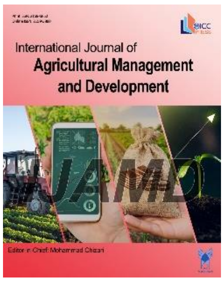

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Transformation of Agriculture through Machine Learning, Deep Learning, and the Internet of Things: Insights from Iran – Challenges and Opportunities

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Abstract

Agriculture is a fundamental pillar of livelihoods, food security, and employment in Iran, particularly in rural areas. Challenges such as population growth, water scarcity, climate change, and inadequate resource management significantly affect this sector. Recent advances in Machine Learning, Deep Learning, and the Internet of Things present promising opportunities to improve productivity, sustainability, and smart management in Iranian agriculture. his paper explores the integration of Machine Learning, Deep Learning, and the Internet of Things in agriculture to support data-driven decision-making in crop management, soil analysis, irrigation, and weather forecasting. IoT systems enable real-time monitoring, intelligent control, and reduced resource wastage. Despite challenges such as poor data quality, limited communication infrastructure, and insufficient farmer training, targeted policies, government support, and investment can help Iran achieve smart agriculture, strengthen food security, and promote sustainable development. By reviewing the current status, challenges, and future prospects, this study highlights the transformative potential of Machine Learning, Deep Learning, and the Internet of Things in shaping the future of agriculture in Iran.

Keywords: Smart Agriculture; Machine Learning; Deep Learning; Internet of Things (IoT); Water and Soil Resource Management

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INTRODUCTION

Despite the gradual decline in agriculture's share of Iran's gross domestic product (GDP), it remains a strategic pillar of the national economy. The sector plays a vital role in ensuring food security, generating employment, promoting balanced rural development, and safeguarding essential natural resources. In some provinces, such as Kerman, more than 10% of the active population is employed in agriculture (Sedaghat, 2018), primarily consisting of smallholder farmers and subsistence producers with limited access to technology and market resources.

Iran's agricultural sector faces a combination of structural and climatic challenges that threaten the continuity and sustainability of production.

Inefficiencies in the supply chain, weak logistical infrastructure, the absence of cold storage networks, and limited access to consumer markets have resulted in reduced product quality and increased agricultural losses (Sadati et al., 2021). Furthermore, a traditional production structure, heavy reliance on rainfall, and insufficient utilization of modern technologies have led to low productivity, reduced farmer incomes, and heightened vulnerability to climatic and economic fluctuations (Abebaw, 2025).

As illustrated in Figure 1, agricultural transformation has progressed through four main stages: traditional agriculture, which relied on human and animal labor; mechanized agriculture, which employed machinery; automated agriculture, which utilized modern technologies; and smart agriculture, which is driven by advanced technologies (Huang et al., 2020). Smart agriculture leverages information and communication technologies such as IoT, ML, DL, cloud computing, and robotics to improve farm management and promote the long-term sustainability of agricultural production (Fortino et al., 2018; Ghahramani et al., 2017).

The pivotal role of IoT devices in collecting vast amounts of environmental and agricultural data is undeniable. Once collected, this data can be analyzed using ML and DL algorithms to develop optimal resource management strategies. For example, smart irrigation systems can use real-time soil moisture data to supply the precise amount of water required. This approach not only reduces resource wastage but also improves crop health and growth.

Furthermore, ML and DL models can identify complex patterns and relationships that often remain undetectable to the human eye. This capability enables farmers to refine their agricultural strategies, select the most appropriate fertilizers or pesticides, and receive recommendations tailored to the specific conditions of their farms. Consequently, these technologies support the early detection of diseases and pests, accurate crop yield forecasting, and the adoption of more sustainable and efficient farming practices.

Numerous studies have confirmed the effectiveness of this technological integration. For example, Pangarkar et al. (2020) demonstrated that accurate yield prediction is essential for stakeholders such as farmers, agribusinesses, traders, and government organizations. By comparing different models, they found that the Support Vector Regression (SVR) model with a linear kernel performed best in predicting cluster bean yields in the Bikaner region of Rajasthan. The model achieved a coefficient of determination (R^2) of 98.31%, making it the most accurate model tested and a highly reliable tool for agricultural yield prediction.

Liu & Wang (2021) employed deep learning algorithms to detect plant diseases and pests, providing solutions for preventive pest management. Ikram et al. (2022) developed an innovative IoT-based device enhanced with machine learning algorithms. Equipped with various soil sensors and analytical algorithms, this device assessed soil conditions and offered recommendations tailored to specific crops. The results demonstrated that the tool effectively improved crop yields and optimized resource management.

