Advances in Deep Learning Algorithms for Agricultural Monitoring and Management

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Abstract
This study examines the transformative role of deep learning algorithms in agricultural monitoring and management. Deep learning has shown remarkable progress in predicting crop yields based on historical weather, soil, and crop data, thereby enabling optimized planting and harvesting strategies. In disease and pest detection, image recognition technologies such as Convolutional Neural Networks (CNNs) can analyze high-resolution images of crops to identify early signs of diseases or pest infestations, allowing for swift and effective interventions. In the context of precision agriculture, these advanced techniques offer resource efficiency by enabling targeted treatments within specific field areas, significantly reducing waste. The paper also sheds light on the application of deep learning in analyzing vast amounts of remote sensing and satellite imagery data, aiding in real-time monitoring of crop growth, soil moisture, and other critical environmental factors. In the face of climate change, advanced algorithms provide valuable insights into its potential impact on agriculture, thereby aiding the formulation of effective adaptation strategies. Automated harvesting and sorting, facilitated by robotics powered by deep learning, are also investigated, as they promise increased efficiency and reduced labor costs. Moreover, machine learning models have shown potential in optimizing the entire agricultural supply chain, ensuring minimal waste and optimum product quality. Lastly, the study highlights the power of deep learning in integrating multi-source data, from weather stations to satellites, to form comprehensive monitoring systems that allow real-time decision-making.

Keywords: Deep Learning, Agricultural Monitoring, Precision Agriculture, Remote Sensing, Supply Chain Optimization

Introduction
These early farming techniques were elementary, dictated largely by rudimentary knowledge of seed germination, water requirements, and seasonal cycles. The significant challenges faced in these times revolved around an inherent unpredictability of climatic conditions, pest infestations, and variable soil fertility. Practices such as shifting cultivation and slash-and-burn methods were employed, leading to rapid soil nutrient depletion and contributing to the environmental distress. The lack of monitoring and management

techniques made it extremely difficult to maintain or increase productivity, with famines and crop failures a regular occurrence.

The Agricultural Revolution in the 18th and 19th centuries introduced a myriad of advancements that altered the dynamics of farming. This period saw the advent of systematic crop rotation, selective breeding, mechanization, and the development of synthetic fertilizers and pesticides, which drastically improved yield productivity. The impact of these advancements was momentous, driving an increase in population density and urbanization due to the surplus food production. However, this came at an environmental cost. The extensive use of synthetic chemicals led to soil degradation, water pollution, and loss of biodiversity. In the mid-20th century, the Green Revolution further intensified these practices by promoting high-yielding crop varieties and the extensive use of synthetic inputs. Though it succeeded in addressing global food shortages, the environmental consequences further exacerbated.

In the late 20th and early 21st century, a significant transition from traditional to digital farming began, introducing the concept of 'precision agriculture.' Precision agriculture leverages advancements in Information and Communication Technology (ICT), combining GPS, remote sensing, and Big Data analytics to maximize yield and minimize environmental impact. This digital transformation facilitates the collection and processing of real-time data on various factors such as soil conditions, crop health, weather patterns, and pest infestation, allowing for more informed and precise decision-making. Variable-rate technology (VRT) enables the application of inputs like water, fertilizers, and pesticides at optimal rates and timings, significantly reducing waste and environmental impact. This evolution in farming represents a paradigm shift towards sustainability, with the potential to address the global food demand without compromising ecological integrity.

An agricultural monitoring system can be defined as a suite of tools and methodologies designed to track, analyze, and report on different parameters within the agricultural environment [1]. These parameters might include soil properties, weather patterns, crop health, pest activities, and farming practices. The system typically consists of sensors for data acquisition, databases for data storage, and analytical software for data processing and interpretation. Sensors, both on-ground and remote, collect real-time data on various parameters, ranging from soil moisture and nutrient content to meteorological conditions and crop health. The collected data is then stored in databases, which can be on-site or cloud-based. Analytical software, often empowered by artificial intelligence (AI) and machine learning (ML) algorithms, processes this data, providing insights into the current state of the agricultural system and potential future trends.

Agricultural management systems, on the other hand, are strategic and operational frameworks designed to optimize the agricultural process in terms of productivity, sustainability, and profitability. These systems incorporate the principles of agronomy, economics, and technology to plan, organize, and control agricultural operations. These operations range from selecting suitable crops and making decisions about planting, fertilizing, and irrigation strategies to managing pests and diseases, harvesting, and post-harvest storage. Agricultural management systems also involve making decisions about marketing, logistics, and the allocation of resources. These decisions are often supported by digital tools, including predictive models, decision support systems, and farm management software, to assist farmers in making informed and timely decisions.

The interplay between agricultural monitoring and management systems is critical for the overall efficiency and effectiveness of the agricultural process. In essence, the monitoring system serves as the eyes and ears of the management system. The real-time and precise data provided by the monitoring system informs the management system, enabling adaptive and precision farming practices. For instance, based on the data about soil nutrient content and weather forecasts provided by the monitoring system, the management system can decide when and where to irrigate or apply fertilizers, minimizing waste and optimizing crop yield. Similarly, data on pest activities can guide pest management strategies. On the other hand, the outcomes of the decisions made by the management system feed back into the monitoring system, providing data for further analysis and learning. This iterative feedback loop allows for continuous improvement and adaptation in the face of changing conditions, making agriculture more resilient and sustainable.

As the agriculture industry increasingly adopts digital and automation technologies, vast amounts of data are being generated and stored in digital formats. These data include information about crop yields, soil health, weather conditions, and pest patterns. Moreover, precision agriculture has necessitated the use of various IoT devices, unmanned aerial vehicles (UAVs), and satellites for real-time monitoring of agricultural fields. While these innovations have undoubtedly improved efficiency and productivity, they have also introduced new data security vulnerabilities. As the value of agricultural data rises, so too does the risk of cyberattacks, with hackers potentially seeking to steal proprietary data or disrupt operations.

The proliferation of data-driven agricultural technologies has created a landscape where data security is an increasingly complex challenge. On one hand, farmers and agricultural businesses need to share data with various stakeholders – from seed companies to equipment manufacturers, and from advisors to regulators. On the other hand, they must ensure that the shared data is protected from unauthorized access and misuse. Furthermore, many of these technologies collect, transmit, and store sensitive data that could potentially compromise the privacy of individuals involved if not properly protected. Consequently, the issue of data security extends beyond the mere safeguarding of information to encompass a broad range of ethical, legal, and societal implications. The repercussions of inadequate data security measures could have severe impacts on individual farms, local communities, and the global food supply chain.

