Smart Farming using AI towards Bangladeshi Agriculture

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Abstract

Agriculture is the largest employment sector in Bangladesh. Which has a great impact on the economy, employment generation, poverty alleviation, human resources development, and food circuity of Bangladesh. Traditional Farming uses age-old agriculture equipment whereas Smart Farming is driven by modern latest technology-intensive farming methods. This smart farming system is cost-effective and middle-class farmers can use it in the farm field. This article reviews data-driven smart farming solutions incorporating Artificial Intelligence (AI), Internet of Things (IoT), Robotics and the management involved in the implementation of these smart farming systems in low-income countries like Bangladeshi Agriculture.

Keywords: Agriculture, Precision Agriculture, Artificial Intelligence, Internet of Things, Robotics.

1.1 Introduction

The population of Bangladesh has almost doubled since the 1890s, reaching approximately 161 million people in 2016 which causes food demand to increase briskly. While the land areas for cultivation are quite limited makes it challenging to produce enough food, we also have lots of other farming problems. After the adoption of modern agriculture, mechanization and the green revolution we've reached the digital revolution which takes traditional farming to the next level. The concept of smart Farming refers to the management of agricultural operations with the assistance of contemporary and cutting-edge technological solutions, with the goals of enhancing product quality, increasing output quantity, and decreasing the amount of manual labor required. Even though there is a nuanced distinction between the meanings of Digital Farming, Smart Farming, and Precision Agriculture, many people use them interchangeably.

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Farmers generally visit the field to inspect the crop's status and make decisions based on their knowledge and experience. This method is no longer viable since some fields are too vast to be adequately handled, resulting in inefficient resource consumption. Although some farmers have long-term expertise obtained via spending a lot of time working in the field, new technologies can offer a systematic approach for identifying unexpected issues difficult to find by visual examination on periodic tests. Since the global population continues to live a more urban lifestyle, the labor shortage in the farm sector is also becoming an active problem. We also have to deal with challenges such as pest management & agricultural waste alongside both of these. As a result, traditional framing strategies are inefficient to satisfy growing demand and will not take us to agriculture that is productive and sustainable.

Precision agriculture improvements enhanced operating revenue and net return, according to a U.S. Department of Agriculture (USDA) study published in October 2016 (David 2016). There have been significant benefits for farms that chose on being technological in any way, such as reducing effort and conserving resources, increasing productivity or lowering costs with limited manpower, and producing superior food while ensuring environmental sustainability (Díez C., 2017).

The challenge in retrieving crop data using these new technologies is coming up with something consistent and appropriate, whether it is images or numbers because implementation and the information itself are useless. Improved farmer education and training, knowledge exchange, improved access to financial capital, and rising market demand for natural foods are all significant aspects to consider when adopting these technologies (Grand View Research, 2019). Since these technologies are information-based and contain automated services, it's important to remember that the benefits we obtain from them are based on scale economies across each individual farm, as profitability rises as a farm's size grow.

1.2 Agriculture in Bangladesh

1.2.1 Role of Agriculture in Bangladeshi Economic

Agriculture is very essential in Bangladeshi economies where agriculture adds value as a percentage of gross domestic product (GDP). As shown in Figure 1, agriculture accounted for 12.68 percent of Bangladesh's gross domestic product in 2019.

1.2.2 Agriculture Sector of Bangladesh

Crops, livestock, fisheries, and forests are the four key components of the agriculture sector, as shown in Figure 2. Among these, crops make up to 55% of the sector with the most important crops being Aus/Amon/Boro rice paddies, jute, potato, and wheat (Bangladesh Bureau of Statistics (BBS), 2017). Bangladesh is the world's second-largest jute producer after India. The sector currently makes up 15% of GDP and employs 43% of the workforce (BBS, 2018).

