Shahid Bahonar University of Kerman
Agricultural Biotechnology Journal
Iranian Biotechnology Society
Print ISSN: 2228-6705 Online ISSN: 2228-6500

An implementation framework for food security using machine learning and biotechnology algorithms in precision agriculture and smart farming

Nidhi Mishra
*Corresponding Author. Assistant Professor, Department of CS & IT, Kalinga University, Raipur, India. E-mail address: ku.nidhimishra@kalingauniversity.ac.in

Priti Sharma
Research Scholar, Department of CS & IT, Kalinga University, Raipur, India. E-mail address: priti.sharma@kalingauniversity.ac.in

Abstract

Objective

Converting data into digital form has led to a massive influx of data in almost every industry that relies on data-driven operations. The digital data processing has significantly increased the volume of information being processed. The emergence of electronic agriculture management has profoundly impacted Information and Communication Technology (ICT), resulting in advantages for farmers and customers and driving the adoption of technological solutions in rural areas. This study emphasizes the promise of ICT technologies in conventional agriculture and the obstacles to their employment in farming operations.

Results

This study emphasizes the promise of ICT technologies in conventional agriculture and the obstacles to their employment in farming operations. The research provides thorough information on automation, Internet of Things (IoT) gadgets, and challenges related to Machine Learning (ML). Drones are being contemplated for crop monitoring and production optimization in Precision Agriculture (PA) and Smart Farming (SF). The new era of conventional agriculture is represented by precision agriculture. The development of several contemporary technologies, like the internet of things, has made this possible. When relevant, this article emphasizes global and advanced agricultural systems and platforms that utilize IoT technology.

Conclusions

The effectiveness of such techniques in plant disease detection is proven by their ability to achieve exceptional levels of accuracy. This is particularly true when they rely on extensive open-source databases and pre-trained algorithms. Future investigation uncovered that the size of the plant imagery utilized for modeling and the circumstances under which the photos were gathered could significantly affect the accuracy.

Keywords: Biotechnology, food security, machine learning, precision agriculture, smart farming

Paper Type: Review Paper.

Citation: Mishra N, Sharma P (2024) An implementation framework for food security using machine learning and biotechnology algorithms in precision agriculture and smart farming. *Agricultural Biotechnology Journal* 16 (4), 223-236.

Agricultural Biotechnology Journal 16 (4), 223-236. DOI: 10.22103/jab.2025.23996.1604

Received: September 15, 2024. Received in revised form: November 22, 2024.

Accepted: November 23, 2024. Published online: December 30, 2024.

Publisher: Faculty of Agriculture and Technology Institute of Plant Production, Shahid Bahonar University of Kerman-Iranian Biotechnology Society.

Introduction

The agricultural land suitability evaluation is a compelling method for land use planning and achieving food security objectives, with the potential for considerable contributions from emerging technology (Alonso et al. 2018). The digital transition contributes to food security and agricultural planning by collecting information to assist decision-makers and policymakers and analyzing this data to forecast potential outcomes. Cropland mapping is one example where Machine Learning (ML) can provide valuable insights to manage land sustainably (Sood & Singh 2021). This is especially crucial in African nations, where the issues about food security are grave and warrant specific studies to identify appropriate solutions (Nabeesab Mamdapur et al. 2019). Implementing novel innovations in the African environment poses significant challenges.

ML is a subset of artificial intelligence that uses data and methods to learn in a way that is analogous to people. ML techniques utilize remote sensing data to forecast agricultural output and facilitate tailored agricultural planning within digital transformation. As per the International

Food Policy Research Institutions, a nation achieves food security when its entire population consistently has access to sufficient uncontaminated, safe, and nourishing food that fulfills its dietary preferences and nutritional requirements for a healthy existence (Martin-Shields & Stojetz 2019). The preceding description encompasses five essential components of food security. The factors to consider are accessibility (both in terms of quantity and excellence), accessibility (not excessively expensive), availability (within the material, social, and financial reach of citizens), numerous substitutes based on individual tastes, and meeting the nutritional needs of citizens.