Obaideen et al. (2022) implemented IoT-based smart irrigation systems in water-scarce areas to optimize irrigation and reduce water consumption. Similarly, Akilan and Balamurugan (2024) developed an integrated IoT and deep learning system for Indian agriculture. This system automatically forecasts weather conditions and monitors farmland, achieving 94% accuracy in weather prediction and 98% accuracy in farm monitoring, thereby enhancing crop productivity.

Kumar (2021) emphasized the importance of livestock management in agriculture and proposed a multilayer IoT and deep learning framework. This framework incorporated sensors for data collection, data processing to eliminate inaccuracies, and DL algorithms to analyze livestock health conditions. Experimental results demonstrated that this approach could make livestock production more cost-effective and also suggested directions for future research. Additionally, Purandare et al. (2016) utilized ML and IoT to improve harvesting and post-harvest processes, reducing food waste and increasing the efficiency of the agricultural supply chain.

In Iran, the use of smart soil moisture sensors, online weather stations, agricultural drones, smart irrigation systems, and mobile applications for farm monitoring has commenced in select regions. Projects such as the "Smart Agriculture Plan" are being implemented in provinces such as Razavi Khorasan, Isfahan, and Golestan (IRNA, 2020; Nazari, 2025). However, challenges such as high costs, inadequate training, weak rural communication infrastructure, and a lack of sustained financial support from government institutions have impeded the nationwide adoption of these technologies.

Lessons drawn from successful global examples indicate that yield prediction models, the early detection of diseases and pests using drone or satellite imagery, and smart irrigation management based on climatic data can significantly enhance productivity, reduce resource consumption, and improve incomes for Iranian farmers. In this context, effective farmer engagement, dissemination of technical knowledge, government support, and investment in digital infrastructure are essential prerequisites for the large-scale adoption of

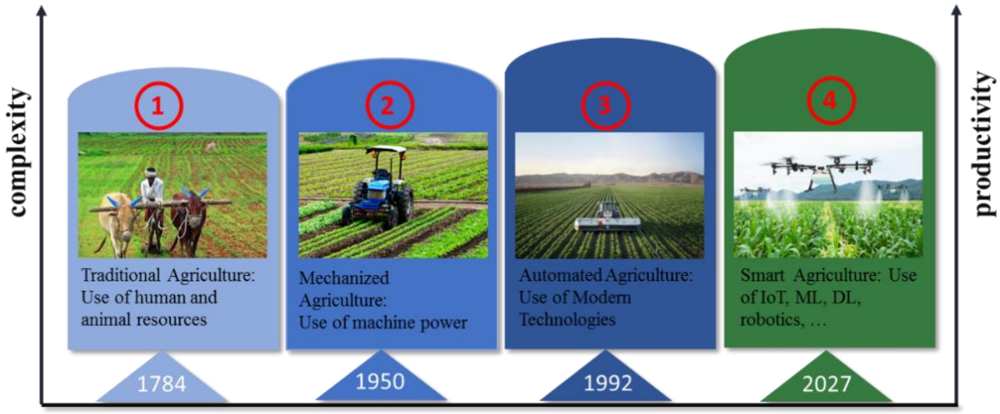

Figure 1. Traditional, Mechanized, Automated, and Smart Agriculture Are Four Stages of Agricultural Revolutions

these technologies in Iran. The formulation of macro-level policies, provision of economic incentives, and delivery of digital skills training to farmers can pave the way for the digital transformation of Iran's agricultural sector.

This paper further explores the potential applications of modern information technologies in Iranian agriculture, focusing on areas such as smart crop monitoring, yield prediction, irrigation and soil management, pest and disease identification, and supply chain optimization. It also proposes strategies to overcome existing barriers. Through a critical analysis of the successes, limitations, and capabilities of these technologies, the study aims to provide valuable insights into how they can be effectively utilized to drive agricultural transformation and promote sustainable development. The significance of this research lies in its potential to guide policymakers, academics, and other stakeholders in developing tailored approaches and initiatives to address the unique challenges facing the agricultural sector.

Moreover, this paper explores the importance of engaging local stakeholders in policy design and technology deployment, and it presents specific policy recommendations for sustainable and inclusive farming practices. By implementing technology-driven solutions, the study aims to promote equitable and sustainable agricultural practices nationwide, ultimately contributing to enhanced food security, poverty reduction, and economic development.