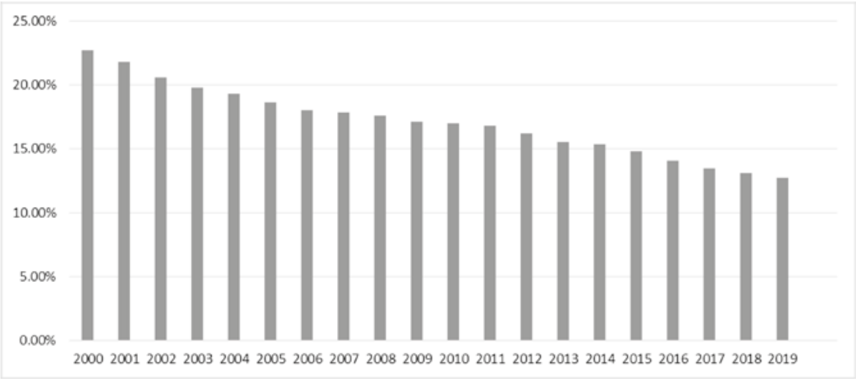

Figure 1: GDP Share of Agriculture

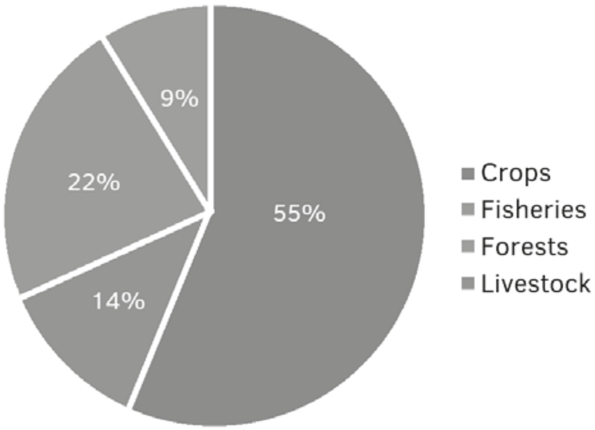

Figure 2: Agriculture Sector Breakdown

Bangladesh's agriculture sector is mainly focused on cereal production. Among cereal grain crops, the primary position is occupied by rice with about 80 percent of the total arable land dedicated to rice cultivation. As a result, rice is the main crop in Bangladesh's agriculture industry, as well as a crucial part of Bangladeshi diets. In Figure 3, it is projected that Bangladesh will be able to supply its own cereal grain with up to 50% of its food grain requirements by 2020.

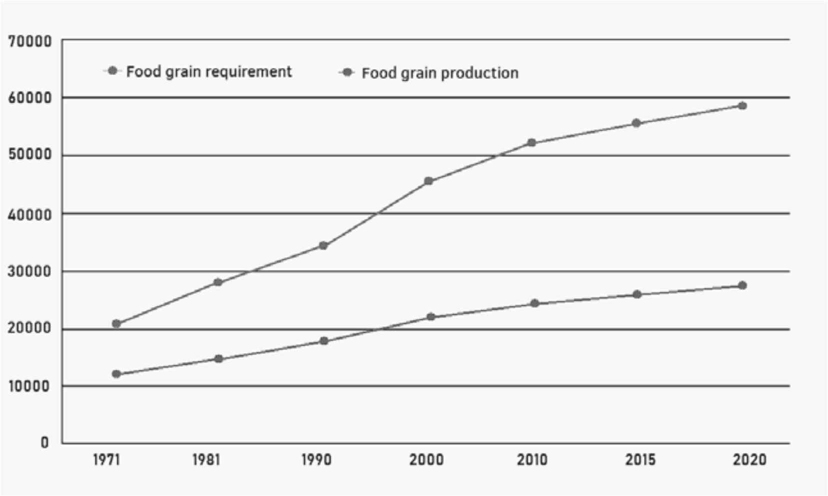

Figure 3: Food grain production and requirement

1.2.3 Present State of Smart Farming in Bangladesh

Technology is like a tidal wave that is not only spreading all over the world but also greatly influencing Bangladesh. In January 2017, The Bangabandhu Sheikh Mujibur Rahman Agricultural University (BSMRAU) started implementing the "E-Village" project while iSoftStone, a joint venture of Chinese Huawei Technologies, who are providing technical support. This device collects real-time data on moisture, air temperature, and leaf health using a number of basic sensors or probes and sends it to the smartphone using Bluetooth in seconds. The online system for receiving real-time support from experienced agriculturalists of BSMRAU makes this much more beneficial.

In April of 2018, Advanced Chemical Industries (ACI) Agribusiness released an android app named 'Fosholi' that serves as the first step toward a comprehensive agriculture platform in Bangladesh. This app can assist farmers by delivering necessary information by coordinating and analyzing ultramodern satellite imagery, advanced agricultural methods, innovative agriculture technology, and climate information.

