Leveraging Artificial Intelligence for Agricultural Advancement: A Comprehensive Review

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Abstract: Artificial Intelligence (AI) is bringing about significant changes across various sectors, with agriculture being one of the fields poised to reap substantial benefits from its applications. This study explores the wide-ranging and transformative ways in which AI is being utilized in agriculture to streamline processes, boost productivity, and tackle the challenges confronting the global food system. Beginning with an overview of AI technologies like machine learning, deep learning, and computer vision, the paper examines their relevance to agricultural contexts. It then investigates specific instances of AI implementation in agriculture, covering areas such as crop monitoring and management, precision agriculture, pest and disease detection, yield prediction, soil health assessment, and autonomous farming systems. Through an extensive review of literature and case studies, the paper showcases how AI-driven solutions empower farmers by providing real-time insights, facilitating data-driven decision-making, and optimizing resource utilization. It underscores the role of AI tools like ChatGPT and Claude in offering agricultural extension services. Additionally, the study addresses challenges and digital AI startups associated with AI adoption in agriculture, including concerns over data privacy, technological hurdles, and the necessity for scalable and cost-efficient solutions. It stresses the significance of interdisciplinary collaboration among agricultural experts, data scientists, and policymakers to fully leverage the potential of AI technology and foster innovation in the agricultural sector.

1 INTRODUCTION

The anticipated global population growth, expected to surpass nine billion by 2050, necessitates a substantial augmentation in agricultural production by approximately 70% to fulfill the escalating demand. However, merely about 10% of this augmented demand can be met by utilizing fallow land, leaving the remaining 90% reliant on intensifying current production methods (FAO, 2015). Given this scenario, leveraging state-of-the-art technological advancements to enhance farming efficiency becomes paramount. Present strategies aimed at intensifying agricultural production often necessitate significant energy inputs, while market preferences gravitate towards high-quality food products. Concurrently, the upsurge in population has resulted in heightened demand for food grains, leading to inflation in agricultural commodity prices. In reaction to these challenges, the agricultural sector has experienced a substantial evolution propelled by technological progressions, with artificial intelligence (AI) emerging as a pivotal catalyst for innovation and efficiency.

The phrase "Artificial Intelligence" was initially coined during the 1955 Dartmouth Conference by John McCarthy, who proposed a study based on the idea that machines could simulate every aspect of learning and intelligence through precise description. Today, AI is a crucial field in computer science, widely applied across various sectors such as education, healthcare, finance, and manufacturing, tackling challenges that are difficult for humans to solve effectively.

Leveraging artificial intelligence enables us to develop intelligent farming practices that mitigate farmer losses and yield substantial harvests. AI's applications span a spectrum of activities within the agricultural value chain, encompassing precision agriculture, crop monitoring, supply chain optimization, and livestock management, thereby reshaping the entirety of this domain.

In recent years, the successful application of deep learning models, notably convolutional neural networks (CNN), has been observed across various

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domains of computer vision (CV). Examples include traffic identification (Yang et al., 2019), medical image recognition (Sundararajan, 2019), scenario text detection (Melnyk et al., 2019), facial expression identification (Kolhe, et al., 2011), and face recognition (Kumar and Singh, 2020). Similarly, in agriculture, deep learning approaches have been extensively employed for the identification of plant diseases and pests, with numerous domestic and international companies developing WeChat applets and photo recognition APP software utilizing deep learning for this purpose. Therefore, methodologies utilizing deep learning for plant disease and pest identification hold substantial research value and possess significant potential for market applications.

Machine learning, an evolving technology, has proven highly effective in precision irrigation systems. It replicates human decision-making processes and addresses complex irrigation management issues, including multiple variables, nonlinearity, and time variation. According to Chlingaryan et al. (2018), machine learning serves as a robust and adaptable framework for data-driven decision-making, providing expert intelligence for the system. The combination of machine learning with big data technologies has opened up new avenues for analyzing large volumes of data from diverse sensors autonomously, without explicit programming (Liakos, et al. 2018).