Smart Farming (SF) is a technique that utilizes ML and the Internet of Things (IoT) to manage farms cyber-physically (Moysiadis et al. 2021). SF effectively tackles several concerns associated with crop production by enabling the monitoring of climate conditions, soil properties, soil moisture levels, and other relevant parameters (Surendar et al. 2024). Precision Agriculture (PA) is the scientific practice of enhancing yields of crops and aiding managerial choices via advanced sensor and evaluation systems (Cisternas et al. 2020). PA is a recently implemented global idea aimed at boosting productivity, minimizing labor requirements, and optimizing the administration of nutrients and irrigation methods. It utilizes a substantial quantity of knowledge and data to enhance the utilization of agricultural assets, harvest rates, and the health of crops (Pržulj & Tunguz 2022). PA utilizes data from various sources to improve farming yields and optimize the cost-efficiency of crop management techniques, such as fertilizer usage, irrigation control, and applying pesticides (Veerasamy & Fredrik 2023).

SF requires continuous development of novel approaches to improve SF productivity due to changing weather patterns, growing populations, and the requirement to provide food security, which challenges its growth. ML is widely acknowledged as a leading technology in the agricultural economy. Due to the complexity or impracticability of this process for humans, it is necessary to automate it using methodologies and tools to simplify decision-making. To tackle those issues in modern agricultural environments, advancements in computer vision and ML algorithms can be employed to accurately and rapidly detect crop diseases from various existing ailments (Haghighi & Far 2014). An advantage of utilizing this method is its ability to rapidly and precisely generate results through computerized detections employing image processing techniques. Effective dissemination methods can facilitate the timely distribution of PA and SF information regarding agricultural conditions and disease prevalence, hence assisting in the control of disease transmission. Moreover, data generation in agriculture and biotechnology has greatly increased in recent years due to the very rapid development of high-performance technologies (Mohammadabadi et al. 2024). These data are obtained from studying products, foods, and biological molecules to understand the role of different aspects of agriculture in determining the structure, function, and dynamics of living systems (Pour Hamidi et al. 2017).

Artificial neural networks have been proposed to alleviate limitation of traditional methods and can be used to handle nonlinear and complex data, even when the data is imprecise and noisy (Pour Hamidi et al. 2017). Agricultural data can be too large and complex to handle through visual analysis or statistical correlations. This has encouraged the use of machine intelligence or artificial intelligence (Ghotbaldini et al. 2019). Thus, this review aimed to improve the efficiency, sustainability and productivity of agriculture using Machine Learning.

History

Various research has examined the issue of food security. Bjornlund et al. cited the government's insufficient funding and excessive reliance on oil as the primary factors contributing to food insecurity (Bjornlund et al. 2022). The research cautioned that industrialized nations employ food as a means of oppression in the future and advocated for the deployment of biotechnology to address food security concerns. Plotnikov et al. stressed that achieving food security is contingent upon establishing national security (Plotnikov et al. 2021). The survey highlighted confrontations as the primary security problems that pose significant dangers to food security. Duffy et al. conducted a study highlighting the issues related to food security (Duffy et al. 2021). They suggested that agricultural biodiversity, environmental management, and policy change are necessary to achieve food security (Angin et al. 2020). Owoo, identified the obstacles to achieving food security (Owoo 2021). They suggested implementing a zero-duty policy on farming equipment and promoting local manufacturing of machines through the Ajaokuta Steel Corporation to address this issue. Sambo et al. evaluated the obstacles to achieving food security (Sambo & Sule 2024). To achieve food security, they proposed enhanced funding, cultivation, fertile soil, and climate-savvy farming (Mustapha et al. 2017).

Several studies have examined how to gauge household food security based on geographical location and specific types of food. Rukwe et al. (2020) employed surveys to investigate the food security of 450 households in Taraba State. The authors' conclusion states that around 71% of the families under investigation experience food insecurity. Adomi et al. conducted a study on households' food security, explicitly focusing on cowpeas (legumes) (Adomi et al. 2023). The researchers made sweeping generalizations by extrapolating the findings in a single state. Vargas et al. examined the strategies employed by maize traders to reduce spoiling caused by global warming (Vargas et al. 2024). The researchers found fumigation, pepper usage, and ash utilization as strategies implemented by maize merchants. The study made a broad generalization by applying the findings of a survey done in a limited number of places in three states to represent the food safety issue. Assaye et al. (2023) examined the constraints hindering the acceptance of

Agricultural Biotechnology Journal; Print ISSN: 2228-6705, Electronic ISSN: 2228-6500

enhanced rice varieties and promoting commercialization amongst rice cultivators in rural areas. This research had a narrow focus, specifically examining rice cultivation practices among small-scale farmers, without including other advanced SF techniques (Camgözlü & Kutlu 2023).