Deep learning

Deep learning algorithms, which are a subset of machine learning techniques, use artificial neural networks with multiple layers, also known as deep neural networks [2], [3], to extract and transform data through a hierarchical learning process [4]. The defining characteristic of deep learning is that these layers of features are not designed by human engineers; they are learned from data using a general-purpose learning algorithm. Each layer within this network serves to parse the input data, abstracting the information through its complex, nonlinear transformations [5], [6]. The layers in a deep learning model build upon one another, with each successive layer learning to identify more intricate features based on the outputs of the preceding layers. The fundamental structure of these algorithms includes an input layer for data intake, multiple hidden layers where the computation takes place, and an output layer where the final prediction is generated [7]. These layers consist of nodes, often referred to as neurons, that mimic the neurons in the human brain.

There exist several types of deep learning models, each having distinct characteristics suitable for various types of tasks [8], [9]. One of the most basic types of deep learning models is the fully connected, or dense, neural network [10]. These models connect every neuron in each layer to every neuron in the following layer. However, while fully connected neural networks can be effective for many tasks, they may not be optimal for specific types of data, such as images, temporal data, and sequential data [11]–[13]. For such data, specialized types of deep learning models, like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are more commonly used. CNNs, typically used for image and video processing, are characterized by their convolutional layers that apply convolutional filters to the input data, effectively enabling the network to focus on local features within the data. On the other hand, RNNs are designed to work with sequential data and are often used in natural language processing and speech recognition [14]. RNNs utilize connections between neurons in a way that creates internal states, allowing them to process sequences of inputs and retain information over time.

The training of deep learning algorithms involves the use of backpropagation and gradient descent methods. Backpropagation is an algorithm used to calculate the gradient of the loss function with respect to the weights in the network [15]. It works by computing the gradient of the error with respect to each weight in the network, starting from the output layer and propagating backward through the network [16]–[18]. This way, it is determined how much each neuron's weights contribute to the final error, and thus, how they should be adjusted to minimize this error [19]. On the other hand, gradient descent is an optimization algorithm used to minimize the loss function by iteratively moving in the direction of steepest descent, defined by the negative of the gradient. The weight parameters are updated iteratively until the algorithm converges to the minimum of the loss function, indicating the most optimal weights for the network [20].

Deep learning algorithms play an integral role in image recognition and processing. Convolutional Neural Networks (CNNs), a specific type of deep learning algorithm, have emerged as the standard for tasks like object recognition, image segmentation, and facial recognition [21]–[24]. The hierarchical feature learning approach of deep learning is well-suited to the task of interpreting the raw pixel data of images [25], [26]. The initial layers in a CNN can automatically learn low-level features like edges and color gradients. Subsequent layers combine these low-level features to learn higher-level attributes, such as shapes and textures. The deepest layers can identify complex structures like faces, buildings, or vehicles. CNNs have been instrumental in making strides in fields like medical imaging, where they are used for tasks ranging from detecting anomalies in X-ray images to automated tumor detection in MRI scans.

Natural Language Processing (NLP) and translation are other areas where deep learning has had a significant impact [27]. Recurrent Neural Networks (RNNs) and more recently, Transformers, have proven particularly effective in understanding the semantics of written and spoken language, and producing human-like text [28]–[30]. In translation, Sequence-to-Sequence (Seq2Seq) models, a variant of RNNs, have revolutionized the field. These models, combined with attention mechanisms, can handle different lengths of input and output sequences, making them well-suited to tasks like machine translation, where the length of the input text may not match the length of the translated output. These algorithms have enabled the development of real-time translation services and sophisticated chatbots, which have both commercial [31], and social implications. In the field of predictive analytics and forecasting, deep learning algorithms have ushered in a new level of precision and reliability. Traditional statistical methods often rely on linear assumptions and may fail to capture complex patterns within data. Deep learning models, particularly those based on Long Short-Term Memory (LSTM) units, a type of RNN, are capable of modeling complex temporal dependencies, making them excellent tools for time series forecasting. These deep learning models have been applied in predicting stock market trends, weather forecasting, sales forecasting, and many other areas where accurate predictions of future events can bring about considerable financial, and operational benefits.

Fuzzy deep learning is a fusion of fuzzy logic principles and deep learning techniques. Fuzzy logic is a form of many-valued logic in which the truth values of variables may be any real number between 0 and 1, as opposed to strictly binary (true or false) in classical logic. It was introduced as a way to manage uncertainty and is particularly effective at handling noise and ambiguity in data [32].

In fuzzy deep learning, the principles of fuzzy logic are used to introduce a degree of uncertainty into the weights and computations of the deep learning model. This allows the model to handle uncertainty in the data and to generalize better when confronted with previously unseen examples [33]–[36]. This approach can be especially valuable in scenarios where data is sparse, noisy, or ambiguous.

One common method of implementing fuzzy deep learning is through the use of fuzzy membership functions. Each input to the model is associated with a membership value that represents its degree of belonging to certain fuzzy sets. This membership value is then used in the computations within the deep learning model, allowing the model to consider the degree of uncertainty associated with each input [14].

Deep learning models, by virtue of their complexity and scalability, are capable of handling large amounts of data, and as such, have the potential to facilitate both extraordinary benefits and immense vulnerabilities. One of the key aspects of data security in deep learning is ensuring the confidentiality [37], integrity, and availability of data [38]–[40]. Deep learning algorithms learn from large datasets to create accurate models; these datasets may contain sensitive information, creating the risk of privacy breaches if mishandled. Adversarial attacks are a prime concern, whereby malicious parties may manipulate inputs to misguide the deep learning model, leading to incorrect predictions. Privacy-preserving mechanisms [41], such as differential privacy, have been proposed to allow the use of personal data while limiting the disclosure of sensitive information [42].

Moreover, the significance of data security in deep learning becomes even more pronounced when applied in specific fields [43], such as agriculture. Deep learning in agriculture leverages multiple types of data, including but not limited to, geographical, meteorological, and soil data, as well as individual farm operations data. This data is harnessed to optimize various agricultural processes such as irrigation, crop yield prediction, and pest detection [44], [45]. The potential to significantly enhance agricultural productivity has led to the proliferation of Precision Agriculture (PA), which relies heavily on data analytics and machine learning. Given the vast quantities of data involved, and the potential economic impact of this data being manipulated or misused, robust data security measures are critical [46].

Recent advances

Crop Prediction and Yield Forecasting

Deep learning models have emerged as a revolutionary technology in the field of agriculture, with their capacity to analyze complex patterns in large data sets and make precise predictions. These models are typically trained on historical data, encompassing a wide range of variables such as weather patterns, soil quality, and crop types [47]. Weather, in particular, holds significant influence on crop growth, affecting factors like germination, flowering, and the development of fruits or grains. Data regarding rainfall, temperature, sunlight, humidity, and wind speed, gathered over decades, provides a comprehensive picture of the weather conditions most conducive to crop growth. Concurrently, the models assess soil quality data, which include soil pH, nutrients, organic matter, texture, and moisture levels [48], [49]. This is combined with crop-specific information such as optimal growing conditions, lifespan, and resistance to pests and diseases. By processing this vast, multidimensional data, deep learning models can predict crop yields with a high degree of accuracy [50].