This review endeavors to present the present state of artificial intelligence in agriculture by elucidating noteworthy considerations and achievements in crop management, soil management, pest and disease management, weed management, water use management, weather forecasting, and supply chain management. Furthermore, it assesses pressing challenges encountered in this domain, such as the uneven distribution of mechanization across regions, concerns regarding security and privacy, and the adaptability of algorithms in practical applications, particularly in scenarios with physical heterogeneity in plants and extensive datasets requiring processing. Ultimately, the review emphasizes the significance of establishing a comprehensive understanding of this field, providing specific examples, identifying major challenges, outlining potential applications, and considering diverse circumstances in different countries.

2 RESEARCH OBJECTIVES

The majority of agricultural processes and tasks still heavily rely on manual labor. However, artificial intelligence (AI) holds the potential to enhance current technologies and assist in both the most challenging and routine farming tasks. Given that agriculture is a labor-intensive sector and labor shortages are prevalent, automation presents itself as a viable solution for farmers. It's crucial to note that farm machinery driven by AI demonstrates greater efficiency, productivity, and speed compared to human workers. The primary objectives of this article's research are as follows:

RO1: To identify and discuss the major applications of AI in agriculture

RO2: To discuss the challenges associated with the adoption of AI in agriculture.

3 APPLICATIONS OF AI IN AGRICULTURE

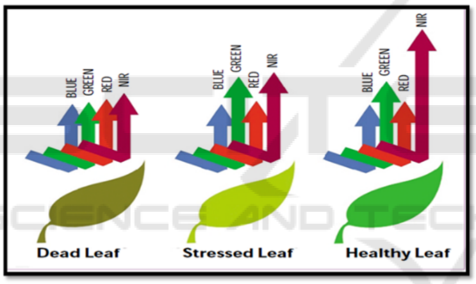
3.1 Crop Management

The concept of integrating artificial intelligence into crop management was initially proposed in 1985 by McKinion and Lemmon, leading to the development of GOSSYM. GOSSYM was a model designed to simulate the growth of cotton crops, leveraging expert systems to optimize cotton production (McKinion and Lemmon, 1985). Today, various IoT sensors, including temperature, weather, soil, and environmental sensors, are utilized to monitor the growth and root activity of crops in real time on farms. Data collected by these sensors is transmitted to cloud storage and displayed on a web application, allowing smallholders in Africa to observe various parameters and crop growth performance. Data collection occurs at one-minute intervals, with IoT sensors transmitting data to cloud storage accordingly. Farmers can access this IoT data via smartphones, enabling them to visualize information and take necessary actions related to irrigation and fertilizer applications on their farms (Barakabitze et al., 2023).

Traditionally, farmers assessed the ripeness of tomatoes by physically inspecting the field daily and using their hands to determine their development. However, modern agricultural practices now require the assessment of tomato maturity on an industrial scale. Fortunately, computers have greatly simplified various aspects of life, including agricultural processes. For example, machines in factories can detect wastage and ripeness, while in the field, different AI technologies enable farmers to evaluate the freshness of tomatoes without physical contact (Chang et al., 2021; Sharma et al., 2022).

A) Drones and Computer Vision for Crop Analysis:

Drones primarily gather information by analyzing the reflected light from crops. In agriculture, growers can utilize specific types of sensors to collect data that identifies areas with issues, allowing them to take appropriate actions. There are two types of sensors used: thermal sensors and hyperspectral sensors. Drones rely on the reflection of light from crops to obtain information. Photosynthesis in plants is driven by the absorption of visible light. However, Near Infrared (NIR) photons do not provide energy for photosynthesis but do emit heat. Plants, as a consequence, have adapted to reflect near-infrared (NIR) light. The decay of this reflection mechanism occurs when the leaf withers. Near-infrared sensors exploit this characteristic by quantifying the disparity between NIR reflectance and visible reflectance, which is referred to as the Normalized Difference Vegetation Index (NDVI).



Source: agribotix

Figure 1: NDVI and Plant health

A strong NDVI signal indicates a high density of plants, while a weak NDVI indicates problematic areas in the field (Ahirwar et al., 2019, Biesel et al., 2018). These NDVI reports are valuable for various agricultural purposes as they differentiate between areas where the crop is growing and areas where it is not (Enouri et al. (2021). This differentiation enables targeted fertilizer applications and also reveals the presence of weeds, pests, and water damage. Therefore, by mathematically combining these two signals, it becomes possible to distinguish between plants and non-plants, as well as healthy plants and sickly plants (Stamford et al., 2023).

