variety of fields in addition to biology, languages, computer programming, arithmetic, psychology, and technology. A succinct description of how agricultural automation is now being used has been described in the present study. Deep learning and machine learning are just two of the numerous fields that build up the foundations of AI. While deep learning is the analysis of deep learning models, artificial intelligence is the science of creating machine intelligence and programs. Machine Learning refers to the ability to learn something without being specifically instructed. The basic goal of AI, which includes Neural network classifier, is to create issues easier to solve. The structure and operation of a humans are used as inspiration for an algorithm or hardware device known as ANN. In terms of self-organization and active learning, artificial neural network excels. In numerous disciplines, including computer programming, arithmetic, physics,

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technology image/signal analysis, finance, philosophy, linguistics, and neurology, it has largely supplanted many old approaches. ANN goes through the learning process. Crop yield forecasting has long fascinated agro-meteorology since it is so important for both domestic and global economic planning, especially for vital crops like wheat, corn, and rice. Today, a number of yield prediction models are available, and they can be roughly split into two groups: Models for statistical data and models for crop simulation, respectively (e.g., CERES). Artificial neural networks, fuzzy sets, and optimization computation have all lately demonstrated increased implementation in threat solving.

They can be used to make complex natural systems with various inputs into models simpler and more accurate. In just this work, a number of artificial neural network-based models for predicting harvest yields have been tested. We can anticipate agricultural productivity in the long or short or medium term and, with more than enough useful data, create a (Artificial Neural) modelling for each place if we develop a system that correctly learns correlations between appropriate and efficient weather conditions and crop yield. Moreover, employing the most efficient techniques for identifying the factors influencing crop yields (Artificial Neural Networks). As a result, some characteristics that are expensive and challenging to quantify can be disregarded. Artificial neural networks (ANN) are evolving into a very adaptable technology to manage such a situation. Education is the process of doing something on one's personal own to adapt to environmental changes. Unsupervised learning and supervised learning are the two categories of learning. In addition to providing a quick overview of the various applications of neural network models and algorithms (ML) in this industry for smart agriculture, the study contains the related ties between the numerous embedded devices and AI technologies compatible with the agricultural area. Agriculture is one industry where AI is still a developing technology. The present agricultural industry has evolved thanks to the employment of Intelligence manufacturing equipment. The sensing robots' locations may be tracked using Google Maps after GPS locators had done so. The Zig-bee wireless standard was used to retrieve the robots' data. The results were displayed on the 16×2 LCD that was built into the LPC2148 micro-controller.

LITERATURE REVIEW

Hybrid Authentication System

The approach we suggest fuses a conventional text-based password with a graphically based technique. The idea behind employing such a system is to try to maximize both the security of the authentication process and the user's ability to memorize the login requirements. Improved security and usability features were built into the new system. The two-step click-based authentication procedure incorporates the idea of dispersed security. The text password used in the authentication procedure is encrypted by the proposed system using the message digest algorithm 5 technique. Since the databases have been spread, all encrypted text passwords are kept in a separate one from those that house all graphical images. All text passwords will not ever be decoded as a security measure; instead, the entire procedure will only use cipher-text without a decryption key. Because hacker won't be able to decode the content on the database even if he accesses it, this prevents the administrator from obtaining access to other user’s accounts. It is also impossible to determine where each image is located from a web browser due to the usage of AJAX technology, which loads and refreshes all images on a single page without changing the URL (address bar or status bar). The study presented in this research work examines how a hybrid authentication system might meet usability requirements while also being secure.

The Scale of Intelligence in Agriculture

The use of artificially intelligent (AI) methods of farming is known as precision farming or AI in farming. The technology is employed for a variety of purposes, including field harvesting, health monitoring, weed and pest management, and the identification of nutritional deficits in the soil. The most recent industry statistics show that businesses are interested in investigating and developing AI solutions for agricultural applications. According to projections, the market for AI in agriculture would increase overall from $ 1 billion in 2020 to 4 billion in 2026. There are additional details in this graph.