Numerous research studies on PA and SF are available, including its enabling techniques and the agri-food supply chain. Several studies have analyzed it from the standpoint of long-term viability cooperation between parties in decision-making, handling energy in intelligent manufacturing facilities, and specialized applications in the farming of animals (Li et al. 2022). Proponents of sustainable development and expansion stressed the importance of stakeholders collaborating in agri-food advancements to guarantee widespread acceptance and long-term viability. Most of this research is focused on either a singular technique or a specific facet of SF. There needed to be an existing structure to implement SF in underdeveloped countries.

Proposed ML-based Food Security Model

Figure 1 depicts the methodology configuration for food production and security processes. The ML model of choice for predicting food-security situations on quarterly and seasonal periods is the Extreme Gradient Boosting (XGB), an Ensemble Decision-Tree (EDT) technique that, similar to random forest regression analyses, can model intricate relationships. This is achieved by its capability to enhance individual trees. The research includes many explanations related to environmental hazards and socio-economic factors as potential factors influencing food insecurity, which the research refers to as characteristics. The XGB algorithm is trained to forecast food security conditions for various time frames. At this step, the research will contrast the projections to three benchmark designs: (a) the perspectives, (b) an ongoing theory, and (c) a seasonal forecast.

Implementation of PA: An Agri-Food Supply Chain (AFSC) refers to a series of physical and decision-making procedures that involve the movement of agricultural products, data, or money, ultimately meeting the needs of the end consumers. AFSC encompasses various interconnected agricultural company divisions that work together to reduce expenses, decrease waste and risk, and optimize earnings or profits by meeting customers' needs. AFSC Management encompasses the strategic oversight of all Agrifood corporate divisions and operations in producing and distributing agri-food products that meet market demands. It involves planning, implementing, coordinating, and controlling these activities to ensure efficiency. AFSC management encompasses six core processes or duties: planning, analyzing, developing, integrating, delivering, and returning. The processes related to AFSC management are depicted in Figure 2.

Agricultural Biotechnology Journal; Print ISSN: 2228-6705, Electronic ISSN: 2228-6500