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red})}$$

The Normalized Difference Vegetation Index (NDVI) values typically range between -1 and +1, with higher values indicating higher levels of chlorophyll content in vegetation.

3.2 Soil Management

Soil plays a pivotal role in the success of agriculture, serving as a vital source of nutrients essential for optimal crop growth and development. It stores key elements such as water, nitrogen, phosphorus, potassium, and proteins, which are fundamental for sustaining healthy plant growth (Eli-Chukwu and Ogwugwam, 2019; Zha, 2020).

The Soil Risk Characterization Decision Support System (SRC-DSS) is an AI-based system that employs fuzzy logic to characterize soil and identify contaminated soils posing accidental risks. Fuzzy logic is advantageous for eliminating imprecision or uncertainty in soil management data, as it requires only a few parameters to quantify the soil (López et al., 2008). Parameters that would typically take hours to estimate can be easily measured by neural networks. For example, the measurement of soil hydraulic conductivity presents a direct challenge, however, it can be accurately predicted by utilizing measurable soil parameters such as soil texture data (including sand and clay contents), soil water retention curve (such as G retention model parameters), bulk density, and effective porosity (Ghanbarian-Alavijeh et al., 2010). Moreover, through the utilization of artificial intelligence, it is possible to predict biological parameters like soil enzyme activity. Research studies have demonstrated that when it comes to prediction, Artificial Neural Networks (ANN) surpass Multiple Linear Regression (MLR), and when combined with a Digital Terrain Model (DTM), ANN offers a superior means of mapping soil enzyme activity (Tajik et al., 2011).

PEAT, a Berlin-based agricultural technology startup, has developed a state-of-the-art deep-learning application known as Plantix. This groundbreaking application is specifically designed to discern potential anomalies and deficiencies in soil using a sophisticated analysis. The analysis is conducted through the utilization of advanced software algorithms that establish correlations between distinct foliage patterns and an array of soil defects, plant pests, and diseases. By harnessing the capabilities of the user's smartphone camera to capture images, the image recognition application can identify plausible anomalies. Consequently, users are furnished with invaluable insights about soil rejuvenation techniques, beneficial advice, and alternative remedies. The company asserts that its software possesses the capability to swiftly identify patterns with an impressive, estimated accuracy rate of up to 95 percent. Furthermore, the application is conveniently accessible in most of the local languages spoken in India (Kumar and Karthikeyan, 2019).

3.3 Pest and Disease Management

Crop diseases pose significant challenges for farmers, but computer-aided systems offer effective solutions for disease diagnosis and control. One approach involves a fuzzy logic model designed to predict diseases based on the duration of leaf wetness. In this method, leaf images are pre-processed and segmented into different areas, such as the background, non-diseased part, and diseased part. The diseased part is then sent to remote laboratories for further diagnosis. Additionally, image processing techniques can be applied for pest identification and recognition of nutrient deficiencies. For more accurate and early disease detection, a deep learning-enabled object detection model has been developed. This model focuses on multi-class plant disease detection, particularly targeting different apple plant diseases in real orchard environments. The effectiveness of this model has been demonstrated in complex scenarios, showcasing its potential for fine-grained and multi-scale disease detection (Roy and Bhaduri, 2021).

The process of detecting plant diseases and pests involves three distinct stages. The initial stage revolves around classification, where the primary focus is on determining the category of the image. Subsequently, the second stage entails locating the diseases and pests within the image, a critical step in ensuring accurate detection. This stage, akin to the location task in computer vision, not only identifies the types of diseases and pests present but also provides specific spatial information, often represented by rectangular boxes highlighting the affected areas, as seen in the case of gray mold. Finally, the third stage resembles the segmentation task in computer vision, where lesions caused by diseases such as gray mold are meticulously delineated from the background, pixel by pixel. This detailed segmentation facilitates the extraction of various attributes like length, area, and precise location, which in turn contribute to a more comprehensive evaluation of disease severity and pest infestation levels. (Wang and Tao 2021).