Benefits of using AI in Agriculture

Agriculture is the foundation of any sustainable economy [1]. While it may differ by country [2], it is crucial for a period of economic development and organizational change [3–5]. Growing crops and producing food were the only concerns of agriculture in the past [6]. It has changed into the production, marketing, and distribution of agricultural and animal products over the last 20 years, though. The main means of subsistence are currently agricultural operations, which also boost GDP [7], expand the economy, increase interstate commerce, lower unemployment, and provide raw resources for other industry [8–10]. Given the view of the exponential growth in the global population, agriculture practices must be reassessed to provide innovative solutions for maintaining and enhancing agricultural activity. Further technical advances, such as big data analytics, automation, the IoT, the accessibility of inexpensive sensing devices, drone tech, or even widespread internet access on geographically distributed farms, will enable AI to be used in agriculture. AI systems should be able to estimate which crops to plant in a given year and when the best times to sow and harvest are in a given location by analyzing soil management data sources such as temperatures, climate, soil testing, humidity, and previous crop performances. This will boost crops produced while installing less water, fertilizers, and pesticides. By installing AI technology, it is feasible to reduce the negative effects on natural ecosystems and enhance worker safety, which will assist in ensuring that agricultural production will maintain up with growing populations and to while keeping food costs reasonable. Agricultural production has a significant impact on Nigeria's economy. It does offer jobs, food, and raw resources. Today, crop production is also acknowledged to include marketing, processing, distribution, and after-sales support. Crop cultivation and other core industries are prioritized in regions with low real per capita income. Increasing crop yield and productivity have indeed been demonstrated to have a significant positive impact on a nation's overall economic growth. So, moving forward, it will be essential to prioritize agricultural production growth [11].

- The essential nutritional sources needed to develop cropland is an essential component of successful agriculture. All farming, forestry, and fishing production methods are based on soil. In order to ensure that crops can grow and develop properly, soil retains nutrients, proteins, and water.
- One of the biggest dangers to all agricultural activity is weeds. Weeds damage cattle occasionally, decrease farm and forest output, infiltrate pastures, and suffocate crops. They fiercely contend with the crops for sunshine, nutrients, and water, which lowers agricultural productivity and degrades crop quality.

Automatic Weeding

Weeds deprive crops of nutrients and sunshine while also making it simpler for pests to harm them. Farmers now have a new tool in their arsenal, one that eliminates laborious labor. Farmers' anticipated production and profit are constantly decreased by weed [12]. According to a survey, uncontrolled weed infestations will result in a 50% decrease in the output of dried bean and maize crops. Due to weed competition, wheat output is reduced by roughly 48% [13, 14]. These losses could occasionally reach 60% [12]. A study on the effects of weeds on soybean output revealed a yield drop of between 8 and 55%. They account for between 50 and 75% of the yield losses in sesame crops. The number of times crops were exposed to weeds and the spatial heterogeneity of weeds may both contribute to the variability in yield losses. In furthermore, cannabinoids affect the ecology in a variety of ways, both positive and bad. Weed impacts include floods during storms, some kinds clearing away during hurricanes, some causing irreparable liver disease if consumed, and they outpace plants or harvests by fighting for water, nutrients, and sunshine, according to a paper from the Weed Research Association of America. Some weeds are toxic, produce allergies, or even pose a threat to the public health and environment.

FOLLOWING ARE SOME HIGHLIGHTS FROM OUR RESEARCH

Up to 12 acres can be processed in under 9 h. Camera navigation allows for complete autonomy (GPS and camera). Automating weed elimination seems to be a really effective tactic for technologies for farmer producer weed management. Through the use of robotic weeding and mechanical sprays, it is possible to significantly increase labor productivity in specialty crops without endangering the crop. It looks unlikely that new pesticides would be the answer because hand weeding, a vital need in so many specialized products, is becoming less and less common. Instead, improvements in high performance computing, machine vision, and accuracy weed elimination set special crop weed growth apart [15]. Start-up companies mostly manufacture commercial weeding machines in the United States and Europe to reduce the cost of field labor in specialty crops. But there is a likelihood that a lot of this equipment will be employed in agronomic crops, particularly in organic farming techniques that can largely eradicate weed in vegetable crops [6]. It is true that the legal and financial firms creating these technologies are far smaller than traditional pesticide firms and are less bound by the established herbicides that pesticides firms hold and are required to defend. However, it is impossible to foresee how the commercial development of integrated weed-removal machinery will proceed in the future. It is likely that in the future, weed control innovation will come primarily from small, creative businesses.