MACHINE LEARNING, DEEP LEARNING, AND THE INTERNET OF THINGS: EMPOWERING AGRICULTURAL INNOVATION

Overview of machine learning in Iranian agriculture

Machine Learning is a crucial subfield of artificial intelligence that enables computer systems to learn from data and make independent decisions or predictions without explicit programming. Unlike traditional programming approaches, where rules are manually defined, ML algorithms identify complex patterns within data, offering users dynamic and flexible analytical capabilities. These features make ML an ideal choice for sectors such as agriculture, which are characterized by dynamic conditions and diverse, sometimes incomplete, datasets (Balducci et al., 2018).

In Iran's agricultural sector, ML plays an increasingly important role in analyzing data obtained from remote sensing, satellite imagery, weather stations, soil samples, meteorological data, and IoT sensors. Given the challenges of water scarcity, climate change, and small-scale farming plots in Iran, ML serves as an effective tool for optimizing resource management and enhancing crop productivity (Khosravi, 2025).

Types of machine learning and their applications in agriculture

As illustrated in Figure 2, machine learning techniques in agriculture can be broadly categorized into supervised, unsupervised, and reinforcement learning approaches.

Supervised learning: This approach involves training models using labeled data. In Iranian agriculture, supervised learning can be applied to tasks such as wheat yield prediction, plant health assessment, or estimating water requirements during critical growth stages (Ansari, 2022). Projects conducted in provinces such as Khuzestan and Kerman have demonstrated that the use of supervised models can effectively reduce crop losses and enhance the accuracy of cultivation planning (Modiri et al., 2024).

Unsupervised learning: In this approach, algorithms independently identify patterns within unlabeled data. Notable applications in Iranian agriculture include clustering farms based on irrigation behavior, or detecting climatic anomalies in different regions of the country (Youssefi et al., 2019).

Reinforcement learning: This approach involves interacting with an environment and learning from rewards. In the context of smart irrigation in Iran—especially in the central and semi-arid plains—reinforcement learning can be employed to develop self-regulating drip irrigation systems that optimize water usage while maintaining plant health (Alkaff et al., 2025).

Commonly used algorithms in Iranian agriculture

Decision tree: With its transparent and interpretable structure, the decision tree algorithms have been used for crop classification, pest detection, and yield prediction for crops such as saffron, wheat, and pistachio in the provinces of Khorasan, Fars, and Yazd (Khosravi, 2025). The main advantage of this method is that they simplify decision-making for farmers with moderate or limited technical expertise.

Random forest: As one of the most powerful ensemble models, the random forest algorithm has been widely applied in academic and industrial projects in Iran, including the identification of wheat leaf spot disease and the prediction of soil fertility in the northern regions of the country. The model's high accuracy in the presence of noise and variable-quality data makes it well-suited to Iran's agricultural conditions (Molaeinasab et al., 2025).

Support vector machines (SVM): SVM are effectively used for classifying complex datasets such as satellite data from Sentinel or MODIS in Iran. Its ability to analyze high-dimensional data and accurately detect areas under heat or drought stress makes it valuable tools in agricultural applications (Abiyat et al., 2022).

Ensemble methods: By combining multiple learning models, these methods enhance accuracy and reduce errors. Algorithms such as AdaBoost and Gradient Boosting have been applied in studies on rapeseed yield prediction in Golestan (Youssefi et al., 2019). Although computationally intensive, these methods provide significantly more precise results (Xu et al., 2022).

Deep learning algorithms for agricultural applications

Deep learning algorithms have gained a prominent position in the field of smart agriculture in recent years. These algorithms have been applied to tasks such as crop classification, disease detection, yield prediction, and weed identification (Bal & Kayaalp, 2021). The commonly used models in this domain include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), Generative Adversarial Networks (GANs), Autoencoders, Deep Belief Networks (DBNs), and Capsule Networks.

Convolutional neural networks

Due to their exceptional ability to extract spatial features from image data, CNNs have been widely employed in various agricultural applications. Leveraging a hierarchical structure and weight sharing, these networks can accurately identify both local and global patterns in images (Lopez Pinaya et al., 2020). Their effectiveness in plant disease detection, crop classification, and weed identification has been confirmed by numerous studies. For instance, a review by Boulent et al. (2019) of 19 research articles demonstrated the significant role of CNNs in disease identification. Moreover, the use of pre-trained architectures such as DenseNet, ResNet, and Inception for fine-tuning models has led to remarkable results (Sutaji & Rosyid, 2022).