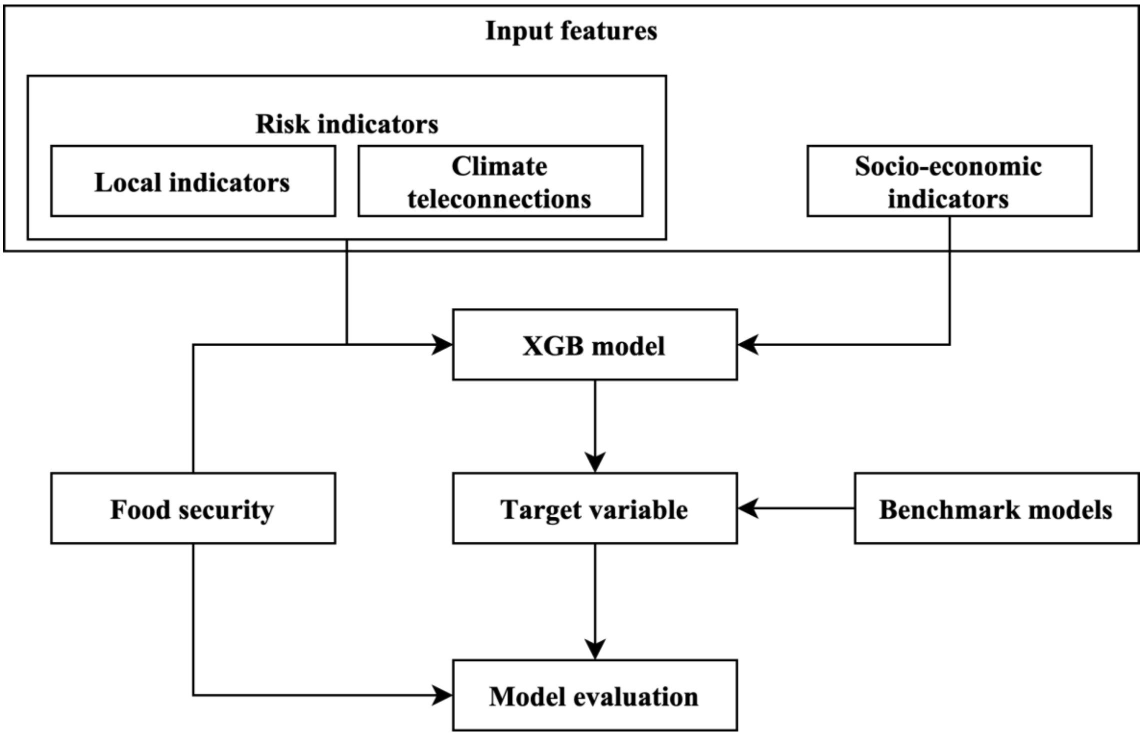

Figure 1. Workflow of the food production and security process

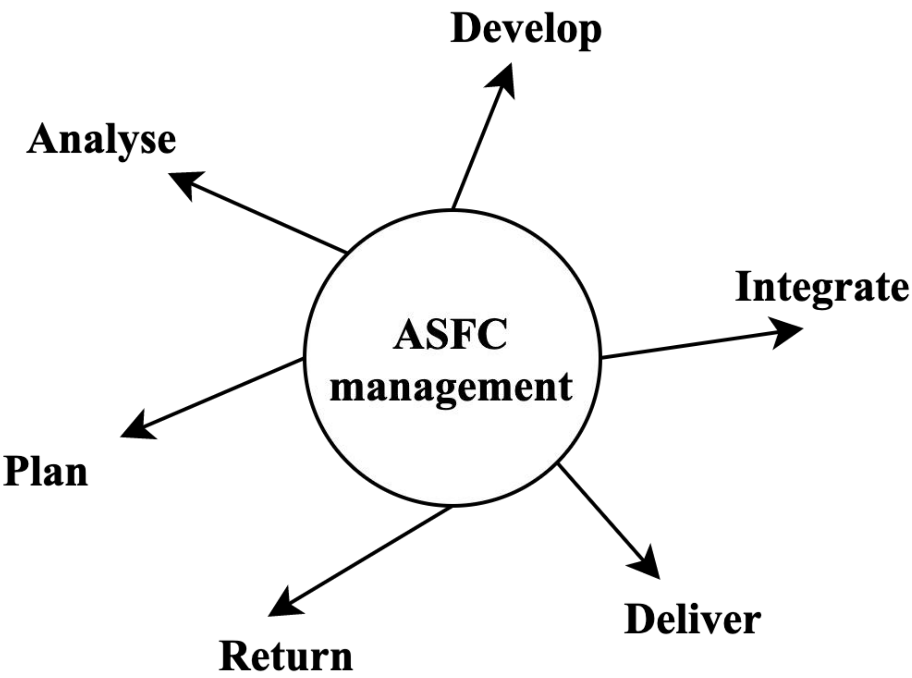

Figure 2. Agri-food supply chain (AFSC) management process

PA will be implemented across all eight interconnected and different stages of food production, from the farm to the consumer (Figure 3). The tasks performed at every phase of manufacturing are contingent upon the elements. The first factor to consider is the sort of food that is grown. The second factor is the precise spot of the farming operation and the prevalent circumstances in that area. The third determinant is the methodology and magnitude of SF output (How is the food generated?), and lastly, the specific target marketplace (For whomever is the food intended?).