AUTOMATIC HARVESTING

These are the terms used to describe the manual harvesting of numerous goods. Agriculture-related firms are losing money as a result of slow pace and inefficiency. Because of this, autonomous harvesting devices have just entered the market.

Features of Autonomous Harvesting Robots

An Autonomous Harvesting Robot has the following features

Like systems, such as cameras, AI software, and mechanical arms, are employed in harvesting. When the program detects fruits or veggies, it utilizes the camera to tell the arms to pick them up. Although it can seem like a slow system, reports claim that robots are more productive than people, work continuously, and are over 90% successful. There are currently robots for picking apples, strawberries, lettuce, tomatoes, peppers, and other fruits and vegetables. For instance, Sweeper, the self-driving robot you'll meet in the video below, can even tell when peppers are ripe and prepared for harvest. Predictive analytics is the innovation's pulsating heart. A group of algorithms driven by AI and machine learning analyze historical data to forecast future events. Simply said, AI engineers "teach" the algorithm to recognize items (in this case, fruits and vegetables), so it operates on its own. Something like this might be captured by the functioning camera of an autonomous harvesting robot. Each reachable object that was spotted would have been identified, possibly with ripeness percentages. The most recent uses automated systems for selected picking in conservatory, orchards, and open-field environments were described in the section titled "Advanced in Selected Harvest". Selective picking robots no longer fulfilled the threshold for economic success in terms of harvesting success and speed after several decades of development. The perception (ability to detect the crop and other plant parts), the harvesting equipment, and the harvesting technique all play a role in harvesting success.

Perception

Advances in artificial intelligence have significantly boosted perception's sensitivity to the variance problem. Deep-learning existing studies algorithms can adapt to changes in the environment and the appearance of the objects. The techniques also readily accommodate various conditions and cultivars. Operating in complicated commercial-scale scenarios still present a significant barrier when dealing with veiled information. This is particularly true in conservatories and orchard, where plant care is more involved than in open areas.

Harvesting Tool and Operation

In this the end-design effector's does not exhibit any obvious paradigms. Each study created a unique harvesting tool. The majority of harvesting equipment was heavy and rigid. The detachment was typically carried out with an automated cutting knife, though suction or a twisting action were occasionally used as well. Harvesting success decreased in complicated, congested surroundings, frequently as a result of the instrument being unable to reach the proper position due to plant collisions or being unable to pinpoint the correct location due to perceived limits. Additionally, the tools usually caused damage to the plant and its fruits.

Operation Speed

Robots frequently have cycle time duration in greenhouses and orchards of around 30 sec. It has a limited wide range of applications and operates much more slowly than human action. Robotic vegetable harvesting is frequently much faster on the field than in a greenhouse because the environment is more conducive.

The Complexity of the Environment

In numerous greenhouse studies, the crop's picking success rate increased noticeably when certain leaves and fruits were removed to make the space more structured. The harvesting procedure was more efficient now that the tool had more room for a collision-free approach, and the identification accuracy of the perceptive algorithms significantly improved as vision problems happened less frequently.

Task Variation

All of the robots included in this review have harvesting as their sole function. The crop growth process includes more than just harvesting, which is outside the scope of this study. When contemplating completely automated agriculture in the future, there are numerous crop maintenance tasks to take into account which demonstrated the dual functioning of a robot system for the picking and leaf cutting of cucumber plants generated in a high wire cultivation, albeit in a very crude manner.

Safety

Numerous studies that frequently included fruit and plant damages, periodically examined the security of the robot in its surroundings of plants and fruit. Although safety issues for open-field agriculture's usage of autonomous robotic systems have received a lot of attention, research on safety in human-robot collaboration is still in its early stages.