Recurrent neural networks (RNNs)

RNNs known for their ability to model temporal dependencies, are powerful tools for analyzing sequential data such as agricultural time series. Numerous studies have demonstrated the effectiveness of these networks in multi-temporal remote sensing data analysis for crop detection and mapping. For example, Gafurov et al. (2023) achieved an accuracy of 93.7% in crop identification using LSTM, while Bermúdez et al. (2017) reported better performance of GRU compared to LSTM. These findings underscore the strong potential of RNNs in agricultural applications involving temporal data.

Long short-term memory networks (LSTMs)

LSTMs, with their specialized architecture, are designed to capture long-term dependencies in sequential data (Schmidt, 2019). Several studies have reported the successful performance of these algorithms in agriculture. For example, Gafurov et al. (2023) demonstrated that LSTMs outperform MLP and Random Forest models. Additionally, Reuß et al. (2021) evaluated LSTM performance in crop classification using Sentinel-1 data. Robotic applications have also been explored, such as irrigation timing prediction by Wu et al. (2020) using LSTMs.

Generative adversarial networks (GANs)

GANs consist of two neural networks—a generator and a discriminator—that compete in a process enabling the

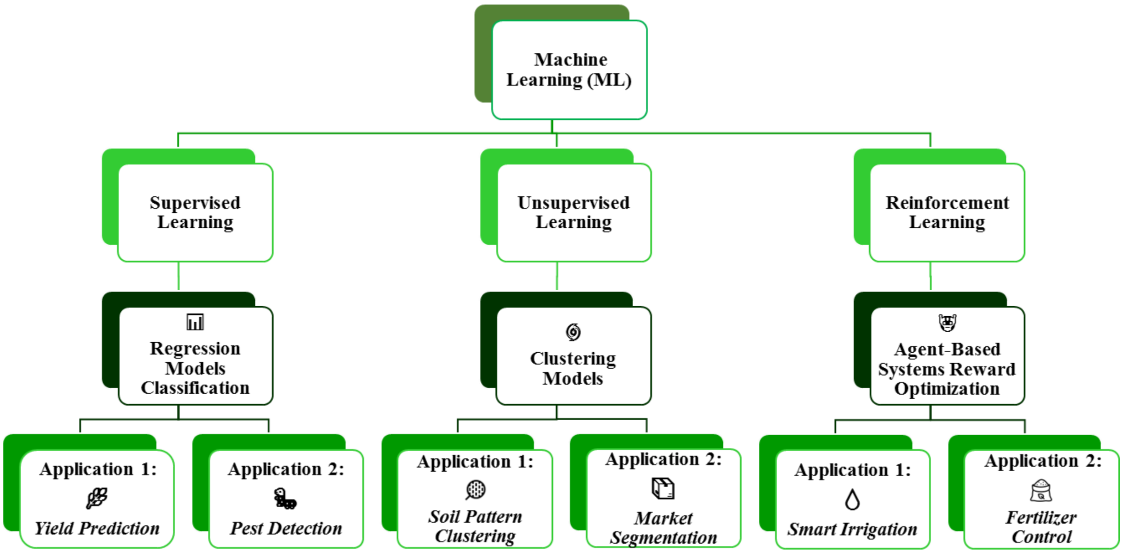

Figure 2. Types of Machine Learning and Their Applications in Agriculture

creation of synthetic data resembling real data (Pan et al., 2019). In agriculture, GANs have been used to generate synthetic datasets for data augmentation, environmental condition simulation, and enhancement of model training. Studies by Fawakherji et al. (2020) and Zhao et al. (2020) have specifically explored the use of GANs for data generation under conditions of limited data availability.

Autoencoders

Autoencoders are employed for dimensionality reduction, learning compact representations, and anomaly detection (Chen & Guo, 2023). In agriculture, they have been applied to plant health monitoring, anomaly detection, and noise reduction. Models such as IAEAD have been developed to enhance anomaly detection accuracy under noisy training data conditions (Cheng et al., 2021).

Deep belief networks (DBNs)

DBNs consist of layers of Restricted Boltzmann Machines (RBMs) and are commonly used for unsupervised learning tasks such as feature extraction and clustering (Liu, 2021). In agriculture, they have been applied to analyze unlabeled data and predict crop yields. The study by Salakhutdinov and Murray (2008) emphasized the capability of DBNs to cluster continuous data effectively. Although their use has declined with the advent of newer models, DBNs remain valuable for applications involving unlabeled datasets (Raj & Hareesh, 2020).