The application of deep learning models in predicting crop yields promises more efficient planting and harvesting strategies. Traditional farming methods often rely on heuristics and experiences passed down through generations, which, while valuable, may not always provide optimal solutions given the rapidly changing climate and emerging challenges. Deep learning models, however, can process the entire history of crop growth under different conditions and identify patterns that may not be apparent to human observers. The models can offer guidance on the best times to plant and harvest crops based on the predicted weather patterns and crop behavior, helping to maximize yield and reduce waste. This could also contribute to more stable food supplies, as there would be fewer surprises or shortages caused by unexpected weather conditions or crop failures [51]–[53].

Moreover, these predictive models can support farmers in making informed decisions about irrigation, fertilization, and pest control. Irrigation is a critical aspect of farming, especially in regions that suffer from irregular or insufficient rainfall. The amount and timing of watering can significantly impact crop health and yield. Deep learning models can predict the optimal irrigation schedule based on the expected weather patterns, soil quality, and the water needs of the specific crop. This not only ensures the efficient use of water resources but also prevents over-irrigation, which can lead to problems such as waterlogging, leaching of nutrients, and increased susceptibility to pests.

In the same vein, deep learning can provide insights into the most effective fertilization strategies. Like irrigation, fertilization must be tailored to the crop's needs and the soil's current nutrient levels. Over-fertilization is not only wasteful and costly, but it can also harm the environment through the leaching of chemicals into the water supply. By accurately predicting the optimal levels of fertilization based on the crop type and soil quality, deep learning models can maximize crop productivity while minimizing the environmental impact.

Lastly, pest control is a complex issue that can greatly affect crop yields. Pests can quickly ravage entire fields if not properly managed, but overuse of pesticides can lead to resistance, harm beneficial insects, and negatively impact the environment and human health [54]. Deep learning models can aid in pest control by predicting pest populations based on historical data, weather patterns, and crop types. This allows for targeted interventions when pest populations are predicted to rise, and reduces the need for blanket pesticide applications.

Disease and Pest Detection

Convolutional Neural Networks (CNNs) and other image recognition technologies are playing an increasingly pivotal role in modern agriculture, particularly in disease detection and pest control. CNNs, a type of deep learning algorithm, are particularly suited for processing visual data due to their ability to analyze spatial relationships between pixels in an image [55]–[57]. They work by applying filters to different sections of an image, identifying and learning important features such as edges, textures, and shapes, which can be vital for recognizing the early signs of crop disease or pest infestation [58]. These early signs often manifest as changes in the color, texture, or shape of plant leaves or fruits, which, to the naked eye, can be extremely hard to spot until the disease has progressed substantially. However, CNNs can identify these changes at the earliest stages, enabling farmers to take timely preventive or corrective actions.

Drones equipped with high-resolution cameras serve as a perfect tool for capturing images of vast tracts of farmland in a short time span. These drones can fly low over fields, capturing detailed images that would be impossible to gather from the ground or through traditional aerial photography. This kind of imaging allows farmers to monitor their crops frequently and consistently, enabling them to spot anomalies quickly. Moreover, by automating image collection, farmers can focus more on problem-solving and strategic decision-making, rather than spending hours manually inspecting crops.

The incorporation of CNNs with drone technology has led to the advent of real-time image processing [59]–[61], which is a significant breakthrough in agricultural technology. Rather than capturing images to be processed later, these systems can analyze images on the fly, providing immediate feedback to the farmers. This real-time analysis allows for rapid response times, a crucial factor in managing diseases and pests that can spread rapidly and devastate crops. If a problem is identified, the farmer can quickly deploy resources to address the issue, minimizing potential damage and economic loss.

In addition to disease detection, these image recognition technologies are also proving invaluable in pest management. Just as with diseases, pests often cause visual changes to plants, such as holes in leaves or characteristic patterns of damage. CNNs trained on a database of images showing these changes can effectively identify pest infestations even before they become visible to the human eye. This early detection allows for targeted use of pesticides, reducing the overall quantity required and mitigating the harmful environmental impacts associated with their overuse.

Looking forward, the integration of CNNs, drone technology, and real-time image processing holds immense potential to revolutionize pest and disease management in agriculture. By spotting problems early, farmers can react quickly to safeguard their crops, enhancing productivity and sustainability. Moreover, as these technologies continue to advance, they may be able to predict outbreaks of diseases or pests based on the analyzed data and historical patterns. Such predictive capabilities would further empower farmers, allowing them to take preventative measures and optimize crop health, contributing to greater food security and a more sustainable agricultural sector.

Precision Agriculture

Precision agriculture represents a paradigm shift in farming practices, moving away from a "one-size-fits-all" approach to a more customized, data-driven methodology. At the heart of this revolution are deep learning algorithms capable of processing and interpreting vast amounts of data gathered from various sensors embedded within the agricultural ecosystem. These sensors monitor a multitude of variables [62], including soil moisture, nutrient levels, temperature, humidity, light intensity, and more. By analyzing this high-resolution, real-time data, deep learning algorithms can generate actionable insights into the optimal management of resources such as water, fertilizer, and pesticides, increasing the efficiency and productivity of agricultural practices.

One of the key advantages of precision agriculture is the efficient management of water resources. Traditional irrigation techniques often involve watering the entire field uniformly, without considering the varying water needs across different sections. However, deep learning algorithms can analyze data from soil moisture sensors and weather forecasts to provide precise irrigation schedules. These schedules are tailored to the specific needs of different areas within the field, ensuring that each plant receives the optimum amount of water. Not only does this targeted irrigation improve crop health and yield, but it also helps conserve water, a precious resource in many farming regions.

The application of fertilizers can also be dramatically improved with precision agriculture. Traditional practices often involve uniform application, which can lead to over-fertilization in some areas and under-fertilization in others. This not only wastes valuable resources but can also cause environmental problems such as nutrient runoff into water bodies. Deep learning algorithms can analyze sensor data on soil nutrient levels and crop health to determine the optimal amount and type of fertilizer for each section of the field. This precision fertilization maximizes crop nutrition while minimizing waste and environmental impact.

Pest and disease management is another area where precision agriculture can make a significant difference. By using image recognition technology and sensors to detect early signs of pest infestation or disease [63], deep learning algorithms can identify problem areas within a field before they spread widely. This allows for targeted application of pesticides or other treatments, reducing the overall amount of chemicals used and minimizing their impact on the environment and non-target species.