Rothe and Rothe (2019) adopted a novel strategy for image segmentation aimed at identifying bacterial leaf blight, Myrothecium, and Alternaria. They employed Otsu's segmentation technique to precisely delineate the image of an infected leaf while retaining its background, ensuring the accurate isolation of the affected region from the leaf's natural backdrop. In the subsequent classification stage, they utilized a Backpropagation Neural Network (BPNN). Their approach yielded impressive accuracy rates of 97.14% for Alternaria, 93.3% for bacterial leaf blight, and 96% for Myrothecium, showcasing the effectiveness of their methodology in disease identification and classification.

3.4 Weed Management

Weeds hinder the appropriate growth of crops by engaging in competition for light, moisture, and nutrients, as well as by causing interference with harvesting machinery. Additionally, they contribute to health issues in both humans and animals and have a detrimental impact on both the natural ecosystem and aquatic resources (Ministry of Agriculture, Land and Fisheries, 2020). Remote sensing techniques, including the use of Unmanned Aerial Vehicles (UAVs) and satellites, offer the ability to obtain high-resolution imagery. This imagery is capable of detecting weeds at an exceptionally detailed level due to the advanced camera and spectral band employed. Consequently, precise identification and monitoring of weed patches can be achieved. Through the combination of UAVs and remote sensing techniques, a highly efficient and timely approach to field scouting and weed management is made possible (Ghatrehsamani et al., 2023). Correa et al. (2022) have devised a neural network model named RetinaNet, which exhibits remarkable proficiency in forecasting the presence of the most invasive weeds in tomato fields. The model accurately identified 98.4% of tomato plants and 0.91% of weed plants. The implications of this model are significant, particularly in relation to site-specific weed management and the implementation of robotic technology. By doing so, the use of herbicides can be reduced in comparison to conventional farming practices. Deep learning techniques were assessed to identify weeds in bell pepper fields, using RGB images. The selected models exhibited an overall accuracy ranging from 94.5% to 97.7%. This indicates the potential integration of these models with image-based herbicide applicators, thereby enabling precise weed management (Subeesh et al., 2022).

The robot integrated two visual systems. The initial system utilized gray-level vision to construct a row structure, guiding the robot through rows. The second system relied on color-based vision, essential for distinguishing individual weeds from others. The VIIPA (Variable Injection Intelligent Precision Applicator), an automated weed-killing robot, administers the precise dosage of herbicide required to manage weeds on the farm swiftly (Wu et al.2020).

3.5 Water Use Management

Automation in agriculture is increasingly gaining importance on a global scale. By incorporating sensors such as moisture, temperature, and humidity, alongside IoT devices and machine learning techniques, irrigation systems can be automated to cater to the specific needs of various crops, soil types, and climate conditions.

The incorporation of artificial intelligence (AI) methods into hydro-meteorological forecasting has significantly progressed the prediction of extreme weather events such as floods and droughts, leading to enhanced preparedness and mitigation strategies (Zhu et al.2023). The creation of the WaterWise platform aimed at efficiently managing and analyzing data from an intelligent Internet of Things (IoT) system, facilitating tasks like online water leakage detection, water demand prediction, and water quality assessment (Allen et al., 2018). This platform employs a layered model consisting of application, information communication, and device perception layers to establish an effective water supply management system for automating domestic water management (Marjani, 2017). A smart IoT system equipped with sensors for water flow, pH, and other parameters, controlled by a Raspberry core controller and accessible through a web interface, ensures efficient control and monitoring of water storage systems (Shah, 2017).

In agricultural irrigation management, sensors capture environmental and meteorological data transmitted to a cloud server database, enabling farmers to remotely adjust water valves and other controls based on trends in soil, plant, and weather data (Chen et al., 2021). Vellidis et al. (2008) devised a prototype for scheduling irrigation to cotton fields based on soil moisture and temperature, utilizing smart nodes for real-time monitoring and irrigation scheduling (Bisaria et al., 2019). The Korea Water Resources Corporation, in collaboration with the International Water Resources Association (IWRA), implemented a smart water management system utilizing Information and Communications Technology (ICT) to provide real-time water data globally for intelligent resolution of water issues, including water quality monitoring, efficient irrigation, leak detection, and flood management using AI mechanisms (Rocher, 2018). Additionally, a layer of irrigation architecture supported by machine learning and digital farming solutions was developed, incorporating data from UAVs, satellites, soil, and weather stations to offer predictive recommendations for irrigation decisions and scheduling (Abioye et al., 2022).