In 2019 January, Grameenphone introduced the country's first IoT-based digital livestock management solution ‘Digi-Cow’ for livestock farmers. This solution consists of a Base solution and individual Smart tags. Benefits include tracking body temperature and hormonal changes, determining the right time of insemination, and being informed about cow's illness 48 hours before head. After the reader receives signals sent from the smart tag, it sends signals to the control unit, where its data is inspected and transmitted in real-time as a notification over the internet.

A smart irrigation system has been implemented with an Arduino Uno, micro-controller, sensor integration and water pump. The sensor, which is located in about 15 locations throughout the University of Chittagong, Bangladesh, is used to activate a pump depending on data from the integrated sensor. This process records moisture levels and, as a result, automated the control of the motor consequently (Iqbal A., 2020).

Since 2011, the e-Agriculture pilot project has been carried out by the local administration of Bhatbour Block, Dhighi Union, under Sadar Upazila, in Minikganj District. Data was gathered by the authors between September 1 and September 30, 2015, and they describe the difficulties Bangladeshi farmers encountered when using e-Agriculture services. (M. Rezwan I., 2016)

Juthi Kundu et al. presented a web portal in 2017 that offers an integrated solution to all agricultural issues and confirms the social, economic, and agricultural development of Bangladesh. This website will considerably aid in Bangladesh's growth by eliminating poverty and opening up opportunities for self-employment for the vast majority of the populace.

2. Technologies Used in Advanced Agriculture

2.1 IoT and Big Data

Farmers can use IoT devices to collect environmental metrics and make decisions based on the information. In agriculture, the IoT refers to the use of sensors and other technologies to convert any agricultural feature or activity into data. By 2050, advances in these technologies are expected to boost agricultural productivity by up to 70% (Joe M., 2016). Increased crop output and lower prices are two important benefits of using IoT (Preston G., 2018). The idea of Big Data is popular across a wide spectrum of enterprises in today's technology-driven culture. To collect operational information from bulk data, an automated technique must be applied to the continually growing amount of data collected to manage fields. According to Kunisch, big data looks to be significant in some agricultural scenarios, depending on the farm and the level of technology utilized [Martin Kunisch, 2016). The Consortium of International Agricultural Research Centers

(CGIAR), Montpellier, France has developed a Big Data Platform for Agriculture in order to employ Big Data methods to address agriculture growth concerns more efficiently, swiftly, and effectively much quicker and at a greater level than before (CIAT and IFPRI, 2016).

2.2 Robotics and AI

These days world has evolved from a rural population including a large number of farmers to a city-based system. As a result, farms face the problem of a lack of staff. Agricultural robotics combining Artificial Intelligence (AI) characteristics are one approach to cope with this lack of staff. Robotic agricultural applications are increasing rapidly (Shamshiri R.R, 2018), providing Smart Farming with promising solutions to handle labor shortages and a long-term decrease in profitability. Nevertheless, like other technologies, there are significant constraints to deal with in the present early stages. These technologies are still too expensive for many farmers, particularly anyone with a small farm (Lamborelle, A., 2016), since economies of scale cause small-sized farms less lucrative for food producers (Sonka, S., 2014). Robotic technologies are boosting the global demand for agriculture and crop production, as agricultural robotics would be able to execute field activity more accurately than farmers, as reported by Verified Market Intelligence (VMI, 2018). Modern sensing technologies in agriculture will help solve the problem by providing precise information about land, crop condition, including environmental factors, allowing for accurate application with phytosanitary products, reducing the use of herbicides and pesticides, enhancing the efficiency of water use and increasing crop quality and yield (Zhang Y. 2019).

3. Smart Farming: Management

In advanced-technology adopted farms, field management may differ according to the information-based control process regarding developed agriculture (Sáiz R., 2020). This control strategy, which is focused on realistic field observations with intelligent decision-making, takes place with the crop to be managed, using its internal spatiotemporal versatility. The Information-Based Control Process regarding Developed Agriculture follows the sequence: Crop, Platform, Data, Decision, Actuation.