The ability to tailor treatments to specific areas within a field, known as site-specific crop management (SSCM), is a cornerstone of precision agriculture. This high level of customization reduces waste and ensures each plant or section of a field receives the exact care it needs. This leads to healthier crops, higher yields, and more efficient use of resources [64], [65].

Remote Sensing and Satellite Imagery Analysis

The advent of satellite technology has opened new frontiers in the realm of agriculture, providing an eagle-eye perspective that helps in the monitoring of large tracts of agricultural lands. Deep learning models play a critical role in deciphering the complex information contained within the vast amounts of satellite imagery data. These models can process the multi-spectral images to extract valuable information about crop growth, soil moisture, and other essential factors affecting agricultural productivity. Satellite images can provide information on a range of wavelengths, many of which are outside the human visual spectrum, allowing these models to detect subtle changes in vegetation health, soil moisture levels, and even biochemical processes in plants.

One significant advantage of using deep learning models to analyze satellite data is their ability to track changes over time. Changes in the color and texture of crops or the spectral properties of the land can indicate potential issues such as disease infestation, pest attacks, nutrient deficiencies, or water stress. For instance, these models can identify patterns of drought or flooding based on changes in vegetation color and soil moisture levels. By comparing current images with historical data, deep learning algorithms can identify the onset of these adverse events, often before they become apparent to ground-based observers. This ability to detect early signs of such events can provide farmers and agricultural authorities with crucial lead time to implement remedial measures and mitigate potential damage.

Deep learning models also contribute significantly to planning and executing remedial actions. For instance, in the event of a drought, these models can predict its potential impact on crop yield by analyzing the severity and duration of the drought and its timing within the crop's growth cycle. This can guide decisions about irrigation scheduling, crop rotation, or even switching to drought-resistant crop varieties. Similarly, in the case of flooding, these models can help determine which areas are most affected, and hence where drainage efforts should be concentrated. They can also provide insight into the likely long-term effects on soil fertility, guiding post-flood recovery efforts [66].

Furthermore, satellite imagery analysis can also aid in crop yield prediction, an essential aspect of food security and commodity markets. By monitoring crop growth stages and health through satellite data, deep learning models can predict yields with a high degree of accuracy, often several weeks before harvest. These predictions can help farmers, commodity traders, and policy-makers make informed decisions regarding pricing, storage, and distribution, helping to stabilize food markets and prevent shortages.

Climate Impact Modeling

As the global climate continues to change, agricultural practices must evolve to ensure food security and sustainability. Advanced algorithms, particularly those using deep learning techniques, are emerging as critical tools for predicting the impact of climate change on agriculture. These models use historical data on weather patterns, crop yields, and other relevant factors, alongside climate change projections, to generate predictions about future agricultural conditions. By identifying potential challenges and opportunities, these models can guide the development of effective adaptation strategies.

One of the major impacts of climate change on agriculture is the potential shift in growing seasons. Rising temperatures, altered precipitation patterns, and increasing occurrences of extreme weather events could disrupt traditional planting and harvesting schedules. Advanced algorithms can analyze these factors to predict changes in growing seasons for different crops and regions. By providing farmers with information about the optimal times to plant and harvest under the changing climate, these tools can help to maintain or even improve crop yields, despite the challenging conditions.

Changes in water availability pose another significant challenge for agriculture in a changing climate. Droughts are expected to become more frequent and severe in many regions, while others may experience increased rainfall and even flooding. Advanced algorithms can analyze regional climate models, soil data, and crop water requirements to predict future water availability and demand. This information can be used to plan water storage, irrigation systems, and water conservation measures. For instance, in regions where water scarcity is projected, farmers might be advised to shift towards more drought-tolerant crops or adopt irrigation techniques that minimize water use.

Adapting crop types to new climatic conditions is another crucial aspect of agricultural adaptation strategies. As temperatures rise, some crops that were traditionally grown in certain regions may no longer be viable, while others may become more suitable. Advanced algorithms can analyze the tolerance levels of different crops to various climatic stresses, such as temperature extremes, drought, and high salinity. They can also consider factors such as the crop's water and nutrient requirements, growth cycle, and economic value. By synthesizing this information, these models can recommend the most suitable crops for each region under future climate scenarios.

Automated Harvesting and Sorting

In the era of digital agriculture, robotics powered by deep learning are transforming traditional farming practices, particularly in labor-intensive tasks such as harvesting and sorting produce. These automated systems leverage the power of machine vision and deep learning algorithms to identify and manipulate crops based on their size, color, and ripeness [67]. This fusion of robotics and artificial intelligence is paving the way for a new level of efficiency and precision in agriculture, promising numerous benefits for farmers and the wider agricultural industry.

Harvesting is one of the most labor-intensive tasks in farming, and the implementation of robotics can significantly reduce this burden. Deep learning algorithms can train on vast amounts of visual data to recognize when a fruit or vegetable is ripe and ready for harvest based on its color, size, and shape. Coupled with advanced robotic arms and grippers, these systems can navigate complex environments, locate ripe produce, and carefully detach it without causing damage. This can speed up the harvesting process substantially, as these robots can work round the clock and in a variety of weather conditions. Furthermore, they can significantly reduce the risk of injury and physical strain associated with manual labor, contributing to safer working conditions.

In addition to harvesting, these advanced systems can also be used for sorting produce, a task traditionally done by hand

and highly prone to human error. By using machine vision and deep learning, automated sorting systems can quickly and accurately classify fruits and vegetables based on size, color, and quality. These robots can process thousands of pieces of produce per hour, sorting them into different grades for sale or further processing. This not only enhances productivity but also reduces waste, as the precise classification of produce can ensure that each item reaches the appropriate market, from premium-grade fresh produce to lower-grade items suitable for processing or animal feed [68].

The integration of robotics and deep learning also leads to significant cost savings. While the upfront investment in these technologies can be considerable, they can reduce labor costs dramatically over time, contributing to the long-term financial sustainability of farming operations. In regions where labor is scarce or costly, these systems can ensure that farming practices remain viable and competitive.

Moreover, these technologies can contribute to better crop management. The data collected by these systems - on factors such as crop ripening times, yield per plant, and quality distribution - can provide valuable insights for decision-making. This data can help farmers optimize their planting schedules, irrigation, and fertilization strategies, contributing to improved crop health and productivity.

In summary, robotics powered by deep learning are revolutionizing the agricultural sector. By automating tasks such as harvesting and sorting produce, these systems can work quickly and accurately, significantly reducing labor costs and improving efficiency. As the technology continues to evolve, we can expect these systems to become even more sophisticated and widespread, contributing to a new era of precision and productivity in agriculture [69].