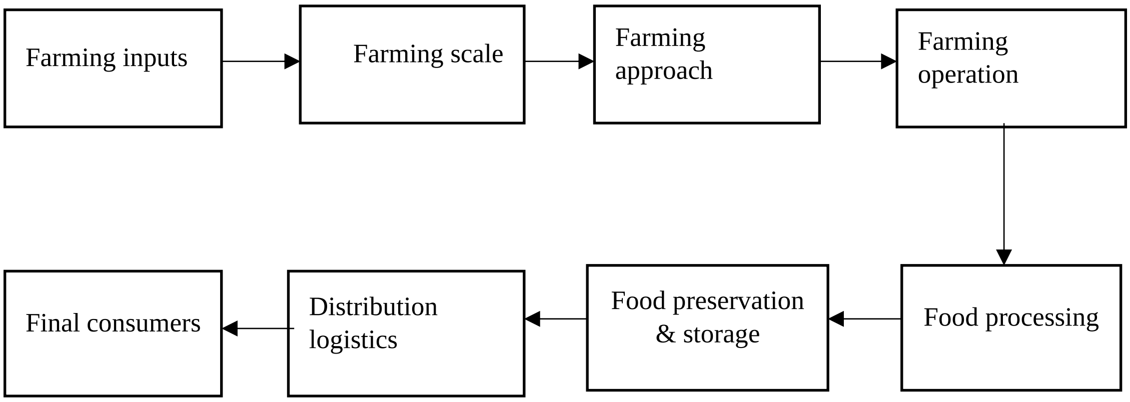

Figure 3. Agri-food supply chain (AFSC) stages

PA implementation risks: Agricultural risk encompasses various sources of uncertainty, such as weather conditions, crop yields, expenses, governmental regulations, global market dynamics, and other factors that can lead to significant fluctuations in farm revenue. Risk assessment involves choosing strategies that minimize the financial impact of potential hazards. Risks can be avoided, transferred, acknowledged, or minimized depending on the selected evaluation choice.

1) The first is production risks, which pertain to the procedures for cultivating crops and raising livestock. Weather, sickness, insects, and other factors can impact the amount and quality of items supplied.

2) This refers to the risk farmers face in receiving the appropriate price for their commodities or the expenses they incur for inputs. The nature of pricing risk differs significantly across different products.

3) The risk arises when producers borrow money and are obligated to repay the loan. Economic risk factors encompass the escalation of interest rates, the potential for lenders to demand debt repayment, and a decrease in credit availability.

4) Institutional risks are related to the potential consequences of government activities. Political actions with the potential to substantially impact the agricultural industry include tax

legislation, limitations on pesticide usage, regulations on managing animal waste, and the implementation of market or financial assistance programs.

5) Human hazards are Risks linked to the farmer's health conditions or intimate connections that could impact the farm company. Human crises that potentially jeopardize the ongoing operations of a farm business include physical injuries, illnesses, fatalities, and marital dissolution.

Implementation of AFSC lifecycle management: The AFSC life cycle refers to the sequential stages through which digitalized food production advances, from its initiation to its culmination. A production stage refers to a sequence of interconnected tasks to accomplish one or more outputs. The stages can be consecutive, continuous, or overlapped. Computerized AFSC control combines methods, techniques, skills, and expertise to achieve specific production objectives for agricultural goods. The successful execution of the task necessitates the utilization of a cross-functional team comprising individuals from multiple divisions and with diverse skills. It requires the use of specific tools and technology.

There are seven limitations to the management of AFSC (Figure 4(a)). The restrictions in this context are price, quality, duration, scope, hazards, assets, and client fulfillment. Efficient AFSC management improves effectiveness, service growth, item quantity and volume, and customer happiness. Additional advantages of this strategy encompass enhanced teamwork derived from a partnership of participants, a more pronounced competitive advantage over competing products, and efficient management of risks. The AFSC life cycle has five stages, as Figure 4(b) depicts. The stages encompassed in the process are beginning, organizing, execution, tracking, and closure.

