Cloud Cultivation: Optimizing Agricultural Automation Practices through Deep Learning

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Abstract
Background: Modern agricultural operations collect data from a variety of sources that provide a better knowledge of the constantly shifting conditions of the crop, soil, and environment. This suggests that the processes involved in agriculture will become more and more data-driven. The goal of this study is to demonstrate how to handle diverse data and information from actual datasets that gather physiological in nature, biochemical processes. The agricultural industry only seems to be resistant to digital technological advances, and the "smart farm" concept is becoming increasingly common by using time-series data and the Internet of Things (IoT) paradigm to apply environmental and historical information. In recent years, deep programming has been effectively used for voice recognition, picture recognition, and processing of natural language. **Aim:** By examining cloud data with crop development trends, examine the potential of deep learning algorithms to optimise the use of agricultural resources, such as water, fertilisers, and pesticides. **Method:** The present study focuses on the design and implementation of real-world tasks, such as predicting agricultural harvest or recreating data from missing or incorrect sensors, by comparing and using different machine learning algorithms to recommend which way to spend efforts and resources. **Results:** The results of this study demonstrate the manner in which there are plenty of potential possibilities for innovation to coexist with requests and requirements from businesses who want to establish an optimised and sustainable agriculture industrial use business, making investments not only in technology but also in the expertise and skilled employees necessary to make the most of it. **Conclusion:** The conclusions presented in this study suggest that better accuracy and faster inference times may be attained by using novel deep learning techniques, and that applications in reality can benefit from the models. Lastly, a few suggestions are made for future study directions in this field.
Keywords: Agriculture Industrial, Internet of Things (Iot), Technology, Optimized, Deep Learning, Machine Learning, Smart Farm, Cloud Computing, Image Recognition, Precision Agriculture, Big Data, Productivity and Environmental Sustainability.

1. Introduction

In recognition of the growing global population, the agricultural sector uses around 85% of the freshwater that is readily accessible, necessitating a rise in food production. Challenges with the traditional irrigation management approach include inadequate production and inefficient use of water. Furthermore, the dynamics of global warming and climate change often have an influence on the quantity of rainfall that is required to provide plants with water. Similar to this, the water needs and biological functions of plants are seasonal, vary from plant to plant, and are impacted by external elements like the weather [1]. In a greenhouse, the environment is easily managed, but in an open-field cultivation farm, these variables are more difficult to manage [1, 2]. Precision irrigation systems must be used to control the fluctuating environmental circumstances in an adaptable manner. In order to achieve water-saving measures to offset rainfall variability and the impact of water shortages due to drought in many regions of the globe, sustained precision irrigation is essential for ensuring food security. The goal of precision planning for irrigation is to avoid over- and under-irrigation by using water efficiently for each plant at the appropriate times and locations to make up for water loss via evapotranspiration, erosion, [2], or deep percolation. Water may be conserved with appropriate irrigation management via efficient monitoring and control, which also reduces other indirect expenses associated with energy consumption, such as power or fossil fuel for expressing, for maximum the effectiveness of costs.

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Today, digital agriculture refers to agritechnology and precision agriculture. It is a new field of study that uses data-intensive methods to increase agricultural output while reducing its detrimental impacts on the environment. In contemporary agricultural operations, data is gathered from many different kinds of sensors, photos, and satellite imagery [2, 3]. They improve knowledge of the environment, soil, and crop dynamics, as well as the proper utilisation of equipment, enabling more accuracy and improved decision-making.

Artificial Neural Networks (ANNs) find use in hydrological research such as microclimate prediction, rainfall-runoff prediction, groundwater level prediction, urban flood forecasting, and water supply and quality monitoring. Because Artificial Neural Networks (ANNs) can evaluate tremendous amounts of data fast and effectively [3, 4]. They are finding growing usage in the prediction of greenhouse microclimates. Furthermore, ANNs have shown to be capable of providing precise microclimate prediction when sensors are placed within greenhouses. Machine learning techniques are becoming more popular when combined, and the results show significant increases in prediction accuracy [4]. The capacity of Artificial Neural Networks (ANNs) to take into account the complex interactions among several elements of the environment, such as humidity, lighting, and temperature intensity, which may alter the microclimate conditions inside the growing facility, is one of its main advantages.

It has been discovered that adding additional statistical and machine- learning techniques may increase the predictability of ANNs for agricultural microclimates. A helpful linear method for assessing multichannel time series statistics with time-varying dynamics and finding similar patterns across many time series is the Dynamic Factor (DF) model [5, 6]. Different fields have seen the use of the DF model, such as PM2.5 factor analysis, psychological evaluation, and economic forecasting. Additionally, survey-based trust among customers has been examined and predicted using a DF-based model. Additionally, hybrid models combining ANN and DF have been created for a variety of uses, including comparative performance and evaporate prediction.