Discussions focused on societal demands, technological advancements, technical challenges, and potential pathways for solutions. That, however, only tells part of the story about the application of robotic technology in agriculture. The usage of robotics and the utopian notion of agricultural food production are somewhat at odds with one another. Technology advancement should still be given top priority in research programs in order to address societal challenges, but this development should be complemented by thoughtful thought of how these improvements will affect society. It is important to take seriously the subject of robot ethics in connection to agri-food [16]. One final observation is that agricultural production methods are evolving. Inter-cropping and pixel farming are being revaluated as superior options in view of rising concerns surrounding the long-term viability of conventional large-scale mono-cropping cultures [17]. But in order to achieve this, agriculture as a whole and, in particular, the farming technology, must be rethought. Robotic technology may support and aid such advancements in agronomy given the present and future restrictions on the availability of human laborers. For robotic agricultural production and selective harvesting as a whole, this poses substantial issues because it further increases variability and ambiguity.

Plant Disease Detection

Pests and plant diseases cause 20 to 40% of the world's food production to be lost. Because of this, numerous plant disease diagnosis applications have started to appear everywhere. They assist firms uncover and treat crops affected by diseases and pests and utilize AI algorithms to identify health issues.

It is easy to see how this Intelligent Farming Method is Beneficial

Get a picture of a plant. The app will use image recognition technologies to process the picture. The program generates information on diseases, suggests treatments, and/or detects a plant that is a pest. One of the applications demonstrating the value of this AI agriculture invention is Plantix. An image recognition algorithm powered by AI is utilized by the app's creators to diagnose over 60 diseases from a library of 100,000 pictures of sick plants. For instance, Powdery Mildew, a widespread fungus that affects lettuce, tomatoes, peppers, melons, and peppers, is quickly identified by Plantix. Here is a two-minute video that explains the operation of the app.

Machine Learning Analysis

Results are produced by comparing input photos to a database of sick plants via AI-powered image recognition software. In order to locate the issue, the machine learning system searches for the distinctive patterns of plant illnesses (such as spots and discolorations that resemble mosaics). Additionally, drones, other agricultural machinery, and greenhouse cameras can all be equipped with disease-detection AI software. Farmers are better able to identify crop diseases quickly and take preventive action as a result. Drones equipped with AI software are now in use all over the world to check the health of areas like vineyards. In this instance, the technology assisted in lowering losses due to the wine grape disease by up to $ 15,000/acre. In the last few years, convolutional neural networks have considerably improved at classifying images and identifying objects. In the past, learning algorithms have been used to solve picture classification issues in feature spaces built by manually designing features like SIFT. As a result, the success of these tactics was significantly influenced by the underlying existing features. The feature engineering procedure itself must be carried out whenever there is a major change in the current situation or in the relevant data collecting. It is challenging and intricate. Since they rely on manually created features, picture augmentation techniques, and a variety of other intricate and time-consuming processes, this problem persists in all conventional attempts to detect plant diseases using computer vision. Additionally, conventional methods for disease categorization using machine learning frequently concentrate on a constrained set of classes, typically within a single crop. For instance, to identify between tomato leaves with good skin and tomato leaves with tomato powdery mildew, a feature extraction and classification pipeline was utilized; employed RGB pictures, Rgb-d images, and other methods to identify apple scab. Fluorescence Imaging Spectroscopy to identify citrus. Huanglongbing Citrus species were discovered utilizing near-infrared spectral patterns and aircraft-based sensors. Using a pipeline of support vector machines and a set of customary feature extraction methods, the tomato yellow leaf curl virus was identified. An extensive summary of the research on this subject may be found in a recent paper on the use of machine learning to study the plasticity of plant phenotypes, although neural networks have been employed in the past to identify plant diseases [18]. For the neural network to identify the photos (for the classification and detection of illnesses that can affect Phalaenopsis seedlings, such as bacterial soft rot), the method needed that the images be represented using a carefully chosen collection of textural features. Our method is based on recent research by, which demonstrated for the first time that end-to-end supervised training with a deep convolutional neural network architecture is an effective solution even for image classification problems with a very large number of classes, outperforming conventional techniques using palm features in benchmark datasets. They are a particularly intriguing option for a practical and scalable method to the computational inference of plant diseases due to the lack of the labor-intensive feature engineering step and the generalization of the solution. Our strategy is based on recent research which demonstrated for the first time that end-to-end supervised training using a deep convolutional neural network architecture is an effective solution even for image classification problems with a very large number of classes, outperforming conventional methods using hand-engineered features in standard benchmarks. They are a particularly interesting option for a practical and scalable route to the computer inference of plant diseases since they do not require the time-consuming feature engineering stage and the answer is generally applicable. Thus, in 993 out of 1000 images, the model properly categorizes crop and disease from 38 plausible groups without the aid of feature engineering. Importantly, the classification itself is rapid (takes less than a second on a CPU), despite the lengthy model training process (several hours on a high-performance GPU cluster computer). As a result, using a smartphone for it is simple. This shows a clear path to the widespread adoption of smartphone-assisted agricultural disease diagnoses around the world.