Supply Chain Optimization

The integration of machine learning models into the agricultural supply chain has the potential to optimize the journey of produce from the field to the consumer's plate. These models, capable of interpreting vast datasets and making predictive analyses, can be instrumental in decision-making at every stage of the supply chain - from harvest timing to transportation logistics, and even market demand forecasting. The result is a more efficient, sustainable, and responsive agricultural sector that can deliver fresh, high-quality produce while minimizing waste and cost.

Harvest timing is one of the critical factors in ensuring the quality of agricultural produce. Picking fruits and vegetables too early or too late can adversely affect their flavor, nutritional content, and shelf life. Machine learning models, by analyzing historical data on weather conditions, crop growth stages, and market demand, can accurately predict the optimal time for harvest. This ensures that the produce is picked at its peak, maximizing its quality and value [70], [71].

Once the produce is harvested, it needs to be stored, processed, and transported to markets, all of which can have a significant impact on its condition and shelf life. Machine learning can play a crucial role here by optimizing these processes. For example, these models can predict the optimal storage conditions for different types of produce, minimizing spoilage and waste. They can also optimize transportation routes and schedules based on factors such as traffic conditions, weather forecasts, and the shelf life of the produce. This ensures that the products reach the market as quickly as possible, retaining their freshness and nutritional value.

Furthermore, machine learning models can predict market demand for different products, helping farmers and suppliers to align their production and distribution strategies accordingly. By analyzing data on consumer preferences, seasonal trends, and socio-economic factors, these models can forecast which products will be in high demand at different times of the year. This can help farmers decide what to plant and when to harvest, while suppliers can plan their storage and transportation logistics to meet the anticipated demand.

In addition, these predictive models can play a significant role in reducing waste. By optimizing harvest times, storage conditions, and transportation logistics, they can minimize spoilage. By predicting market demand, they can help prevent overproduction and surplus inventory. Reducing waste in this way not only saves resources and money, but it also contributes to environmental sustainability [72], [73].

Integrating Multi-Source Data

By integrating and analyzing these diverse data streams, deep learning models can create comprehensive monitoring systems that enhance agricultural practices, promoting real-time decision making and overall efficiency.

The process begins by ingesting and preprocessing data from these different sources. Weather station data, for instance, offers valuable information about rainfall, temperature, humidity, wind speed, and solar radiation, which can directly influence crop health and productivity. Soil sensors provide insights into soil moisture, pH, nutrient levels, and temperature, critical parameters for crop growth. Drones equipped with cameras and other sensors can capture high-resolution images of crops, providing real-time information about their health, growth stage, and any signs of disease or pest infestation. Satellites, on the other hand, can monitor larger scale phenomena such as regional weather patterns, vegetation health, and changes in land use over time.

Deep learning models can integrate this diverse data into a single analytical framework. They are capable of processing large amounts of structured and unstructured data, identifying patterns, correlations, and trends that might not be evident to the human eye [46]. These patterns can then be used to make predictive models. For instance, a deep learning model might use data from weather stations, soil sensors, and satellites to predict the risk of drought or disease outbreaks. Similarly, data from drones and soil sensors can be used to optimize irrigation and fertilization schedules, minimizing resource use while maximizing crop health and productivity.

By providing real-time, data-driven insights, these comprehensive monitoring systems can significantly enhance decision-making in agriculture. Farmers can respond rapidly to changing conditions, such as the onset of drought or the detection of disease, implementing remedial actions before significant damage occurs. They can also make proactive decisions, such as when to plant or harvest, based on predicted weather patterns and market demand. This level of responsiveness and precision can lead to improved crop yields, reduced resource use, and increased profitability.

These systems can contribute to long-term sustainability. By optimizing resource use, they can reduce the environmental impact of farming. By providing early warning of potential problems, they can prevent crop losses and ensure food security. And by enabling farmers to adapt to changing conditions, they can support the resilience and sustainability of the agricultural sector in the face of challenges such as climate change and population growth.

Conclusion

The past decade has witnessed a remarkable surge in the development and application of deep learning algorithms. This transformative technology has permeated a wide array of sectors, with agriculture standing out as a field where the impacts are particularly pronounced. Notwithstanding the historical perception of agriculture as an old-fashioned industry, it is progressively becoming a sector heavily reliant on cutting-edge technology. The integration of deep learning techniques into agriculture helps to address a multitude of challenges related to productivity, sustainability, and efficiency. By offering sophisticated solutions to complex problems, these tools are steadily redefining the dynamics of agricultural practices, ultimately paving the way towards a sustainable future.

A salient example of how deep learning is revolutionizing the agricultural sector lies in the realm of crop prediction and yield forecasting [74]. Here, deep learning models are diligently trained on vast sets of historical data encompassing weather patterns, soil quality, and crop types. Leveraging the inherent capabilities of these models to discern patterns and extract insights from such intricate datasets, farmers can forecast crop yields with a previously unattainable degree of precision. The resultant insights empower farmers to devise more efficient planting and harvesting strategies, enabling them to optimize resources and maximize yield. Moreover, these predictive capabilities provide invaluable information that can inform decision-making processes related to irrigation, fertilization, and pest control, all of which contribute to the overall improvement in crop management.

Deep learning's contributions extend to the critical area of disease and pest detection, where it serves as a potent tool to combat crop losses. Through the utilization of Convolutional Neural Networks (CNNs) and other image recognition technologies [75], farmers can efficiently analyze images of crops to identify early signs of disease or pest infestation. Deploying drones equipped with high-resolution cameras, they can capture comprehensive images of their fields. These images are then processed by the sophisticated algorithms, capable of identifying problematic signs in real-time, providing farmers with the opportunity to intervene promptly and effectively.

The introduction of precision agriculture epitomizes the profound transformation deep learning is catalyzing in the field of agriculture. This innovative approach employs deep learning algorithms to scrutinize data harvested from an array of sensors, facilitating the efficient management of resources like water, fertilizer, and pesticides. The primary strength of precision agriculture lies in its ability to facilitate more targeted and customized treatments of specific areas within a field. This level of granularity allows farmers to minimize waste and maximize crop health, fostering a more sustainable and productive agricultural environment.

The use of deep learning has also vastly expanded the capabilities for remote sensing and satellite imagery analysis within the field of agriculture. Utilizing these advanced algorithms, vast amounts of satellite imagery can be efficiently processed to monitor vital indicators such as crop growth and soil moisture. These models have the power to detect subtle changes over time, like the effects of drought or flooding, which may otherwise go unnoticed. The timely insights derived from this comprehensive analysis prove invaluable in assisting the planning and execution of remedial actions, thereby mitigating adverse effects and preserving crop health.