Agricultural operations are going to be more and more data-guided as smart tools and sensors multiply on farms and the sheer number and range of agricultural data increase. Conversely, however, the rapid advancement of cloud computing and the Internet of Things (IoT) is driving the growth of Smart Farming. While Smart agricultural takes into account the scenarios generated by occurrences in real-time, Precision Agriculture just relates to managing agricultural variability. With the help of everything mentioned above, farmers are able to respond swiftly to unforeseen events, such disease or weather-related alerts, or to abrupt changes in their operational environment. Typically, such characteristics include astute support throughout the adoption, upkeep, and usage of the technology.

As high-performance bioinformatics technologies, both machine learning and big data have emerged as new avenues for deciphering, quantifying, and comprehending data-intensive processes in the context of agricultural operations [5]. Big Data and machine learning have become widespread in multiple environmental fields, including predicting the weather, weather management, catastrophic events, smart water and electricity management systems, and remote sensing. These fields have benefited from the rapid advancements in High Resolution (HR) satellite imagery techniques, intelligent technological advances in communication and information, and the use of social media.

The application of Machine Learning (ML) algorithms to big data has long been a crucial area of study, therefore assessing the effectiveness and quality of both new and old ML methods has gained significant importance [6]. These algorithms' operating velocity, effectiveness, and reliability have already been shown. However, given the complicated nature of Big Data today, new issues have surfaced, making it difficult to create and construct a new machine learning algorithm for Big Data.

A branch of artificial intelligence called Machine Learning (ML) use computer algorithms to transform unprocessed data from the actual world into usable models and recommendations for actions. The system may autonomously acquire information from past events and advance by using machine learning models. Support Vector Machines (SVM), [7], trees of choice, Bayesian learning, K-mean clustering, regression, and neural networks, rule-based associations learning, and many more are examples of Machine Learning (ML) approaches. Gave a brief overview of how the ML model is being used in different agricultural tasks.

ML incorporates Deep Learning (DL) as a subfield. DL algorithms are more intricate than those of conventional ML models. The layers of a network that are between the input and the output are known as hidden layers. A deeper network contains several concealed layers, while a shallow network just has one [8, 9]. Deep neural networks are capable of learning data attributes and handling more difficult issues because to their many hidden layers. The most popular models in recent years have been Deep Learning (DL) models because they are both quicker and more effective than Machine Learning (ML) shallow methods, and because they have the ability to automatically deduce characteristics from the input data. Alex Net was victorious in the 2012 LSVRC classification competition [9]. Shown the potential of deep learning models for the categorization authentication, and positioning with remarkable outcomes. These successes motivate scientists to use DL models in different fields that individuals endeavour, such as agriculture.

1.1Objective of the study

- Implement deep learning algorithms that can recognise symptoms of crop illnesses or stress in cloud photos, enabling farmers to take early action to stop yield loss.
- Investigate at ways to reduce the cost, increase accessibility to cloud farming technologies for a larger group of farmers, taking into account infrastructure needs, technological know-how, and other variables.
- Provide training materials and instructional resources to help farmers and other agricultural professionals use cloud agriculture technology.

2. Literature Review

(Khan, A., Hassan, M., 2023) [10] Modern methods of farming have been entirely rewritten by smart agriculture, which is powered by the convergence of cloud computing and Internet of Things (IoT). In this work, we provide a systematic approach to optimise onion crop cultivation via the use of systems running on the cloud and Internet of Things sensors. Critical information on the onion crops can be collected and transferred to a central data centre via the use of a variety of Internet of Things (IoT) sensors, such as soil moisture and temperature, relative humidity, and aerial drones. Real-time data processing is made possible by optional edge computing devices, which reduce latency and bandwidth consumption.

(Ojo, M. O., 2022) [11] Higher yields, reduced space requirements, and resource efficiency characterise the unconventional production method known as Controlled Environment Agriculture (CEA). Recent advances in CEA have brought Deep Learning (DL) to the field for a variety of purposes, such as microclimate prediction, irrigation, and crop growth prediction, stress both abiotic and biotic detection, and crop monitoring. Nevertheless, no review research evaluates the present situation of the art in DL to address various CEA concerns. In order to close this gap, we thoroughly examined DL techniques employed during CEA. A set of guidelines for inclusion and exclusion were followed in order to create the review framework. Following a thorough screening procedure, we examined 72 paperwork in total to obtain the correct information.