However, there are already a few drawbacks that will require attention in subsequent growth. The model's accuracy is examined on a set of images captured under conditions different from those used for training, and it substantially decreases to slightly over 31%. This accuracy is substantially better than the one based on a subset of 38 classes chosen at random (2.6%), but it can still be improved with more diverse training data. According to our most current research, simply adding more (and more varied) data will not be sufficient to significantly boost accuracy, hence efforts are being made to obtain this additional information. The second drawback is that at this time, we are only able to classify individual leaves that are set against a constant background. Despite how straightforward these situations are, a real-world system ought to be able to categorize pictures of a disease as it manifests itself on the plant. We do, however, believe that the idea provides a workable alternative strategy to aid in reducing yield loss, especially in light of the forecast that by 2020 there will be more than 5 billion cell phones worldwide, of which, roughly a billion would be in Africa (GSMA Intelligence, 2016). In the future, smartphone image data may also contain location and time data to further reduce inaccuracies.

Improved Soil Health Monitoring

To avoid crop loss, it is crucial to be able to identify illness in the soil. The majority of farmers use conventional soil analysis methods, but the outcomes are frequently insufficient to stop diseases and other problems.

Soil analysis with AI works like this

To identify all bacteria and soil components, a sample of the soil is obtained. The data from the sample are compared to a sizable database of soil data using the machine learning algorithm. The findings reveal the amount of moisture, nutritional deficits, pH level, bacteria present in the sample, as well as other elements. Specialists review the findings, determine the risks of particular diseases, and suggest treatments based on the soil composition and bacteria. For instance, the Schweigert family farms are owned by Matthew and Joe Schweigert. Sustainable agriculture is built on healthy soil. However, poor land use and management techniques have the potential to worsen soil health [19]. Global food security as well as social, environmental, and economic sustainability are at risk due to soil health degradation, which has emerged as a major issue for the agricultural production system. Effective soil health evaluation and management techniques and approaches are required to maintain, improve, and restore the soil health of agricultural land. Researchers, farmers, politicians, and other stakeholders have different ways of understanding and interpreting the services, functions, processes, and features of the soil ecosystem. To create a workable soil health index system, extensive study has been done. A number of soil physical, chemical, and biological parameters were used to evaluate the viability of soil health indicators [20]. There are several techniques for evaluating the health of the soil. However, almost all of the assessment techniques need to be further supported and improved in terms of relevance, scientific validity, usability, and regional adaption. Five fundamental concepts and a number of management techniques have been promoted to maintain and improve the soil health of agricultural production systems. The best soil health management measures should also incorporate other tried-and-true soil management techniques, such as agronomic fertilization, desalinization, liming, and vegetated buffer strips. To promote localized adaption, adoption, and implementation of soil health assessment and management, further research, education, and outreach initiatives are required [21].

More efficient Irrigation of Farmland

70% of all water use worldwide is for irrigation in agriculture. Farmers are seeking for solutions to get rid of waste and use resources as efficiently as possible because crops require enormous volumes of water. AI in agriculture is useful. Already, drones with AI software installed employ high-resolution aerial images and complex analytics to gather data on irrigation systems on fields. Continuous observation identifies issues like blockages and leaks and assesses soil health.