Another promising application lies in the arena of climate impact modeling. Climate change has increasingly become a concern for the agricultural sector due to the potential drastic shifts in growing conditions it can cause. Advanced algorithms, trained to predict the potential impacts of climate change on agriculture, provide invaluable assistance in strategizing adaptations. These models can foresee possible shifts in growing seasons, alterations in water availability, and the need to adapt crop types to new climatic conditions. This predictive capacity empowers farmers and policymakers to proactively devise strategies that cater to the evolving conditions, securing agricultural productivity in the face of climate change.

Automation is another critical aspect of agriculture where deep learning has been instrumental. In automated harvesting and sorting, deep learning-powered robotics can efficiently handle tasks that were traditionally manual and labor-intensive. These automated systems can discern the size, color, and ripeness of fruits and vegetables, thereby sorting produce quickly and accurately. The implications of these technologies are substantial, ranging from reducing labor costs to improving overall operational efficiency, thereby enhancing the economic viability of farming practices [76], [77].

Deep learning has also left its mark on the realm of supply chain management within the agricultural industry. Machine learning models can optimize the entire agricultural supply chain by accurately predicting demand, minimizing waste, and ensuring that products reach consumers in the best possible condition. These sophisticated models can determine the ideal timing of harvest, storage conditions, and transportation logistics, enabling a seamless and efficient supply chain that maximizes profits and minimizes resource wastage.

Given the multifaceted nature of agricultural practices, a multitude of data sources like weather stations, soil sensors, drones, and satellites can contribute to a comprehensive understanding of the conditions affecting crop growth. Deep learning algorithms can process and analyze this diverse data to create comprehensive monitoring systems. The resulting information enables real-time decision-making based on a wide range of factors, thus significantly enhancing the efficiency and effectiveness of agricultural practices.

There's the risk of farmers' proprietary data being exposed or used without consent, potentially leading to financial losses. Additionally, incorrect or manipulated data could lead to inaccurate predictions, which could potentially result in significant yield losses or environmental damage. Hence, protocols need to be established to manage access to data, secure data during transmission, and protect it from unauthorized alterations [78]–[80]. Encryption and blockchain technologies are potential tools to ensure the security and integrity of data in the agricultural sector [81], [82].

References

[1] S. Gadde, E. Karthika, R. Mehta, S. Selvaraju, W. B. Shirsath, and J. Thilagavathi, "Onion growth monitoring system using internet of things and cloud," *Agricultural and Biological Research*, vol. 38, no. 3, pp. 291–293, 2022.

[2] T. Li, J. Zhang, P. S. Yu, Y. Zhang, and Y. Yan, "Deep Dynamic Network Embedding for Link Prediction," *IEEE Access*, vol. 6, pp. 29219–29230, 2018.

[3] J. Chen, X. Wang, and X. Xu, "GC-LSTM: graph convolution embedded LSTM for dynamic network link prediction," *Applied Intelligence*, vol. 52, no. 7, pp. 7513–7528, May 2022.

[4] A. Nallathambi and K. Nova, "Deep Learning-Enabled Edge Computing and IoT," in *Convergence of Deep Learning and Internet of Things: Computing and Technology*, IGI Global, 2023, pp. 71–95.

[5] J. Chen *et al.*, "E-LSTM-D: A deep learning framework for dynamic network link prediction," *arXiv [cs.SI]*, 21-Feb-2019.

[6] C. Chiu and J. Zhan, "Deep Learning for Link Prediction in Dynamic Networks Using Weak Estimators," *IEEE Access*, vol. 6, pp. 35937–35945, 2018.

[7] S. Jahandari and D. Materassi, "How Can We Be Robust Against Graph Uncertainties?," in *2023 American Control Conference (ACC)*, 2023, pp. 1946–1951.

[8] N. Zhu *et al.*, "Deep learning for smart agriculture: Concepts, tools, applications, and opportunities," *International Journal of Agricultural and Biological Engineering*, vol. 11, no. 4, pp. 32–44, Aug. 2018.

[9] Q. Zhang, Y. Liu, C. Gong, Y. Chen, and H. Yu, "Applications of Deep Learning for Dense Scenes Analysis in Agriculture: A Review," *Sensors* , vol. 20, no. 5, Mar. 2020.

[10] S. Jahandari and A. Srivastava, "Adjusting for Unmeasured Confounding Variables in Dynamic Networks," *IEEE Control Systems Letters*, vol. 7, pp. 1237–1242, 2023.

[11] K. El Asnaoui, Y. Chawki, and A. Idri, "Automated Methods for Detection

and Classification Pneumonia Based on X-Ray Images Using Deep Learning," in *Artificial Intelligence and Blockchain for Future Cybersecurity Applications*, Y. Maleh, Y. Baddi, M. Alazab, L. Tawalbeh, and I. Romdhani, Eds. Cham: Springer International Publishing, 2021, pp. 257–284.

[12] M. Yang, J. Liu, L. Chen, Z. Zhao, X. Chen, and Y. Shen, "An Advanced Deep Generative Framework for Temporal Link Prediction in Dynamic Networks," *IEEE Trans Cybern*, vol. 50, no. 12, pp. 4946–4957, Dec. 2020.

[13] M.-G. Zhang, W.-W. Yan, and Z.-T. Yuan, "Study of nonlinear system identification based on support vector machine," in *Proceedings of 2004 International Conference on Machine Learning and Cybernetics (IEEE Cat. No.04EX826)*, 2004, vol. 5, pp. 3287–3290 vol.5.

[14] S. Jahandari and D. Materassi, "Identification of dynamical strictly causal networks," *Proc. IEEE Conf. Decis. Control*, 2018.

[15] S. Jahandari and A. Srivastava, "Detection of Delays and Feedthroughs in Dynamic Networked Systems," *IEEE Control Systems Letters*, vol. 7, pp. 1201–1206, 2023.

[16] T. Li, B. Wang, Y. Jiang, Y. Zhang, and Y. Yan, "Restricted Boltzmann Machine-Based Approaches for Link Prediction in Dynamic Networks," *IEEE Access*, vol. 6, pp. 29940–29951, 2018.

[17] X. Li, N. Du, H. Li, K. Li, J. Gao, and A. Zhang, "A Deep Learning Approach to Link Prediction in Dynamic Networks," in *Proceedings of the 2014 SIAM International Conference on Data Mining (SDM)*, Society for Industrial and Applied Mathematics, 2014, pp. 289–297.

[18] P. Baldi, "Autoencoders, Unsupervised Learning, and Deep Architectures," in *Proceedings of ICML Workshop on Unsupervised and Transfer Learning*, 2012, vol. 27, pp. 37–49.