Capsule networks (CapsNets)

Capsule Networks are a novel architecture designed to overcome the limitations of CNNs. They represent features as vectors within spatial and semantic information (Sun et al., 2020). This approach enhances the model's ability to understand hierarchical relationships among image components. Although less commonly used than CNNs in agricultural applications, CapsNets have demonstrated promising performance in specific tasks such as hyperspectral image classification and fabric defect detection (Seyrek & Uysal, 2021).

Internet of things (IoT)

IoT refers to a network of interconnected devices capable of collecting and exchanging data via the internet without direct human intervention (Raja et al., 2023). These devices are typically equipped with sensors, software, and advanced technologies that enable communication between devices as well as connectivity with centralized systems. In simple terms, IoT includes objects such as household appliances, vehicles, wearable devices, and industrial tools that can connect to the internet and exchange data. This technology allows these objects to interact, share information, and perform tasks autonomously or with minimal human involvement. IoT applications span a wide range of sectors, including agriculture, healthcare, transportation, manufacturing, and smart cities (Friess & Vermesan, 2022).

In agriculture, IoT is driving a revolutionary transformation by enabling farmers to collect and analyze data from diverse sources such as sensors, drones, and satellites (Zamir & Sonar, 2023). This technology facilitates optimized decision-making in areas such as crop management, irrigation, and resource allocation, ultimately leading to increased efficiency and productivity in agricultural processes. For example, Rajeswari et al. (2017) highlighted the synergy between cloud-based big data analytics and IoT for advancing smart agriculture. IoT generates massive volumes of data that require cloud-based storage and analytical infrastructure; this integration enables process optimization and enhances decision-making capabilities.

Furthermore, Jouini et al. (2023) examined the transformative impact of IoT and demonstrated that it enables practices such as precision and sustainable agriculture. Their research indicates that IoT can collect data on weather, soil conditions, crop monitoring, and pest detection, while facilitating remote farm management through wireless sensor networks, microcontrollers, and smartphones. This technology also helps reduce costs and increase productivity in traditional farming methods (Khanna & Kaur, 2019).

Despite these benefits, challenges remain in fully implementing IoT in agriculture, including the high cost of equipment, the need for reliable communication infrastructure in rural areas, and the lack of comprehensive standards for IoT technologies. Consequently, although IoT holds great potential to revolutionize agriculture through data-driven systems, realizing this potential requires overcoming these barriers. It is expected that, with ongoing research and infrastructure development, IoT will continue to be a key driver of innovation in agricultural technologies (Ojha et al., 2021).

APPLICATIONS OF MACHINE LEARNING, DEEP LEARNING, AND THE INTERNET OF THINGS IN AGRICULTURE

Emerging technologies such as machine learning, deep learning, and the Internet of Things are increasingly being applied in agriculture, offering a wide range of transformative applications (Jouini et al., 2023). These technologies play a crucial role in shaping the future of agriculture by optimizing resource utilization, enhancing productivity, and promoting sustainability.

Crop monitoring and yield prediction

Continuous crop monitoring and yield prediction are essential components of modern agriculture, facilitating data-driven decision-making and optimal resource management. The integration of ML, DL, and IoT has significantly improved these processes by enabling real-time monitoring and accurate forecasting. For instance, the use of vegetation indices extracted from satellite imagery combined with stepwise linear regression algorithms has resulted in precise yield predictions under saline soil conditions, with an average error below 10% (Satir & Berberoglu, 2016). Furthermore, the combined application of multirotor drones, remote sensing, and machine learning models has demonstrated high accuracy in wheat yield prediction, with a relative mean squared error of 0.1030 (Fu et al., 2020).

Rodriguez-Sanchez et al. (2022) demonstrated that ML-based models such as Support Vector Machines achieved 89% accuracy in identifying cotton pixels. Additionally, by applying morphological processing and clustering algorithms, they predicted yield with an R^2 value of 0.93. Furthermore, Ikram et al. (2022) developed a system called Smart Crop Selection (SCS) that utilized IoT sensors and various ML algorithms—including SVM, Random Forest, KNN, Decision Tree, and Gaussian Naïve Bayes—to achieve an accuracy range of 97% to 98% for optimal crop selection.

Disease and pest detection and management

Early identification of diseases and pests is crucial for maintaining crop health and ensuring food security. Technologies such as ML, DL, and IoT have significantly transformed this field by providing real-time data and precise analyses, enabling prompt intervention and effective decision-making.