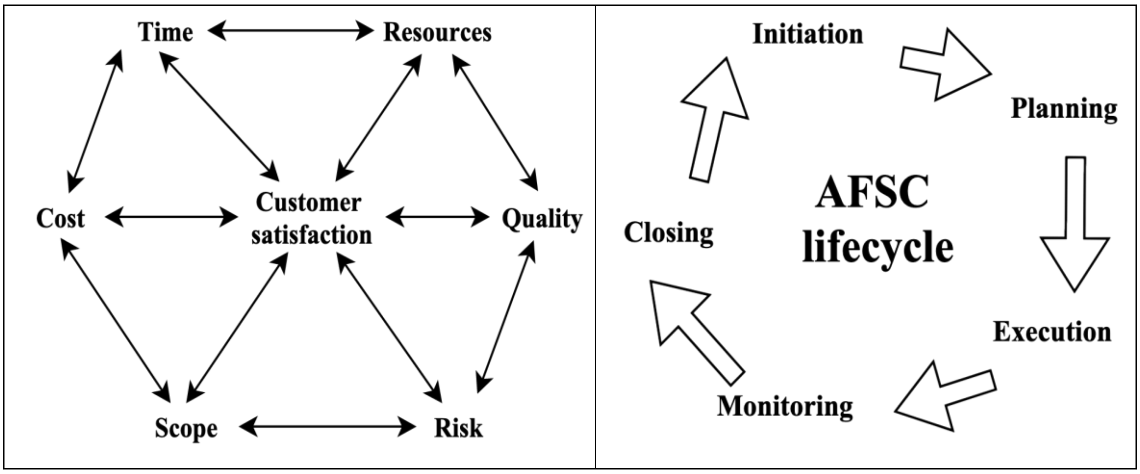

Figure 4(a). AFSC management limitations, 4(b). Phases of AFSC lifecycle

Agricultural Biotechnology Journal; Print ISSN: 2228-6705, Electronic ISSN: 2228-6500

Limitations and Threats

Limitations: The research recognizes the subsequent constraints in the investigation: The study acknowledges the following limitations.

1) The proposed paradigm focuses mainly on crop production. Alternative agricultural practices such as fishing, livestock farming, and forests differ dramatically from the paradigm the research has provided.

2) The study is exclusively restricted to papers written solely in English. The research acknowledges the significant reservoir of knowledge in various languages that the study needs to include.

3) The study topics and search choice technique do not include all essential English language articles. The research made meticulous efforts to prevent this occurrence. The study must encompass the potential for crucial contributions to this subject.

4) The study focused on publications from 2015 to 2023 in specific online libraries. More research should be included in this scope, which the research needs to look into.

Threats: Here are some procedures the research implemented to reduce the risks to the accuracy and reliability of this study.

• The research established a clear and precise approach and study protocol from the outset.

• The research utilized specified online libraries (records) that accurately represented the geographic variation of writers and ideas.

• The research has developed precise inquiries that direct the research and selection procedures.

• The research employed clearly stated search terms and conducted searches within specific periods (2015 – 2023) to guarantee that other scholars could replicate the search methods.

• The research conducted a thorough review to eliminate duplicate research and conducted reference checks to guarantee that no significant studies were overlooked.

Conclusions: The significance of ML is generally acknowledged in various industries, including farming. ML is anticipated to improve resource efficiency, promote friendly resource consumption, and facilitate significant environmental benefits. If stakeholders in the agricultural process can recognize and adopt this technology, and if sufficient money can be secured, it has the potential to bring about a substantial impact in agriculture. The agricultural sector faces several challenges, such as inadequate irrigation infrastructure, weed infestation, low crop productivity, difficulties in monitoring plants due to their height, and the impact of extreme weather. By harnessing the power of technology, it is possible to enhance performance and address these concerns. The research's implementation strategy for PA focuses on critical factors at each stage of the agriculture process. These include farming components, agricultural scale, strategy, operation, food preparation, preservation, marketing and transportation, and end customers. The research conducted a project management evaluation of the life cycle of the farming process. The study has emphasized the tasks linked to the five phases of the farming and SF life cycle: beginning, organizing, carrying out, monitoring, and closure. The effectiveness of such techniques in plant disease detection is proven by their ability to achieve exceptional levels of accuracy. This is particularly true when they rely on extensive open-source databases and pre-trained algorithms. Future investigation uncovered that the size of the plant imagery utilized for modeling and the circumstances under which the photos were gathered could significantly affect the accuracy.

Acknowledgement: The author states that no funding, money, or other assistance was obtained in order to prepare this paper.

Conflict of Interest: There is no conflict of Interest.

References

Adomi AA, Abdoulaye T, Mohammed AB, et al. (2023) Impact of improved hermetic storage on food insecurity and poverty of smallholder cowpea farmers in Northwestern Nigeria. J Stored Prod Res 100, e102042.

Alonso EB, Cockx L, Swinnen J (2018) Culture and food security. Glob Food Secur 17, 113-127.

Angin P, Anisi MH, Göksel F, et al. (2020) Agrilora: a digital twin framework for smart agriculture. J Wirel Mob Netw Ubiquitous Comput Dependable Appl 11(4), 77-96.

Assaye A, Habte E, Sakurai S (2023) Adoption of improved rice technologies in major rice producing areas of Ethiopia: a multivariate probit approach. Agric Food Secur 12(1), e9.

Bjornlund V, Bjornlund H, Van Rooyen A (2022) Why food insecurity persists in sub-Saharan Africa: A review of existing evidence. Food Secur 14(4), 845-864.