The platform corresponds to the real means through which information is collected. It is the sensors via which element, objective data is gathered. The information in the data is obtained straight from the plant, soil, and atmospheric parameters. The decision stage is concerned with the use of routines and Artificial

Intelligence Algorithms for sorting out incorrect data and assisting its producer in making the best choices. Lastly, actuation is the process of carrying out a decision-making system-controlled action, which is usually conducted by specialized instruments which would accept instructions from a computerized control unit. The loop continues and closes at the crop level since every activity is carried out on the crop.

4.1 Variability Analyzation

As per Searcy (Stephen W. S., 2011), weather affects natural variability in growing seasons, often throughout the year. So, data from many years could be necessary to establish patterns in any variables of interest. As a result, data contribute significantly to the farm management system on a regular basis. Thus, the importance of crop surveillance arises because variability persists, but the producer must also handle the variability in a proper and efficient manner, which is best accomplished by establishing in-field management zones. Subfield regions of similar traits are referred to as management zones which allows field operations to be tailored to each of them, leading to a realistic and cost-efficient Smart Farming method (Miao Y, 2018).

A number of management zones depend on an area's natural variability, field scale, as well as some management variables (Zhang N., 2002). Besides specifying working areas, it's crucial to carefully pick particular parameters that will be monitored within those zones ahead of time. Klassen, S.P., 2014, stated that, while performing characterization of soil variance in the rice field, there could be particular instances where a field's spatial variability is very poor, in that case, a single mapping event is enough.

4.2 Sensor Integrated Platforms

To track crops and extract objective information from them, sensors are the universal devices. Often, these sensors are integrated into some kind of platform. Such platforms might well be attached to the off-road vehicles and perhaps installed on the ground in areas like local weather stations. Although not every variable of importance can currently be calculated non-invasively or at a distance from its target, but certain developments are seeing major advances, like multi-spectral and hyper-spectral image processing.

4.2.1 Artificial Satellites and Aircraft Systems

As field data from artificial satellites has become readily accessible, remote sensing became very important in the development of Smart Farming. Several reports on satellite sensing applications have been carried out with recent research focusing on the future uses of remote sensing thermal technology as well as the nutritional status of commodity crops (Rudd J.D., 2017). As sensors work near the target, finer observations are possible. With aircraft systems, the gap between the land and aircraft seems to be about 100 meters. Rotary-wing Unmanned Aerial Vehicles (UAVs) are very stable fliers since they can take off and land vertically, but the problem with these is that they are slow and are incapable of covering much distance throughout their battery life. As fixed-wing platforms cover more area with each flight holding greater payloads, they break quite easily after several landings and tend to be very costly (Rudd J.D., 2017). UAVs have the ability to collect data even from difficult areas that traditional machinery cannot stand as opposed to land vehicles. Although, they require expert travel route planning in advance and certain computer vision implementations may necessitate flight during noon to prevent vegetation shadows which causes image data errors. Because they have limited payload capacity it restricts the maximum number of sensors on board and their inability to travel in high winds. This is an important downside of UAVs.

4.2.2 Autonomous Ground Systems

The space between sensors and the target crop decreases to less than two meters as surveillance platforms work from the ground. Environmental factors like heavy sunshine and insufficient lighting are no longer an issue when active sensors are included and real-time activities like weed spraying with advanced identification of pests are possible when on-the-fly processing is used (Lameski, E., 2018). Aravind addressed land robotics for tillage, crop scouting, soil inspection, planting, pest extermination, replanting, removing weeds as well as harvesting, with crop scouting described as a method of continuous field observation to obtain information regarding crop condition, disease occurrence as well as crop growth-inhibiting infestations (Aravind, K.R., 2017).

4.3 Managing Data

Sensors make it possible to obtain data within the field. However, the unique combo of non-invasive technologies and on-the-fly sensing via moving platforms have unlocked the way to vast data gathering, the precursor to big data in agriculture. Excess data, however, is also a serious challenge to deal with as noise can obscure sensitive information. Since mapping is able to distinguish spatial trends as well as homogeneous regions, a very popular method to view agricultural data seems to be in the form of maps. The aim of constructing maps is to acquire a few management zones with the criteria of importance in order to accurately implement with care. Kriging became a very common interpolation method for delimiting manageable-sized regions to achieve plausible management zones (Buttafuoco, G., 2016). A coordination system must be provided along with the map when creating a map. The Local Tangent Plane (LTP) coordinate system uses Euclidean geometry, enables user-set origin as well as uses the intuitive east-north coordinate frame, making it an ideal alternative for agricultural maps.