3.6 Weather Forecasting (Predictive Analytics)

With the advent of climate change, the significance of forecasts for crop yields has increased as farmers are no longer able to rely solely on traditional knowledge. The utilization of more precise forecasts could empower farmers to select the most favorable days for planting or harvesting. Artificial intelligence techniques, specifically reinforcement learning, are employed to analyze previous predictions and compare them with actual outcomes. To enhance weather forecasting, data is inputted into an algorithm that utilizes deep learning techniques to acquire knowledge and generate predictions based on historical data. Artificial intelligence in the realm of farming, in conjunction with satellite data, can be employed to forecast weather conditions, evaluate the sustainability of crops, and assess the presence of pests and diseases on farms. The implementation of Artificial Intelligence (AI) in farming enables the provision of an extensive volume of data points, encompassing temperature, precipitation, wind speed, and solar radiation. Pierre et al. (2023) devised Fuzzy logic, a machine learning technique, to forecast weather and predict the timing and quantity of rain expected within a 24-hour period based on dynamic changes in air temperature, air humidity, atmospheric pressure, and wind speed.

To tackle the challenge of determining appropriate sowing timings for crops in India, particularly considering the risks associated with droughts and excessive rainfall, Microsoft collaborated with the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) to create an AI Sowing App. This application leverages machine learning and business intelligence from the Microsoft Cortana Intelligence Suite. A notable aspect of this app is its accessibility, as farmers only require a basic feature phone capable of receiving text messages, without the need for installing sensors or incurring additional expenses (ICRISAT, 2017). To determine the optimal sowing period, historical climate data spanning three decades (from 1986 to 2015) for the specific region of Andhra Pradesh was analyzed using AI techniques. The Moisture

Adequacy Index (MAI) was calculated as part of this analysis to identify the most favorable sowing window. The MAI is a standardized measure used to assess how effectively rainfall and soil moisture meet the water requirements of crops, providing valuable insights for farmers (Sure and Dikshit 2019).

3.7 ChatGPT: Concerns in Agricultural Extension

A recent IFPRI blog explores using chatbots powered by large language models (LLMs) to aid agricultural extension services, but real-world testing in Nigeria highlighted significant challenges. LLM-generated recommendations for cassava farmers lacked specificity and practicality for smallholders. To address these issues, a collaborative approach is needed, involving AI and farming experts, ensuring accessible data and local knowledge, employing user-centered design, and enhancing digital literacy among farmers and extension agents (Jawoo Koo, 2023).

A comparative analysis between two AI chatbots, ChatGPT and Claude was done to understand their ability to provide agricultural advice specifically tailored to the context of wheat farming in Faisalabad, Pakistan, in both English and local languages. The evaluation covers their responses regarding the best time to plant wheat and recommendations for wheat varieties, as well as their performance in Urdu, Pashto, Sindhi, and Punjabi languages.

In the English language, both ChatGPT and Claude provided generally correct information about the optimal timing for planting wheat in Faisalabad. However, Claude demonstrated a deeper understanding of specific wheat varieties suitable for the region, including newer varieties, whereas ChatGPT's response was more generic and noncommittal. When tested in local languages such as Urdu, Pashto, Sindhi, and Punjabi, both chatbots struggled to provide accurate and contextually relevant responses, with varying degrees of success. While Urdu responses were somewhat satisfactory, responses in other local languages were less accurate or outright incorrect. AI chatbots like ChatGPT and Claude show promise in providing agricultural advice, but they are not yet ready to serve as agricultural extension agents, especially in areas with limited data and content in local languages. However, it suggests the potential for customized agricultural advisory chatbots trained on localized content to better serve farmers in specific regions (AESA, 2021)

Farm Radio International (FRI), in collaboration with CGIAR, has developed an AI-based solution, Uliza, to analyze voicemails from over 12 million listeners of radio shows in rural Africa. This initiative aims to harness farmers' knowledge and perspectives, addressing challenges in analyzing the large volume of responses. The solution utilizes transfer learning in machine learning models to adapt to local languages and dialects. Moving forward, the team plans to further improve transcription accuracy and apply the solution to new projects, aiming to evaluate its impact on food security, gender equality, and livelihood outcomes in 2024 (CIMMYT and IFPRI, 2022).