Camgözlü Y, Kutlu Y (2023) Leaf Image Classification Based on Pre-trained Convolutional Neural Network Models. Nat Eng Sci 8(3), 214-232.

Cisternas I, Velásquez I, Caro A, Rodríguez A (2020) Systematic literature review of implementations of precision agriculture. Comput Electron Agric 176, e105626.

Duffy C, Toth GG, Hagan RP, et al. (2021) Agroforestry contributions to smallholder farmer food security in Indonesia. Agrofor Syst 95(6), 1109-1124.

Ghotbaldini H, Mohammadabadi M, Nezamabadi-pour H, Babenko OI et al. (2019) Predicting breeding value of body weight at 6-month age using Artificial Neural Networks in Kermani sheep breed. Acta Sci - Anim Sci 41, e45282.

Haghighi HFF, Far LM (2014) Combining Data Mining and Agricultural Sciences. Int Acad J Sci Eng 1(2) 1–8.

Li C, Chen Y, Shang Y (2022) A review of industrial big data for decision making in intelligent manufacturing. Eng Sci Technol Int J 29, e101021.

Martin-Shields CP, Stojetz W (2019) Food security and conflict: Empirical challenges and future opportunities for research and policy-making on food security and conflict. World Dev 119, 150-164.

Mohammadabadi M, Kheyrodin H, Afanasenko V, et al. (2024) The role of artificial intelligence in genomics. Agric Biotech J 16(2), 195-279.

Moysiadis V, Sarigiannidis P, Vitsas V, Khelifi A (2021) Smart farming in Europe. Comput Sci Rev 39, e100345.

Mustapha SB, Alkali A, Zongoma BA, Mohammed D (2017) Effects of Climatic Factors on Preference for Climate Change Adaptation Strategies among Food Crop Farmers in Borno State, Nigeria. Int Acad J Innov Res 4(1), 52-60.

Nabeesab Mamdapur GM, Hadimani MB, Sheik AK, Senel E (2019) The Journal of Horticultural Science and Biotechnology (2008-2017): A Scientometric Study. Indian J Inform Sourc Serv 9(1), 76-84.

Owoo NS (2021) Demographic considerations and food security in Nigeria. J Social Ec Dev 23(1), 128-167.

Plotnikov V, Nikitin Y, Maramygin M, Ilyasov R (2021) National food security under institutional challenges (Russian experience). Int J Sociol Soc Policy 41(1/2), 139-153.

Pour Hamidi S, Mohammadabadi MR, Asadi Foozi M, Nezamabadi-pour H (2017) Prediction of breeding values for the milk production trait in Iranian Holstein cows applying artificial neural networks. J Livest Sci Technol 5(2), 53-61.

Pržulj N, Tunguz V (2022) Significance of Harvest Residues in Sustainable Management of Arable Land I. Decomposition of Harvest Residues. Arch Tech Sci 1(26), 61-70.

Rukwe DT, Aboki E, Luka P, Nyam CM (2020) Economics of sesame production among small scale farmers in Southern Part of Taraba state, Nigeria. J Agric Econ Environ Soc Sci 6(1), 103-112.

Sambo U & Sule B (2024). Impact of climate change on food security in Northern Nigeria. Green Low-Carbon Econ 2(1), 49-61.

Sood S, Singh H (2021) Computer vision and machine learning based approaches for food security: A review. Multimed Tool Appl 80(18), 27973-27999.

Surendar A, Veerappan S, Sindhu S, Arvinth N (2024) A Bibliometric Study of Publication-Citations in a Range of Journal Articles. Indian J Inform Sourc Serv 14(2), 97-103.

Vargas CM, Liverpool-Tasie LSO, Reardon T (2024) Vulnerability of Nigerian maize traders to a confluence of climate, violence, disease and cost shocks. J Agribus Dev Emerg Econ 214, 1-19.

Veerasamy K, Fredrik ET (2023) Intelligent Farming based on Uncertainty Expert System with Butterfly Optimization Algorithm for Crop Recommendation. J Internet Serv Inform Secur 13(3), 158-169.