In a study by Johannes et al. (2017), intelligent models achieved high accuracy in disease detection. Ngugi et al. (2021) also emphasized the importance of early detection using machine vision and deep learning algorithms. Türkoğlu & Hanbay (2019) evaluated nine different deep neural network architectures and demonstrated that combining features extracted by DL models with classifiers such as SVM and Extreme Learning Machines (ELM) significantly improved detection accuracy. Their dataset consisted of real images of diseases and pests collected under field conditions in Turkey.

These studies indicate that employing a variety of machine learning and deep learning algorithms, combined with IoT-based sensing systems, can lead to faster and more accurate detection of diseases and pests, thereby enabling more effective control strategies for their management.

Intelligent irrigation and water resource management

Effective water management in agriculture, particularly in water-scarce regions, remains a significant challenge. The integration of IoT, machine learning, and deep learning technologies offers an innovative approach to developing smart and optimized irrigation systems. IoT sensors—such as soil moisture, temperature, and rainfall sensors—collect real-time environmental data, which are analyzed by ML and DL algorithms to accurately predict soil water requirements (Kashyap et al., 2021). Additionally, algorithms such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and logistic regression have been employed in intelligent irrigation systems to enhance decision-making accuracy and reduce water consumption (Kashyap et al., 2021).

In some studies, these systems have been integrated with mobile applications and weather data, enabling farmers to monitor soil moisture conditions remotely and make proactive decisions via smartphones (Malekian et al., 2024). These approaches have not only saved water resources but also improved land productivity and contributed to greater agricultural sustainability.

Soil and nutrient management solutions

The integration of IoT, machine learning, and deep learning technologies has fundamentally transformed soil and nutrient management in agriculture by enabling real-time monitoring and data-driven analysis. For instance, Hossain et al. (2023) proposed an IoT-based system that monitors soil nutrients and provides crop recommendations using ML algorithms. By continuously analyzing soil data, the system delivers precise advice for crop selection. This approach reduces fertilizer use, lowers labor requirements, and increases productivity at both the farm and national levels.

The integration of IoT technology with Geographic Information Systems (GIS) has enabled continuous monitoring of soil health and nutrient levels, facilitating precise decision-making for water and fertilizer application (Sivakumar et al., 2023).

Beyond soil management, the applications of IoT and ML have become increasingly significant in areas such as crop growth monitoring, disease detection, and water management, where ML algorithms play a crucial role in prediction and decision-making. Additionally, sensor-based infrastructures and cloud servers have been employed in soil monitoring and crop productivity systems, facilitating the development of farmer-centric applications (Bah et al., 2012). These examples illustrate the diverse applications of emerging technologies in enhancing soil resource and nutrient management in agriculture.

Agricultural supply chain management

Supply chain management in agriculture encompasses all stages, from on-farm production to the delivery of the final product to consumers. It faces challenges such as price volatility, product spoilage, transportation delays, and lack of transparency. The coordinated integration of IoT, ML, and DL technologies can make this supply chain more transparent, efficient, and responsive.

IoT technology, which utilizes sensors for temperature, humidity, GPS, and transport conditions, enables real-time product tracking. Based on this data, ML and DL algorithms can detect route anomalies, transport delays, or adverse conditions, providing timely information to support managerial decision-making. For example, a study on predicting the shelf life of fresh products utilized environmental data collected via IoT devices and applied machine learning algorithms to model spoilage dynamics. This approach led to accurate estimates of product consumption lifespan and a reduction in food waste (Srinivasagan et al., 2023; Li et al., 2024).

Furthermore, concerning traceability and transparency, a review study demonstrated that a blockchain- and IoT-based framework can secure food supply chains by immutably recording information at every stage, from production to consumption, thereby enhancing consumer trust (Kaur et al., 2022; Demestichas et al., 2020).

In another study, IoT and blockchain architectures were developed for products such as olives, enabling the automatic recording of quality data—including storage temperature, chemical composition, and source origins—and transmission via smart contracts. This approach ensured transparency, quality assurance, and reduced fraud throughout the supply chain (Vitaskos et al., 2024).

Iranian case studies and pilot projects

While most global studies on digital agriculture emphasize the potential of ML, DL and IoT, several pilot initiatives in Iran demonstrate that these technologies are already being localized and adapted to the national agricultural context. The following examples illustrate emerging patterns of innovation and highlight both achievements and limitations in practical implementation.

Smart greenhouse automation (Alborz Province)

A series of smart greenhouse projects in Alborz Province have integrated IoT-based sensing systems to monitor air temperature, humidity, and soil moisture (Binaei et al., 2024).