Here's how this AI agriculture system works

Drones are equipped with AI software. Each week, drones are flown over fields. Drone cameras capture aerial photos of fields. AI software analyses the video and points up irrigation system issues as well as potential irrigation or fertilizer shortages. Farmers use their computers to get the analysis and make decisions to avoid issues (sometimes weeks before they manifest), this is also an example of AI-analyzed aerial video. Farmers may maintain healthy crops with less water and, consequently, less chemicals by using this AI agriculture technology. In the long-term, they can increase yields, reduce costs, and raise product quality. Evidence suggests that irrigation in Brazil may be a useful strategy for addressing climate vulnerability and eradicating poverty [17, 22]. In this study, we use a comprehensive dataset on nearly 5 million farms to quantify the impact of irrigation on the technical efficiency of farms of various sizes in Brazil. It is a step forward to estimate impartial technical efficiency while improperly accounting for the impact of these qualities. We distributed survey forms to 1680 soybean growers in Louisiana. In total, 451 envelopes were returned due to address mistakes or the fact that some of the farmers had already left their farms, out of the total set of questions that were distributed. 123 replies were received from the entire sample of 1229 persons after sampling correction. 10% of respondents to the survey made this choice. Only 67 of the 123 replies have all the necessary information to be used in this investigation. The cost of irrigation, the yield of soybeans produced per acre, and the volume of water pumped per acre as verified by a thorough verification study carried out in 2016 were all included in the 16 samples that we used. As a result, the efficiency of the study is calculated using one outcome variable and six input variables. Each acre, 109,500 gallons of water are used. We were given data on how much water is pumped per hour, how many waterings are carried out during a crop year, and how much water is pumped overall during each irrigation. By dividing the entire volume of water pumped by the total number of irrigated acres, the average amount of water applied per acre is determined. While the average cost of labor and poly pipe per acre was $ 25, the average yield per acre was 58 bushels of soybeans. The amounts of soybeans in 1 Mt in 36.67 bushels. Over the course of a crop year, farmers averaged spent $ 2807 on irrigation system upkeep and repairs (repair and maintenance costs represent the average total dollar amount spent during a crop year).

Application of Pesticides and Herbicides

Additionally, AI and machine learning in agriculture can identify when plants are ill or harmed. Once more, this technology analyses aerial photos of fields to pinpoint the best locations for pesticide and herbicide spraying. As an illustration, the pictures below were captured by drones. They display pest damage and plant withering, the two distinct issues identified by AI-enabled image recognition software. AI assists in identifying issues even on small scales by routinely evaluating thousands of drone-shot photos.

BENEFITS OF SUCH AI ANALYSIS

Use of AI analysis determines pest infestations and plant health issues; helps in avoiding using insecticides and herbicides excessively and boosts the upkeep of soil fertility. Autonomous drones can spray insecticides and herbicides in specifically designated field regions in addition to monitoring human health. Agricultural-spraying drones are excellent in streamlining field management, lowering labor costs, and boosting crop yields, according to research. Below are some examples of crop spraying drones and associated models used in intelligent farming techniques. You can hire programmers to create unique AI algorithms that you can utilize in your fields as an agricultural company [23]. Studies on environmental-health risk assessment may provide information that can be used to better understand the problem. Statistics on the prevalence of pesticide-related illnesses among particular demographics in underdeveloped countries are few. As a key tool for ensuring the safe use of pesticides, worker education and training are becoming increasingly important. Pesticides offer the ideal chance for individuals who balance risk-benefit analyses because of the numerous benefits that man derives from them. Pesticides are thought to have an annual economic cost of about $ 8 billion in poor nations when used on non-target species like people. For instance, a variety of human characteristics, including age, sex, race, socioeconomic class, nutrition, level of health, etc., affect how much exposure humans have to pesticides. The effects of these factors are, however, largely little understood. Concurrent exposure to other pesticides, poisons in the air, water, food, and medications, as well as by pollutants present in these habitats, dramatically influence the long-term effects of low-level exposure to pesticide. In metropolitan areas, pesticides are frequently seen as a quick, simple, and economical way to get rid of weeds and insect pests. However, using pesticides has a significant price tag. Our environment has been poisoned by chemicals in almost every way. Pesticide use in urban areas exacerbates the global problem of pesticide residues in soil, air, surface water, and groundwater, the ecosystem and non-target creatures, such as beneficial soil microorganisms, insects, plants, fish, and birds. Agriculture AI software adoption has challenges that are seriously threatened by pesticide contamination.