(Pabitha, C., 2023) [12] Agriculture has a significant impact on an economy's growth. The suggested approach investigates how using digital footprints might enhance farming methods and yield. Digital data related to agriculture is becoming more and more accessible due to the advancement of contemporary technology and the proliferation of interconnected gadgets. Digital footprints that capture all aspects of agricultural production lifetime, from planting to harvesting, may be created using this data. After that, farmers may use algorithms that use machine learning educated to analyse these electronic records to identify trends and predict outcomes to determine when to plant, irrigation, fertilise, and harvesting their crops.

(Guillén, M. A., 2021) [14] The digital revolution is being propelled by the Internet of Things (IoT). AL Palliative measures include the fact that almost every economic sector is becoming "Smart" as a result of the Internet of Things' data analysis. Advanced Artificial Intelligence (AI) approaches are used to do this study, yielding insights never previously possible.

AIoT is a new trend that is arising from the integration of IoT with AI, providing new avenues for digitalization in the modern day. But there is still a significant difference among AI and IoT, namely in the amount of processing power needed for the former and the deficiency of computing resources provided by the latter type of technology.

(Cubillas, J. J., 2022) [15] In any industry that produces goods, predictive systems are an essential tool for directing and making choices. Knowing ahead of time how profitable a farm is is particularly interesting when it comes to agriculture. In this way, major choices that impact the farm's financial balance may be made based on the season during which this knowledge is accessible. The goal of this project is to create a useful model for anticipating crop yields months in advance that farmers and farm managers may utilise with ease via a web-based application.

(Marina, I., 2023) [16] Encouraging social well-being and meeting the world's food demands depend heavily on agriculture. As a strategically important food crop, soybeans provide vital amounts of protein for both people and animals, and their nitrogen fixation improves soil fertility. However, producers face difficulties due to the increasing demand for soybeans worldwide, especially with regard to cultivation efficiency. Threats from diseases, changes in commodity prices, land usage, and climate change all make these problems worse. Technological developments in the agricultural sector, including Internet of Things, artificial intelligence, remote sensing, and predictive modelling, have great potential to increase both the effectiveness and productivity of soybean farming.

3. Methods

In order to offer advances for the management of data and assessment in small-size manufacturing businesses and, [17], in contingent geographical settings that are often resistant to creative thinking, this effort aims at demonstrating practical and empirical results.

1.2 Data Sources

Three separate information sources are taken into consideration during this research (Figure 1), each one of which has distinctive and complimentary qualities that are helpful for designing and testing machine learning techniques:

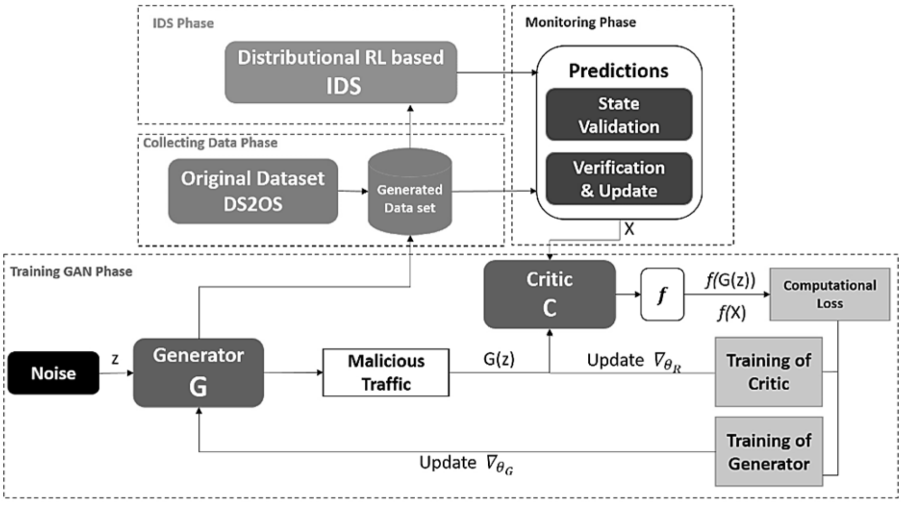

Figure 1: The datasets this research employed.

The annual totals for the value of crops in Italy's (Table 1).

Table 1 Information about the periods of time dataset for culture.