Acceso is piloting ExtensioBot, an AI tool, to enhance agricultural extension services for smallholder farmers in Latin America and the Caribbean. The decision stemmed from user demand and the need to address the scarcity of extension agents. ExtensioBot utilizes Azure AI Speech and Vision technologies to provide personalized advice and identify pests and diseases. While still learning, the tool aims to improve engagement and effectiveness by addressing common issues such as generic responses and language barriers. Collaborative efforts and ongoing training are prioritized to refine the tool and ensure equitable access for all farmers, ultimately revolutionizing extension models to better support smallholders globally (Mendoza,2024).

Limitations of ChatGPT

The knowledge possessed by ChatGPT is confined to data from the year 2021. As the data is derived from the cloud, it cannot exclusively acquire information from a specialized source. The true beauty of ChatGPT lies in its capability to derive data from various sources and generate predominantly unique responses to the same query. Should we depend on ChatGPT to gather information from a particular source, it would not surpass the competence of any expert system or limited-information mobile application. While it can compensate for the scarcity of staff by delivering a comprehensive information resource to users, it is ultimately up to the user's discretion to harness the potential of this technology in the most optimal manner and to exercise caution before applying the acquired knowledge.

Table 1: Digital AI Startups- Implications to Redesigning of Extension Advisory Services

Digital start-ups	**Description**	**Scope of integration in Extension Advisory Services**
Farn2fork	1. Water monitoring solutions for better productivity by using IoT wireless soil sensors and real-time analytics. 2. Farmers are contacted via farmer associations and network	1. Predictive analytics 2. Process automation 3. Forewarning advisories 4. Social networks
Aibono	1. Utilizing AI and data analysis expertise, it gathers an extensive volume of intelligent agricultural data and insights from farmers and industry professionals.	1. Personalization 2. Predictive analytics 3. Process automation
Fasal	1.End-to-end farming app for horticulture farmers 2.Assist customers in making the best farming decisions.	1. Predictive analytics 2. Process automation 3. Forewarning advisories
Agrostar	1. Developed an m-commerce platform called "Direct to Farmer" to revolutionize the agribusiness industry. 2.By simply giving a missed call on the toll-free number 1800, farmers can conveniently obtain agri-inputs delivered right to their doorstep.	1. Aggregates services 2.Access to inputs 3. Supply chain
SatSure	1. IoT and big data are employed proficiently to bestow financial security upon farmers, through the utilization of a database that spans 15 years and comprises satellite images. 2. Furthermore, recommendations regarding clustering techniques are made to farmers, to obtain an approximation of the aggregate agricultural production. This data is subsequently furnished to agri-insurance companies.	1. Financial inclusion credit insurance 2. Aadhar-enabled services 3. Predictive analytics
Farm Again	1. IoT devices are employed for monitoring and documenting the levels of moisture and soil conditions, alongside conduits facilitating the provision of water and fertilizer inputs. 2.A vast expanse of 2500 acres of land has been transformed into organic farming systems.	1. Access to market 2. Process automation and forewarning advisories 3. Predictive analytics

Challenges in Developing and Adopting AI in Agriculture

AI systems require a significant amount of data to train machines for accurate forecasting or predictions, with spatial data being relatively easier to collect compared to temporal data, which poses a challenge in agricultural settings. One of the main obstacles hindering the adoption of AI in agriculture is the lack of access to technology and infrastructure for many farmers. Limited access to AI tools like sensors, drones, and satellite imagery, especially in remote areas with restricted internet connectivity, hampers real-time data retrieval. The rise of AI in agriculture also brings forth concerns regarding data privacy and security. While extensive datasets are vital for AI operations, they also expose farmers to cyber threats, necessitating measures to protect sensitive information. Ethical considerations arise regarding AI's potential to widen socioeconomic disparities, as access to AI technologies could create inequalities among farmers. Moreover, ethical concerns emerge regarding AI's impact on job displacement in agriculture, as automation may replace traditional farming roles, particularly in rural communities heavily reliant on agriculture for employment.

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