Despite the enormous range of possible uses for artificial intelligence in agriculture, most farmers throughout the world are still unaware of cutting-edge machine learning techniques. There is a lot of external influence on farming, including weather, soil, and the existence of pests. Therefore, due to changes in external circumstances, a solution that seemed good during planning at the beginning of harvesting may not be the best. A lot of data is also necessary for AI systems to be taught and able to generate accurate predictions. In the case of a sizable agricultural region, spatial data can be easily obtained, but collecting temporal data is difficult. For example, most crop-specific data may only be collected once a year during the growing season. Due to the length of time required for the development of the data infrastructure, creating a trustworthy machine learning model is time consuming. For this reason, agronomic products like seeds, fertilizer, insecticides, and other such items are frequently used by AI rather than on-the-ground precision solutions.

LIMITATIONS

Limitation 1

Big Data is necessary as the amount of input data is another factor in determining an intelligent agent's power. An enormous amount of data must be monitored by a real-time AI system. Most of the incoming data must be removed by the system through filtering. However, it must continue to react to important or unexpected events [12]. To improve the system's speed and accuracy, a field expert must have a thorough understanding of its purpose. Only the most pertinent data should be used. To establish an agricultural expert system, agronomists from various agricultural sectors must work together, and the producers who will use it must support this effort [14].

Limitation 2

A fundamental element of an intelligent or expert system is its capacity to carry out tasks swiftly and accurately. The majority of systems are either slow to react, inaccurate, or even both. The task strategy, a user chooses, is impacted by a system delay. The cost function that combines the work required to configure accuracy level given with input system availability is believed to be the foundation for strategy selection. Three options are available to those who want to exert the least amount of effort while getting the best results: automated performance, pacing, and monitoring [14].

Limitation 3

Implementation plan, the elegance of an expert system, is found in how it executes. The lookup and training process needs to be adequately described in terms of speed and accuracy because it consumes a lot of data.

Limitation 4

High price of information, since its majority of AI systems are web-based, there are limitations on where they can be used, particularly in remote or rural places. By creating a web service that allows devices with lower tariffs to specifically work with the AI systems for farms, the government can help farmers. A "how to use" instruction will be provided to farmers to help them get used to using AI on their farms (training and re-training).

Limitation 5

Any effective AI system must be flexible. Although it appears that significant progress has been achieved in applying AI techniques to some discrete operations, it appears that the main focus at the forefront of AI-based robotics technology is on the integration of the subsystems into a cohesive environment. This necessitates flexibility within the subsystems themselves [12]. In order to accommodate more user data from the subject matter expert, it should also offer a variety of functions. Despite the enormous potential of AI in agriculture applications, modern, high-tech machine learning technologies are currently not well understood in farms all over the world. Environmental elements like weather, soil, and insect attack danger notably affect agriculture. The initial crop-growing strategy for the season may not seem to be the best when harvesting first begins since it is altered by outside factors. For machine learning and accurate forecasts or predictions, AI systems need a lot of data.

AGRICULTURE-FOCUSED AI START-UPS

Below we discussed how artificial intelligence startups are impacting agriculture.

Prospera

Prospera was established in 2014. The way farming is done has altered thanks to this Israeli startup. It has created a cloud-based system that compiles all the data farmers now possess, including information from soil and water sensors as well as photographs captured from the air, etc. It then incorporates it using a tool that recognizes that everything is local. The Prospera device is powered by a combination of sensors and technologies, including computer vision, and it may be utilized outdoors or in greenhouses. These sensors' inputs are utilized to generate predictions and identify correlations between various data labels.

Blue River Technology

In 2011, Blue River Technology was established. This start-up in California uses robots, computer vision, and artificial intelligence to create the next-generation of agricultural machinery that uses less pesticides and is more cost-effective. Each plant is recognized by computer vision, machine learning determines how to treat each plant, and robotics allows the intelligent robots to act.

Farm-Bot

2011 saw the founding of Farm-Bot. By enabling environmentally aware people to produce crops in their place using precision farming technology, this company has raised the bar for precision farming. Farm-Bot, a tool that costs $ 4000, enables the owner to complete all aspects of farming by himself. This physical bot uses an open-source software system to handle everything from seed planting through weed detection, soil testing, and plant watering.

Table 1. Algorithms of agriculture.