Crp. Type	Year	Province	Altitude	Tot. Area	Cult. Area	Tot. Prod.	Tot. Harvest	Temp. (avg.)
Apple	2006	Trino	256	942	421	243,121	256,124	7.8
Pears	2006	Vercelli	140	25	28	5465	5986	11
Temp. (max)	**Temp. (min)**	**Tot. Rain.**	**Phosph. Minerals**	**Potash Minerals**	**Organic fret.**	**Organic comp.**		
14.2	2.5	365	25.699	125,246	15,256	642,269		
14.9	5.4	896	1462	49,469	98,469	289,986		

This arranged agricultural collection presents scientific and technical data from biological and agricultural research on crops and horticulture species, however values are often missing or only partly arranged [18]. Many valuable data has undergone previous measurements and modifications Table 2.

Table 2 Details of the professional agriculture dataset from the National Research Council (CNR). Leaf Areas Index (LAI), Evapotranspiration Reference Value (ETc), Leaf Area Index (ETO), and Penman-Monteith Measurement (PM).

Beam Plant -2004 Crop				
Date	**Etc (mm/d)**	**ETo Pm(mm/p)**	**ETc/ETo**	**LAI**
9 may 2003	1.48	5.99	0.89	0.04
14 may 2004	1.59	4.58	0.398	0.7

$y_{ip}^{l+1} = f(\sum_{i=1}^{N+1} w_{ij}^{l+1} + y_{ip}^{l} + Q_{j}^{l+1})$	1
$Q_{ij}^{l}(n+1) = Q_{i}^{l}(n) + n.\,err_{jp.}^{l}$	2
$w_{ij}^{l}(n+1) = w_{ij}^{l}(n) + n.\,err_{jp}^{l}.\,y_{ip}^{l-1}$	3
$RAE = \frac{\sum_{i=1}^{N}(\widehat{\theta i}\theta i)}{\sum_{i=1}^{N}(\widehat{\theta i}\theta i)}$	4
$d_e(a,b) = \sqrt{\sum_{i=1}^{N}(a_i + b_i)^2}$	5
$d_m(a,b) = \sqrt{\sum_{i=1}^{N}(a_i + b_i)^2}$	6

4. Results and Discussion

Table 3 presents the results of the experiment regarding the amounts of apple and pear agricultural products, and it also shows the proportion of errors for each of the three prediction models. The error mean values for the municipalities of Friuli the Venezia Giulia in Abruzzo, and Calabria is show that the neural network model works best on the linear regression for both the apple plant (9.19% vs. 30.77%) and the pears plant (19.36% vs. 39.11%).

Table 3 Using neural networks and its polynomial linear model for forecasting on the Istat dataset, the crop error prediction for apples and pears.

Italian Province	**Prediction Error-Apple**		**Perdition Error-Pears**	
	NN	**LR**	**NN**	**LR**
Udine	25.64%	2.64%	2.46%	2.54%
Gorizia	14.69%	4.62%	2.56%	6.4%
Trieste	1.5%	5.64%	5.78%	14.5%
Pordenone	23.5%	6.45%	1.2%	6.4%
L'Aquila	7.12%	2.56%	14.2%	14.25%
Mean	72.45%	21.91%	26.20%	44.09%

Table 4 shows the anticipated and actual values for all of the crops in the province of L'Aquila. The reality values are very comparable to the expected values; in fact, the difference for pears is less than 4.5% and for apples it is less than 2%, indicating the usefulness of applying this approach to this kind of dataset.

Table 4 Task 1: a comparison of the actual and projected amounts using a neural network model for the total crop harvests of pear and apple harvests in the Italian region of L'Aquila using the Istat database.

Method: NN	**Apple**		**Pears**	
Italian province	**Real value**	**Predicted value**	**Real value**	**Predicted value**
L'Aquila	45,764	48,265	3640	3697

In this work, the polynomial simulation model best matches the prediction of LAI values for the three culture under thought as shown using the predicted errors shown in Table 5.

Table 5 Task 2: Using predictive machine learning techniques to contrast the prediction error of the cultures' Leaf Area Index (LAI) value by employing the CNR scientific agricultural dataset.

Culture	**Predicted Error**		
	NN	**LR**	**Polynomial**
Artichokes	163.69%	51.69%	24.60%

Pear	1563.62%	41.65%	10.00%
Pacciamata Eggplant	986.6%	256.1%	6.98%

The matrix of correlations shown in Table 6 extends a correlation coefficient to a set of a component pairs, which are helpful to detect whether there are additional connected features in addition to the geographical ones, by taking consideration of the previous clusters formed by three monitoring stations.

Table 6 Task 3: The correlation matrices for the magnitude of the grouping characteristics.