These systems utilize LoRaWAN or cellular gateways to transmit data to cloud dashboards, enabling automated irrigation and energy management. Early reports indicate significant improvements in water-use efficiency and reductions in manual labor.

Crop yield estimation using machine learning and satellite data (Qazvin and Hamedan)

Research groups in the Qazvin Plain and Hamedan Province have applied ML algorithms such as Random Forest and Gradient Boosting, to estimate wheat yields using Sentinel-1 and Sentinel-2 satellite imagery (Asgari et al., 2024). These models have achieved moderate to high accuracy ($R^2 \approx 0.75–0.85$) and offer valuable insights for regional crop monitoring and food security planning.

Intelligent irrigation systems

Several universities and research centers have developed IoT-enabled irrigation systems that integrate soil moisture sensors, weather data, and edge-based ML models to optimize water allocation (Sharifnasab et al., 2023). These systems enable near real-time decision-making and enhance water resource management in the semi-arid regions of Iran. Pilot projects are currently underway in the Kerman and Isfahan provinces.

Vision-based plant health monitoring

Local startups and university teams are developing mobile and web applications that utilize CNNs for plant disease detection (Borhani et al., 2022). Farmers can upload leaf images, receive diagnostic predictions directly on their devices, and access treatment recommendations. These initiatives represent some of the first efforts to commercialize DL-based agritech solutions in the Iranian market.

Data-driven agricultural supply chain optimization

Several initiatives supported by the Ministry of ICT and private logistics firms have explored ML-based prediction of demand and price prediction for key commodities such as wheat and pistachios. These systems utilize integrated datasets from market transactions, weather conditions, and remote sensing, aiming to improve transparency and reduce post-harvest losses (Alimohammadi et al., 2025).

CHALLENGES AND OPPORTUNITIES IN IMPLEMENTING MACHINE LEARNING, DEEP LEARNING, AND IOT IN AGRICULTURE

Challenges of applying machine learning, deep learning, and IoT in Iranian agriculture

Despite the remarkable potential of emerging technologies such as ML, DL and IoT to enhance productivity, optimize resource consumption, and promote sustainability in agriculture, their widespread implementation in Iran faces numerous challenges, many of which stem from the country’s unique economic, infrastructural, and structural conditions (Rezvani et al., 2022).

Infrastructure limitations in rural and agricultural areas

Many agricultural regions in Iran lack adequate technological and communication infrastructure. Limited access to high-speed internet, the absence of wireless sensor networks, and frequent power outages hinder the effective use of IoT-based systems. This infrastructural deficit means that even willing farmers often cannot adopt these technologies (Rezvani et al., 2022).

High initial investment costs

IoT devices, drones, artificial intelligence platforms, and cloud services generally involve high costs. Considering the large proportion of small- and medium-scale farmers in Iran and the low profit margins in traditional agriculture, personal investment in such technologies is often unaffordable. Furthermore, financial support and technological subsidies remain limited (Memarbashi et al., 2022).

Table 1. Representative Iranian Examples of ML/DL/IoT in Agriculture.

Use Case	Location	Core technologies	Reported outcomes
Smart greenhouse automation	Alborz Province	IoT sensors, LoRaWAN/cellular gateways, cloud dashboard	20–30% water saving; reduced manual control
Wheat yield estimation using ML on Sentinel-1/2	Qazvin & Hamedan	Random Forest, Gradient Boosting, EO datasets	Early yield prediction ($R^2 \approx 0.8$); supports planning
IoT-based intelligent irrigation	Kerman & Isfahan	Soil-moisture sensors, edge ML models, mobile control app	Improved irrigation scheduling; water-use efficiency
CNN-based plant disease detection	Various provinces	Deep learning (CNNs), mobile application	Rapid diagnosis; reduced pesticide misuse
ML for supply chain optimization	National (selected crops)	Predictive analytics, time-series ML models	Price forecasting; post-harvest loss reduction

Lack of large, reliable agricultural data

ML and DL models require well-structured, labeled, and longitudinal data for accurate training and prediction. In Iran, farm-level data are rarely recorded or archived; geospatial and climatic information systems are incomplete, and the collected data often lack standardization. This issue is particularly problematic for tasks such as plant disease detection and crop yield prediction (Whang et al., 2023).

Weak technical skills and training among farmers

Many Iranian farmers have limited familiarity with fundamental digital technology concepts, data analysis systems, and mobile applications. The absence of targeted technology dissemination and training programs has hindered the effective transfer of knowledge from research institutions to farms (Shamshiri et al., 2018).