Agricultural Biotechnology Journal; Print ISSN: 2228-6705, Electronic ISSN: 2228-6500

مجله بیوتکنولوژی کشاورزی
دانشگاه شهید باهنر کرمان
انجمن بیوتکنولوژی ایران
شاپا چاپی: ۶۷۰۵-۲۲۲۸ شاپا الکترونیکی: ۶۵۰۰-۲۲۲۸

یک چارچوب پیاده سازی برای امنیت غذایی با استفاده از الگوریتم‌های یادگیری ماشین و بیوتکنولوژی در کشاورزی دقیق و کشاورزی هوشمند

نیضی میشرا

*نویسنده مسئول: استادیار، گروه علوم کامپیوتر و فناوری اطلاعات، دانشگاه کالینگا، رایپور، هند. آدرس پست الکترونیکی: ku.nidhimishra@kalingauniversity.ac.in

پریتی شارما

پژوهشگر، گروه علوم کامپیوتر و فناوری اطلاعات، دانشگاه کالینگا، رایپور، هند. آدرس پست الکترونیکی: priti.sharma@kalingauniversity.ac.in

تاریخ دریافت: ۱۴۰۳/۰۶/۲۵ تاریخ دریافت فایل اصلاح شده نهایی: ۱۴۰۳/۰۹/۰۲ تاریخ پذیرش: ۱۴۰۳/۰۹/۰۳

چکیده

هدف: تبدیل داده‌ها به شکل دیجیتال منجر به هجوم گسترده داده‌ها در تقریباً هر صنعتی شده است که بر عملیات مبتنی بر داده‌ها متکی است. پردازش داده‌های دیجیتال به میزان قابل توجهی حجم اطلاعات در حال پردازش را افزایش داده است. ظهور مدیریت کشاورزی الکترونیک عمیقاً بر فناوری اطلاعات و ارتباطات (ICT) تأثیر گذاشته است و در نتیجه مزایایی برای کشاورزان و مشتریان به همراه دارد و منجر به اتخاذ راه‌حل‌های فناوری در مناطق روستایی می‌شود. این مطالعه بر نوید فناوری های ICT در کشاورزی متعارف و موانع به کارگیری آنها در عملیات کشاورزی تأکید می کند.

نتایج: این مطالعه بر نوید فناوری‌های ICT در کشاورزی متعارف و موانع به کارگیری آنها در عملیات کشاورزی تأکید می‌کند. این تحقیق اطلاعات کاملی در مورد اتوماسیون، گجت‌های اینترنت اشیا (IoT) و چالش‌های مرتبط با یادگیری ماشین (ML) ارائه می‌کند. پهپادها برای نظارت بر محصول و بهینه سازی تولید در کشاورزی دقیق (PA) و کشاورزی هوشمند (SF) در نظر گرفته شده اند. دوره جدید کشاورزی متعارف با کشاورزی دقیق نشان داده می‌شود. توسعه چندین فناوری معاصر، مانند اینترنت اشیا، این امکان را فراهم کرده است. در صورت لزوم، این مقاله بر سیستم‌ها و پلتفرم‌های کشاورزی جهانی و پیشرفته که از فناوری اینترنت اشیا استفاده می‌کنند، تأکید می‌کند.

نتیجه‌گیری: اثربخشی چنین تکنیک‌هایی در تشخیص بیماری های گیاهی با توانایی آنها در دستیابی به سطوح استثنایی از دقت ثابت می‌شود. این امر به ویژه زمانی صادق است که آنها بر پایگاه داده‌های متن باز گسترده و الگوریتم‌های از پیش آموزش داده شده تکیه کنند. تحقیقات آینده نشان داد که اندازه تصاویر گیاهی مورد استفاده برای مدل‌سازی و شرایطی که عکس‌ها تحت آن جمع‌آوری شده‌اند می‌تواند به طور قابل توجهی بر دقت تأثیر بگذارد.

واژه‌های کلیدی: امنیت غذایی، بیوتکنولوژی، کشاورزی دقیق، کشاورزی هوشمند، یادگیری ماشین

نوع مقاله: مروری.

استناد: میشرا نیضی، شارما پریتی (۱۴۰۳) یک چارچوب پیاده سازی برای امنیت غذایی با استفاده از الگوریتم‌های یادگیری ماشین و بیوتکنولوژی در کشاورزی دقیق و کشاورزی هوشمند. *مجله بیوتکنولوژی کشاورزی*، ۱۶(۴)، ۲۲۳–۲۳۶.

Publisher: Faculty of Agriculture and Technology Institute of Plant Production, Shahid Bahonar University of Kerman-Iranian Biotechnology Society.