Attributes	R_inc	T_min	T_max	T_med	RH_min	RH_max	RH_med	WS
R_inc	**1**	0.569	0.495	0.146	-0.265	-0.658	-0.247	0.146
T_min	0.359	**1**	0.965	**0.986**	**-0.495**	-0.549	**-0.961**	**0.987**
T_max	0.695	0.591	**1**	0.069	-0.546	**-0.164**	-0.146	0.069
T_med	0.596	0.896	0.164	**1**	-0.142	-0.264	-0.692	0.562
RH_min	**0.216**	**0.653**	0.221	0.312	**1**	-0.591	**-0.153**	**0.156**
RH_max	-0.562	-0.655	0.265	0.064	0.056	**1**	0.697	-0.141
RH_med	-0.264	-0.169	0.569	-0.169	**0.426**	0.564	**1**	0.691
WS	**-0.169**	0.561	**-0.542**	-0.264	-0.562	**0.462**	**-0.429**	**1**

Big Data makes land mapping for large-scale agricultural production possible via remote sensing. It is crucial to keep an eye on how agriculture is affecting different nations and regions in the context of reaching their targets for ecological responsibility and productivity [19]. It also serves as a foundation for the creation of structures for policy makers, aids in decision-making for the long-term sustainability of ecological ecosystems, and provides highly accurate and precise quantitative examination of the interactions between plants and their surroundings. The cloud's accessibility to satellite picture data makes all of the preceding feasible. Cloud technologies, however, prove suitable for the necessary analytics [20]. This makes it easier to create new frameworks for big data that make appropriate use of machine learning methods.

By understanding the fundamental connections between the data gathered by converting it into information and other resources, Machine Learning (ML) is used to perform categorization and predictive analytics. Additionally, it conducts a variety of computing methods, [21, 22], comprising statistical analysis, image processing, modelling, simulation, prediction, and early warning, and it offers information assistance for novel operations.

For numerous Big Data usage in agriculture, cloud computing offers platform, hardware, software, and infrastructure services [23, 24]. The cloud platform makes it simpler for firms by lowering the cost of storing by providing farmers with inexpensive data storage services for text, photos, videos, and various other agricultural data.

As a result, the DL model may not be universally applicable. For example, if a model has been trained using a dataset from a specific site or an open-source site like ImageNet, it may not be capable of to be effectively used at another site, or its accuracy might decline when applied to the data set collected within the real world [24, 25]. Neither the environment is distinct in the field of agriculture, and every circumstance nor difficulty necessitate its own dataset. Model performance may suffer as a result of the variations in the physical appearance of the pictures in the training and evaluation datasets [26]. Retraining the previously learned model using a tiny dataset from a fresh setting is one method to get around issue [27].

Deep models, sometimes referred to as "black boxes," have intricate designs. One of the difficulties in training deep learning models is the need for a system with a high level of GPU power. Furthermore, the selection of the optimisation technique, loss functions, and hyperparameters that affects how well these models work [28]. Bayesian optimising is one algorithm that may assist in determining the appropriate hyperparameters. Scientists from Google developed the most advanced MobilenetV3 by using the Neural Architecture Search (NAS) method [29, 30]. NAS is a technique that looks for each potential pairing of submodules of that can be continually placed altogether to produce the whole model accurately as feasible.

5. Conclusion

The research presented in this study deepens the understanding of the smart farm model by introducing beneficial, affordable, and simple-to-develop tasks that can boost an agricultural company's productivity. Technological advancements in fields requiring control and optimisation can actually help preserve the environment, adhere to international and business laws, meet consumer demands, and pursue financial objectives.

Both machine learning and more conventional statistical techniques have been used to leverage the three distinct data sources, with a focus on the IoT sensors dataset. In the initial exercise, a neural network framework with near-ninety percent success rate was able to forecast the total crops of apples and pears on the Istat dataset; in the second task, however, it was found that polynomial anticipatory and regression models were more appropriate for the CNR scientific data due to the dataset's characteristics.

In fact, IoT systems need science and technology and diffusion expenditures that only a wise and imaginative administration can encourage in smart/medium industries; furthermore, the need to invest in knowledge and abilities in order to economically employ the paradigm of the Internet of Things at greater scales emerges from the proposed real cases, which emphasise the necessity of promoting administration and data investigators.

The primary motivation behind the suggested tasks utilising different strategies for machine learning is the use of an experimental and highly hypothetical work; information fusion, along with the corresponding optimisation of methods and outcomes, will be expected as further work, where new tasks and experiments that take advantage of other sensors types and databases will be planned and carried out in order to address the significant diversity of the hardware sensors market and agri-companies.

Future Works

In further work, we want to further enhance the big data and machine learning framework for agricultural and then apply it to a modest smart enterprise.

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