Absence of standardized and integrated agricultural technology frameworks

The lack of clear frameworks for agricultural technology development, the absence of national integrated databases, and the lack of technical guidelines for system integration present additional challenges. Government agencies, universities, and knowledge-based companies often operate in silos without macro-level coordination (Sharifzadeh et al., 2014).

Security and legal concerns regarding agricultural data

As data collection and analysis systems expand, concerns have arisen regarding the ownership, confidentiality, and security of agricultural data. The lack of clear regulations protecting farmers' rights over their data and its use undermines trust in these systems (Jouanjean et al., 2020).

Future outlook for utilizing ML, DL, and IoT in Iranian agriculture

Given the escalating challenges such as water scarcity, climate change, declining land productivity, and the urgent need to enhance food security, the adoption of emerging technologies—including machine learning (ML), deep learning (DL), and the Internet of Things (IoT)—is becoming increasingly critical as a central pillar for agricultural transformation in Iran (Nawaz & Babar, 2025; Risheh, 2020).

The increasing interest among research centers, knowledge-based companies, and technology startups in the field of digital agriculture demonstrates significant potential for the nationwide development of these technologies. In recent years, projects focused on smart crop monitoring, drone-based aerial imaging, intelligent irrigation systems, and data-driven analytical applications have been initiated or are currently under development, indicating a promising shift toward data-centric agriculture in Iran (Khoshnodifar et al., 2025).

Looking ahead, targeted investments in rural communication infrastructure—such as expanding stable internet access in farmlands—establishing national agricultural data repositories, and developing regulatory frameworks for data governance will create a more conducive environment for deploying intelligent algorithms in agriculture. Moreover, promoting technology through practical training for farmers and integrating traditional agricultural knowledge with digital tools will play a pivotal role in accelerating this technological transition.

Additionally, government support for smart agriculture initiatives—through financial assistance, tax incentives for startups, and inter-agency collaboration among the Ministry of Agriculture, Ministry of Communications, universities, and the private sector—can accelerate the adoption of these technologies. Within this ecosystem, Iranian knowledge-based companies play a crucial role in producing indigenous IoT equipment, developing machine learning models tailored to local climates and cropping patterns, and designing multilingual applications accessible to local farmers (Adib et al., 2023).

Overall, the future outlook for Iranian agriculture, through the integration of ML, DL and IoT, is moving toward precision, resource-efficient, sustainable, and intelligent farming. Realizing this vision will not only optimize crop performance and reduce resource waste but also promote technology-driven employment, enhance the export of high-quality agricultural products, and strengthen the country's resilience against future food crises.

CONCLUSION

The convergence of ML, DL and IoT is transforming the future of agriculture in Iran. Confronted with persistent challenges such as water scarcity, climate variability, limited productivity, and fragmented data systems, the integration of these technologies provides practical and scalable solutions to achieve precision, efficiency, and sustainability throughout the agricultural value chain. ML and DL enable predictive and diagnostic intelligence by forecasting yields, detecting pests and diseases, and optimizing farm operations through data-driven insights. Complementarily, IoT provides continuous, high-resolution field data that empowers these algorithms to make adaptive, real-time decisions. Together, they establish a foundation for smart, resilient, and evidence-based agricultural management.

To translate this potential into measurable national impact, Iran must adopt a coordinated policy and innovation agenda focused on:

Expanding digital infrastructure in rural areas to ensure reliable IoT connectivity.

Investing in human capacity by training digital agronomists and local data scientists.

Supporting localized technology development through public–private partnerships and open innovation hubs.

Creating open-access agro-environmental data platforms to promote collaboration and transparency.

In summary, harnessing ML, DL, and IoT can transform Iranian agriculture from pilot-scale experiments into an integrated digital ecosystem that enhances productivity, conserves resources, and ensures food security. With clear governance, sustained investment, and inclusive adoption, these technologies can become the foundation of Iran's transition toward a more sustainable, climate-resilient, and competitive agricultural sector.

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Authors Contribution
Author 1 conceived and designed the study, conducted the literature review, collected and analyzed the relevant information, synthesized the findings, and prepared the original manuscript draft. Author 2 contributed to the development of the study framework, critically reviewed and edited the manuscript, and provided scientific supervision and guidance throughout the research process. Both authors approved the final version of the manuscript and agree to be accountable for all aspects of the work.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests
The authors declare that they have no conflicts of interest regarding the publication of this paper.

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