[19] E. Lee, F. Rabbi, H. Almashaqbeh, A. Aljarbouh, J. Ascencio, and N. V. Bystrova, "The issue of software reliability in program code cloning," in *VII INTERNATIONAL CONFERENCE "SAFETY PROBLEMS OF CIVIL ENGINEERING CRITICAL INFRASTRUCTURES" (SPCECI2021)*, Yekaterinburg, Russia, 2023.

[20] S. Jahandari and D. Materassi, "Optimal selection of observations for identification of multiple modules in dynamic networks," *IEEE Trans. Automat. Contr.*, vol. 67, no. 9, pp. 4703–4716, Sep. 2022.

[21] P. Vincent, H. Larochelle, Y. Bengio, and P.-A. Manzagol, "Extracting and composing robust features with denoising autoencoders," in *Proceedings of the 25th international conference on Machine learning*, Helsinki, Finland, 2008, pp. 1096–1103.

[22] V. François-Lavet, P. Henderson, R. Islam, M. G. Bellemare, and J. Pineau, "An Introduction to Deep Reinforcement Learning," *Foundations and Trends® in Machine Learning*, vol. 11, no. 3–4, pp. 219–354, 2018.

[23] L. Kaiser *et al.*, "Model-Based Reinforcement Learning for Atari," *arXiv [cs.LG]*, 01-Mar-2019.

[24] P. Henderson, R. Islam, P. Bachman, J. Pineau, D. Precup, and D. Meger,

"Deep Reinforcement Learning That Matters," *AAAI*, vol. 32, no. 1, Apr. 2018.
[25] S. Jahandari and D. Materassi, "Optimal Observations for Identification of a Single Transfer Function in Acyclic Networks," in *2021 60th IEEE Conference on Decision and Control (CDC)*, 2021, pp. 852–857.
[26] S. Jahandari and D. Materassi, "Sufficient and necessary graphical conditions for miso identification in networks with observational data," *IEEE Trans. Automat. Contr.*, 2021.
[27] K. Nova, "Machine Learning Approaches for Automated Mental Disorder Classification based on Social Media Textual Data," *CIBSS*, vol. 7, no. 1, pp. 70–83, Apr. 2023.
[28] S. Carberry, *Plan Recognition in Natural Language Dialogue*. Cambridge, MA: Bradford Books, 1990.
[29] A. Le Glaz *et al.*, "Machine Learning and Natural Language Processing in Mental Health: Systematic Review," *J. Med. Internet Res.*, vol. 23, no. 5, p. e15708, May 2021.
[30] M. Tomita, *Efficient parsing for natural language: A fast algorithm for practical systems*, 1986th ed. New York, NY: Springer, 2013.
[31] A. Aljarbouh *et al.*, "Application of the K-medians Clustering Algorithm for Test Analysis in E-learning," in *Software Engineering Application in Systems Design*, 2023, pp. 249–256.
[32] Y. Boujoudar *et al.*, "Fuzzy logic-based controller of the bidirectional direct current to direct current converter in microgrid," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 5, pp. 4789–4797, 2023.
[33] F. Dernoncourt, "Introduction to fuzzy logic," *Massachusetts Institute of Technology*, vol. 21, pp. 50–56, 2013.
[34] E. Trillas and L. Eciolaza, *Fuzzy Logic*. Springer International Publishing, 2015.
[35] M. Hellmann, *Fuzzy Logic Introduction*. epsilon.nought.de, 2001.
[36] L. A. Zadeh, "Is there a need for fuzzy logic?," *Inf. Sci.*, vol. 178, no. 13, pp. 2751–2779, Jul. 2008.
[37] K. Nova, "Analyzing Keystroke Dynamics for User Authentication: A Comparative Study of Feature Extractions and Machine Learning Models," *Sage Science Review of Applied Machine Learning*, vol. 5, no. 2, pp. 67–80, 2022.
[38] I. Sarhan and M. Spruit, "Open-CyKG: An Open Cyber Threat Intelligence Knowledge Graph," *Knowledge-Based Systems*, vol. 233, p. 107524, Dec. 2021.
[39] S. Qamar, Z. Anwar, M. A. Rahman, E. Al-Shaer, and B.-T. Chu, "Data-driven analytics for cyber-threat intelligence and information sharing," *Comput. Secur.*, vol. 67, pp. 35–58, Jun. 2017.
[40] J. Zhao, Q. Yan, J. Li, M. Shao, Z. He, and B. Li, "TIMiner: Automatically extracting and analyzing categorized cyber threat intelligence from social data," *Comput. Secur.*, vol. 95, p. 101867, Aug. 2020.
[41] K. Nova, "Security and Resilience in Sustainable Smart Cities through Cyber Threat Intelligence," *International Journal of Information and Cybersecurity*, vol. 6, no. 1, pp. 21–42, 2022.
[42] S. Jahandari, A. Kalhor, and B. N. Araabi, "Online forecasting of synchronous time series based on

evolving linear models," *IEEE Transactions on*, 2018.
[43] V. Rutskiy *et al.*, "Prospects for the Use of Artificial Intelligence to Combat Fraud in Bank Payments," in *Data Science and Algorithms in Systems*, 2023, pp. 959–971.
[44] S. Samtani, M. Abate, V. Benjamin, and W. Li, "Cybersecurity as an industry: A cyber threat intelligence perspective," *The Palgrave Handbook of*, 2020.
[45] A. de Melo e Silva, J. J. Costa Gondim, R. de Oliveira Albuquerque, and L. J. García Villalba, "A Methodology to Evaluate Standards and Platforms within Cyber Threat Intelligence," *Future Internet*, vol. 12, no. 6, p. 108, Jun. 2020.
[46] A. J. Albarakati *et al.*, "Multi-Agent-Based Fault Location and Cyber-Attack Detection in Distribution System," *Energies*, vol. 16, no. 1, p. 224, Dec. 2022.
[47] S. Alahmari *et al.*, "Hybrid multi-strategy Aquila optimization with deep learning driven crop type classification on hyperspectral images," *Comput. Syst. Sci. Eng.*, vol. 47, no. 1, pp. 375–391, 2023.
[48] R. Singh, S. Srivastava, and R. Mishra, "AI and IoT Based Monitoring System for Increasing the Yield in Crop Production," in *2020 International Conference on Electrical and Electronics Engineering (ICE3)*, 2020, pp. 301–305.
[49] S. Cox, "Information technology: the global key to precision agriculture and sustainability," *Comput. Electron. Agric.*, vol. 36, no. 2, pp. 93–111, Nov. 2002.
[50] S. Jahandari and D. Materassi, "Topology Identification of Dynamical Networks via Compressive Sensing," *IFAC-PapersOnLine*, vol. 51, no. 15, pp. 575–580, Jan. 2018.
[51] L. Doukovska, "Artificial intelligence to support bulgarian crop production," *Eng. Sci.*, 2021.
[52] P. Radoglou-Grammatikis, P. Sarigiannidis, T. Lagkas, and I. Moscholios, "A compilation of UAV applications for precision agriculture," *Computer Networks*, vol. 172, p. 107148, May 2020.
[53] M. Pinaki and V. K. Tewari, "Present status of precision farming: a review," *Int. J. Agric. Res.*, 2010.
[54] K. Nova, "Generative AI in Healthcare: Advancements in Electronic Health Records, facilitating Medical Languages, and Personalized Patient Care," *JAAHM*, vol. 7, no. 1, pp. 115–131, Apr. 2023.
[55] D. Xu *et al.*, "Adaptive Neural Network for Node Classification in Dynamic Networks," in *2019 IEEE International Conference on Data Mining (ICDM)*, 2019, pp. 1402–1407.
[56] W. H. Lopez Pinaya, S. Vieira, R. Garcia-Dias, and A. Mechelli, "Autoencoders," in *Machine Learning*, A. Mechelli and S. Vieira, Eds. San Diego, CA: Elsevier, 2020, pp. 193–208.
[57] C. Doersch, "Tutorial on Variational Autoencoders," *arXiv [stat.ML]*, 19-Jun-2016.
[58] S. Yonbawi *et al.*, "Modified Metaheuristics with Transfer Learning Based Insect Pest Classification for Agricultural Crops," *Computer Systems Science & Engineering*, vol. 46, no. 3, 2023.
[59] D. R. Vincent, N. Deepa, D. Elavarasan, K. Srinivasan, S. H. Chauhdary, and C. Iwendi, "Sensors Driven AI-Based Agriculture