Using Geographic Information Systems (GIS) is a common way of managing field data displayed on maps. Every type of georeferenced data can be stored, analyzed, manipulated, and mapped using these tools. For Precision Agriculture applications (Zhang N., 2001), a particular GIS system named Field-level Geographic Information System (FIS) has been created. The FMIS, which stands for Farm Management Information System is the FIS's modified edition. Its goal is to help the farmers to make the right choices available by minimizing production costs, adhering to agricultural standards, and ensuring good product quality and safety (Fountas S., 2015). Farm management software systems facilitate data acquisition & it's processing and also have the ability to keep track, strategic planning, make decisions, documentation as well as control farm activities (Köksal Ö., 2019), and include essential functionality for keeping records like crop output rates, weather prediction, scheduling of farm tasks, profits and losses, monitoring nutrition level of soil, field mapping, also many complicated capabilities to automate farm and agribusiness field management accounting.

4.4 Making Decisions

People struggle to handle complicated information in circumstances when several field parameters must be evaluated in an attempt to implement effective decisions. AI methods like fuzzy logic, expert systems, neural networks as well as genetic algorithms may aid in these circumstances. AI plays an important part in agriculture, assisting in the interpretation of accessible data, with its modeling as well as reasoning skills. Fuzzy logic, for example, is a method of AI that mimics human thinking by simulating the mechanism of deciding that requires numerous choices than just "true" and "false" options; this strategy utilizes linguistic variables which are well tailored to the complexities of challenges raised by the variety of agricultural decision-making. For potato, corn, and kiwi, Marsili-Libellia and Giusti developed a fuzzy-based Decision Support System (DSS) with rain forecast & soil moisture as input variables (Giusti E., 2015). When various factors are taken into account, DSS can become more stable and efficient, but certain processes remain contentious since priorities may differ solutions at different times depending upon priorities given by policymakers and other individuals interested in the process (Kumar A., 2017).

4.5 Applying Decisions

Actuation is described as taking actions on the crop or in relation to it, and it is achieved by taking decisions directly after acquiring information or at a later period. Variable Rate Machines have the ability to perform a wide range of farming activities driven via smart systems (Tobe, 2017). Variable Rate Technology (VRT) has the ability of benefit maximization while lowering environmental pollution when applied to Site-Specific Crop Management (SSCM), since just what is necessary would be implemented (Kweon G., 2013). If management zone delineation methods are used in variable-rate nutrient implementations, Nawar et al. reported that field productivity is improved in every instance and environmental damages were minimized in comparison to conventional uniform-rate applications (Nawar S., 2017). The production of commercial VRT solutions is being led by manufacturers of machinery. Automatic differential harvesting, also known as Variable Rate Harvesting (VRH), is another optimistic method of variable actuation that tries to harvest as per previously established management areas. Aside from performance & usefulness, the expense is an important factor to remember when deciding whether or not to implement such technology.

1. Getting Value from AI in Agriculture

Numerous modern logics and approaches have been developed and uncovered as a result of AI development, making the problem-solving process easier. Fuzzy logic, Expert Systems, Neuro-fuzzy logic and Artificial Neural Networks (ANN) are examples of those approaches. ANN is the most generally adopted and frequently used approach for research, across all of these. ANN was created from the same idea about how the human brain works in the mind. ANN is a task-oriented approach that informs the system to function based on an in-built task instead of a computationally programmed task. Due to its superiority over traditional systems, ANNs have been implemented several times throughout the agricultural industry. The primary advantage of neural networks is that, relying on parallel logic, they can predict and forecast. Neural networks can be trained rather than thoroughly programmed. For predicting variables of water supply, Maier & Dandy (Maier, H.R., 2000) had been using neural networks. ANN was used by Gliever and Slaughter (Gliever, C., 2001) to distinguish weeds from crops. Song & He combined ANNs and expert systems to predict crop nutrition levels.

Whenever it gets down to choosing a predicting strategy, neural networks still come out on top (Song, H., He, Y., 2005). If a stable collection of variables is fed to neural networks, they are able to predict complex mappings. To fix the effect of frost development in the fields of Sicily, Mort & Robinson established a neural network-based prediction model (Robinson C. and Mort, N., 1997).