S. No.	Algorithm	Evapotranspiration technique and desired calculation	A Different Technology	Advantages/Results
1	Other regression algorithms, such as PLSR	Model for evapotranspiration	IoT hardware implementation, sensors for data collection	Improved economic viability and efficiency
2	Control system based on artificial neural networks	Model for evapotranspiration	Soil sensors, temperature sensors, wind speed sensors, etc.	Automation
3	Machine Learning	Mechanical removal/Rotary harrow	A weed-control robot	Machine vision, 92 percent (detection), sugar beets
4	Algorithms that are based on colour and texture	Fuzzy real-time classifier for identifying greenness	Mechanical removal with robotic arms	Detecting weeds and sugarcane
5	Gyroscope and accelerometer sensors, as well as wireless sensor networks	-	Pesticide application	N/A
6	Pesticide application	spray engine	Pesticide application	When tested on groundnuts and paddy crops, it performed satisfactorily.
7	Crop Watching	software and cameras	-	An accurate technique to keep an eye on numerous farm operations, such as mapping the field digitally and spotting crop health issues.

RESULT AND DISCUSSION

An overview of the use of AI technology in agriculture is provided in this review as shown in Table 1. Since its inception, artificial intelligence (AI) has been researched, developed, and improved by scientists all over the world. This is in response to the current social situation, which is characterized by declining manual labor, a shortage of arable land, and a growing gap between the total amount of food produced and the global population. The Turing Test serves as the review's focal point as it introduces the definitions of AI. The management of soil and weeds and the Internet of Things (IoT), a helpful data analysis and storage technology with widespread applicability in agriculture, are two subfields where AI has been shown to play a significant role. The distribution of modern technology is uneven for a variety of geographic, social, and political reasons, which suggests that the application of AI will be constrained in some regions; secondly, despite significant advancements in recent years, transferring AI-based machines and algorithms from control experiments to actual agricultural environments still requires much more work. These are the three main practical challenges facing AI in agriculture. The development of agricultural robots is then specifically discussed in this review. First, a few examples of agricultural industry-specific robots created to do various duties are provided. This is a developing area with great potential.

CONCLUSION

Weeds, difficulties with plant management owing to crop height, a lack of efficient irrigation systems, and harsh weather conditions are a few of the difficulties the agricultural sector encounters. With the help of technology, though, performance might be improved and these issues might be solved. It can be improved with a variety of AI-driven methods, such as autonomous watering that measures the soil's moisture content using GPS and remote sensors. Farmers confronted the challenge since precision weeding techniques decreased a large number of crops lost during the weeding process. These autonomous machines increase productivity while lowering the demand for unused insecticides and herbicides. Additionally, drones let farmers efficiently monitor their crops and apply insecticides and herbicides to their fields. To begin with, using artificial intelligence to agricultural problems can help in comprehending resource and employment limitations. For agricultural parameters like plant height, soil texture, and composition, previous methods needed a lot of work and repetitive physical testing. The advantages of flexible and favorable activity, on-demand information access, and spatial goals would make rapid and non-destructive high throughput phenotypic plasticity possible with the aid of the various strategies investigated.

Future Scope of AI in Agriculture

A 70% increase in agricultural output will be required to meet the demand by 2050, when it is expected that there will be a population of almost nine billion. Only around 10% of this increased production may come from undeveloped lands; the remaining 90% will likely come from existing intensification of production [12]. Autonomous robots and automation will revolutionize several worldwide sectors (RAS). Large economic sectors with poor productivity now, like the agro-food sector, will be significantly impacted by these technologies (food production from the farm to the retail shelf). In 2016, the UK's agro-food chain generated £ 20 billion in exports and employed 3.7 million people [12]. It also generates about £ 108 billion a year. In order to provide services and solutions for crop nutrient supplements, sowing, and land preparation, Microsoft Corporation is now working with 175 farmers in the Indian state of Andhra Pradesh. Crop output has already increased by an average of 30% compared to previous harvests. The many areas in which solutions for enhancing agriculture that integrate cognitive skills required. Agriculture's many different farming methods have easily adapted to AI. By staying up to date with new advances in the farming industry, farmers can benefit in the field by receiving solutions via platforms like commonly associated.

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