Recommendation Model for Assessing Land Suitability," *Sensors* , vol. 19, no. 17, Aug. 2019.
[60] J. M. Mendel, "Fuzzy logic systems for engineering: a tutorial," *Proc. IEEE*, vol. 83, no. 3, pp. 345–377, Mar. 1995.
[61] A. G. Barto, "Chapter 2 - Reinforcement Learning," in *Neural Systems for Control*, O. Omidvar and D. L. Elliott, Eds. San Diego: Academic Press, 1997, pp. 7–30.
[62] A. J. Albarakati *et al.*, "Microgrid energy management and monitoring systems: A comprehensive review," *Frontiers in Energy Research*, vol. 10, 2022.
[63] S. Shashi Devi, S. Gadde, K. Harish, C. Manoharan, R. Mehta, and S. Renukadevi, "IoT and image processing Techniques-Based Smart Sericulture Nature System," *Indian J. Applied & Pure Bio*, vol. 37, no. 3, pp. 678–683, 2022.
[64] S. A. Billings, H. B. Jamaluddin, and S. Chen, "Properties of neural networks with applications to modelling non-linear dynamical systems," *Int. J. Control*, vol. 55, no. 1, pp. 193–224, Jan. 1992.
[65] J. de J. Rubio and W. Yu, "Stability Analysis of Nonlinear System Identification via Delayed Neural Networks," *IEEE Trans. Circuits Syst. Express Briefs*, vol. 54, no. 2, pp. 161–165, Feb. 2007.
[66] A. K. Singh, "Precision farming," *Water Technology Centre, IARI, New Delhi*, 2010.
[67] K. Nova, "The Art of Elasticity and Scalability of Modern Cloud Computing World for Automation," *American Journal of Computer Architecture*, vol. 6, no. 1, pp. 1–6, 2019.
[68] S. Umamaheswar, L. G. Kathawate, W. B. Shirsath, S. Gadde, and P. Saradha, "Recent turmeric plants agronomy analysis and methodology using Artificial intelligence," *International Journal of Botany Studies*, vol. 7, no. 2, pp. 233–236, 2022.
[69] M. H. Saleem, J. Potgieter, and K. M. Arif, "Automation in Agriculture by Machine and Deep Learning Techniques: A Review of Recent Developments," *Precis. Agric.*, vol. 22, no. 6, pp. 2053–2091, Dec. 2021.
[70] H. Min and G. Zhou, "Supply chain modeling: past, present and future," *Comput. Ind. Eng.*, vol. 43, no. 1, pp. 231–249, Jul. 2002.
[71] B. M. Beamon, "Supply chain design and analysis:: Models and methods," *Int. J. Prod. Econ.*, vol. 55, no. 3, pp. 281–294, Aug. 1998.
[72] T. M. Simatupang and R. Sridharan, "The collaborative supply chain," *The international journal of*, 2002.
[73] D. L. Anderson, F. F. Britt, and D. J. Favre, "The 7 principles of supply chain management," *Supply Chain Management Review*, 2007.
[74] S. M *et al.*, "Analysis of Hydroponic System Crop Yield Prediction and Crop IoT-based monitoring system for precision agriculture," in *2022 International Conference on Edge Computing and Applications (ICECAA)*, 2022, pp. 575–578.
[75] N. Sharmili *et al.*, "Earthworm Optimization with Improved SqueezeNet Enabled Facial Expression Recognition Model," *Computer Systems Science & Engineering*, vol. 46, no. 2, 2023.
[76] S. K. Chakraborty, N. S. Chandel, D. Jat, M. K. Tiwari, Y. A. Rajwade, and A. Subeesh, "Deep learning

approaches and interventions for futuristic engineering in agriculture," *Neural Comput. Appl.*, vol. 34, no. 23, pp. 20539–20573, Dec. 2022.

[77] C. Ren, D. K. Kim, and D. Jeong, "A survey of deep learning in agriculture: Techniques and their applications," *Journal of Information Processing Systems*, 2020.

[78] K. Thiagarajan, C. K. Dixit, M. Panneerselvam, C. A. Madhuvappan, S. Gadde, and J. N. Shrote, "Analysis on the Growth of Artificial Intelligence for Application Security in Internet of Things," in *2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS)*, 2022, pp. 6–12.

[79] Y.-Y. Zheng, J.-L. Kong, X.-B. Jin, X.-Y. Wang, and M. Zuo, "CropDeep: The Crop Vision Dataset for Deep-Learning-Based Classification and Detection in Precision Agriculture," *Sensors* , vol. 19, no. 5, Mar. 2019.

[80] L. Santos, F. N. Santos, P. M. Oliveira, and P. Shinde, "Deep Learning Applications in Agriculture: A Short Review," in *Robot 2019: Fourth Iberian Robotics Conference*, 2020, pp. 139–151.

[81] V. S. Magomadov, "Deep learning and its role in smart agriculture," *J. Phys. Conf. Ser.*, vol. 1399, no. 4, p. 044109, Dec. 2019.

[82] T. T. Nguyen *et al.*, "Monitoring agriculture areas with satellite images and deep learning," *Appl. Soft Comput.*, vol. 95, p. 106565, Oct. 2020.