Using substantially less meteorological data, Arif utilized two ANN models to measure moisture levels in paddy fields. The measured and calculated soil moisture values were then used to corroborate and validate these models. To get the estimate Evapotranspiration (ET), the first ANN model was created. The minimum, average, and maximum temperatures of the air were used. Solar, precipitation, as well as air temperature information were collected for the second model. Each of these models generated precise and consistent soil moisture estimates in paddy fields with the least amount of meteorological data, labor, and time. Hinnell discusses neuro drip irrigation systems, in which ANNs were used to model the spatial distribution of water within the subsurface (Hinnell A.C., 2010). Water distribution throughout the lower level of the soil is important for the drip irrigation system to work properly. Here, the prediction made by ANNs is beneficial for the user, resulting in a quick decision-making phase in turn. After the soil has been infiltrated with water from the emitter on the land's surface, ANN models generate wetting trends (first and second). As a result, the ANN model presents the user with continuous trends. In addition, researchers created a model to analyze the maize crop's yield. A Multi-Layered Feedforward ANN (MLFANN) has been used here. Learning algorithms like Gradient Descent Algorithms (GDA) & Conjugate Gradient Descent Algorithm (CGDA) are used to power such networks. Both of the algorithms were written & simulated using the Neural Network Toolbox in the Matrix Laboratory (MATLAB) (Singh, R.K., Prajneshu, 2008).

6.1 Benefit of Smart Farming in Bangladeshi Agriculture

As a result of the increase in the country's population, there is a greater demand for agricultural production in Bangladesh. As a consequence of this, sustainable smart farming is absolutely necessary in Bangladesh in order to raise crop production despite the country's limited resources. In this paper we figure out that the smart farming implementation in Bangladesh will result in a number of benefits, including the following Table 1:

Table-1: Benefit of Smart Farming in Bangladeshi Agriculture

SN	Benefits of Smart Farming
1	Producing a greater quantity of crops at a lower cost.
2	Because there is a limited of water, reduce the amount of water that is w asted.
3	Producing more crops on a limited amount of land.
4	Automate the Irrigation System.
5	Can be notified in advance of a variety of alarms, such as temperature a nd air humidity, an inadequate water balance at the time of irrigation, or any unusual activities that take place in the field.
6	Decreases the amount of fertilizer and insecticides that are needed.
7	Agricultural Operations can be managed by remote Control
8	The farmer can also administer and monitor the system using his or her smartphone.
9	Enhancing indoor safety.
10	Reduce physical labor in the field and help to reduce the number of workers as well.
11	Bangladeshi people's lifestyles are becoming more comfortable and getting better living environment.
12	The economy of Bangladesh should be increased.

6.2 Challenges of Smart Farming in Bangladeshi Agriculture

The utilization of e-agricultural services is problematic for about 65.8% of farmers (Md. Rezwan Islam, 2016). According to our analysis, the following challenges are faced by Bangladeshi farmers to implement smart farming.

Table-2: Challenges to Implement Smart Farming in Bangladesh

SL	Challenges
a)	Lack of knowledge of the advantages of smart farming.
b)	Farmers' inability to use mobile-based apps due to a lack of e-literacy.
c)	The cost of using, developing, and implementing Smart Farming
d)	Timely and effective delivery
e)	Inadequate government digital services facilities and centers
f)	Essential Data Centers
g)	Internet accessibility
h)	Supply of electricity
i)	Inadequate IT professionals
j)	Inadequate training
k)	Easily Operable Technology

7. Conclusion

In recent decades, as advances in technology have emerged, particularly access to accurate agricultural data and excellent computer tools to extract the most significant information from it, we can ultimately obtain maximum benefits while being environment friendly. It seems that it's the right moment to take steps toward digital, sustainable agriculture capable of demonstrating the maximum potential of data-driven management in the twenty-first century in order to meet the demands of food production. It can perform jobs quicker and better than humans with the integration of Robotics, IoT and AI, leading to very productive farm management. In order to prevent repeated, physically exhausting, and stressful field operations, these modern solutions based on digital technologies allow farmers to serve as supervisors of ones crops instead of just laborers. However, users, especially young farmers eager to understand and apply advanced technologies to agriculture, must undergo intensive training in order to take full advantage of advanced agriculture, and ensure a generational rebirth.

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