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

Utilizing AI to enhance the effectiveness of plant breeding for the development of climate-resilient smart food crops

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Abstract

Objectives

Growing crops is always the primary goal of agricultural operations. Still, worldwide agricultural systems are under increasing stress because of climate change and the growing number of people worldwide who need food. Dealing with climate change, making crops that produce more, protecting the environment, and adapting to changing conditions have become difficult to ensure that the world's population can keep growing. Climate-resilient smart Food Crops (CRSFC) are also needed to control biomass output, a crucial part of keeping the environment working properly globally. Pure-line selections, mass selection, back cross breeding, recurrent selection for improving agricultural CRSFC are limited and time-consuming. Careful selection processes are needed to grow new and better crop types. There is an urgent need to accelerate the process of CRSFC breeding by using artificial intelligence to replicate some features of human intelligence using technology. AI offers significant computing capabilities and a wide range of novel instruments and methods for foreseeable plant breeding (PB) due to the neural network training and classification module.

Results

This review will discuss the use of AI technology in current breeding practices to address challenges in large-scale phenotyping and gene functionality analysis. AI algorithms make it easy for researchers to quickly look at genetic data, find complicated trends, and build predictive models that help with crop breeding and selecting the most beneficial features. It will also explore how advancements in AI technologies create fresh possibilities for subsequent breeding by promoting the widespread utilization of envirotyping information. It is hard to connect gene to trait with the breeding methods we have now. This makes it harder to use high-volume field phenotyping, genomics, and enviromics effectively.

Conclusions

This paper discusses the use of AI as the preferred a method for improving the reliability of high-volume crop phenotyping, genotyping, and envirotyping information. Additionally, we examine the emerging methodologies and obstacles in integrating large multi-omics computational data. Hence, combining AI with "omics" might facilitate swift gene discovery and ultimately expedite agricultural enhancement initiatives.

Keywords: CRSFC, Breeding, Agriculture, Artificial Intelligence, Genotyping

Paper Type: Review Paper.

Citation: Divya, Kumar YD (2024) Utilizing AI to enhance the effectiveness of plant breeding for the development of climate-resilient smart food crops. *Agricultural Biotechnology Journal* 16 (3), 171-188.

Agricultural Biotechnology Journal 16 (3), 171-188. DOI: 10.22103/jab.2024.23990.1598

Received: July 26, 2024. Received in revised form: September 24, 2024.

Accepted: September 25, 2024. Published online: September 30, 2024.

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

Introduction

Food safety has been a top priority since the dawn of agriculture. As one of the first farming methods, plant breeding (PB) has evolved with human development and remains a primary approach to meeting the growing demand for food. Throughout history, humans have engaged in the deliberate cultivation and selection of crops based on their desired flavor, nutritional content, productivity, and ability to withstand both living organisms and non-living factors in the surroundings (Dossa et al. 2017). Following the establishment of Mendel's laws in 1866, PB underwent a significant transformation. Subsequently, hereditary breeding was created using the notion of crossover. The Identification of DNA as genetic material was invented about a significant transformation in PB during the molecular age. As a result, novel breeding methods, including marker-assisted selection (MAS) and genetic engineering (GE) approaches, were adopted (Shen et al. 2022). These findings led toa change in PB methodology, moving away from just selecting plants based on their observable characteristics (phenotype) to a more balanced approach that considers both the genetic makeup (genotype) and observable characteristics (phenotype) of the plants. PB has been categorized into four different groups according to technological advances. These categories include selection by farmers, numerical and experimental approaches to enhance selection, the integration of genetic and genomic information, and the ongoing period of the best and most accurate layout breeding (Shen et al. 2022).

Currently, there is a significant difficulty in providing food for the rapidly increasing global population in climate change, namely due to the reduction of soil fertility caused by the continuous transformation of agricultural land into dry and nutrient-poor regions and the presence of salt and water stagnation (Farooq et al. 2022). Global warming significantly threatens agricultural productivity, particularly key food crops like rice, maize, and wheat (Farooq et al. 2022, Syed et al. 2022). In the coming decades, climate-related variables like severe temperature strains, nutrient pollution or shortages, shifts in rainfall magnitude and frequency, and other climate change-induced problems like salinity, transpiration, drought, and degraded soil will have an enormous effect on crop yields (Teshome et al. 2020, Raza et al. 2021). The fight against climate change can be improved by the use of artificial intelligence (AI). AI systems already exist and have tools that can predict the weather, track icebergs, and find pollution. Global warming has worsened the negative impacts of both abiotic and biotic stresses (insects and fungi) on plants, leading to a considerable decrease in agricultural productivity (Radhika & Masood 2022). Ecological constraints are the main factor behind the decreasing food production, directly influencing economies globally (Surendar et al. 2024). The genetic variation of agricultural plants serves as the foundation for continuously producing new kinds that may effectively tackle present and future challenges (Parmley et al. 2019).

Data generation in biology and biotechnology has greatly increased in recent years due to the very rapid development of high-performance technologies (Oliveira, 2019). These data are obtained from studying biological molecules, such as metabolites, proteins, RNA, and DNA, to understand the role of these molecules in determining the structure, function, and dynamics of living systems. Functional genomics is a field of research that aims to characterize the function and interaction of all the major components (DNA, RNA, proteins, and metabolites, along with their modifications) that contribute to the set of observable characteristics of a cell or individual (i.e., phenotype) (Mohammadabadi et al. 2024). Furthermore, in a breeding program, genetic improvement can be maximized through accurate identification of superior animals that are selected as parents of the next generation, thereby achieving breeding goals (Pour Hamidi et al. 2017). Artificial neural networks have been proposed to alleviate this limitation of traditional regression methods and can be used to handle nonlinear and complex data, even when the data is imprecise and noisy. Omics 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). Therefore, it is necessary to have a fast technique of introducing high-quality climate-smart growers with specific features such as resilience to stress, production, and nourishment. The practice of PB has always played a crucial role in advancing agriculture to meet the increasing need for food from a rising population (Niazian & Niedbała 2020). The advancements in OMICS methodologies, including genomics, transcriptomics, proteomics, metabolomics, and phenomics, significantly enhance the overall effectiveness of the system. This has greatly increased the production of food to meet the rising demand (Muthamilarasan et al. 2019). Using multi-omics approaches in plant research has been essential in understanding the metabolic routes and genetic processes that govern important characteristics and development procedures in many plant species (Razzaq et al. 2019). Advancements in the technology used for next-generation sequencing (NGS) have enabled the rapid collection of large amounts of data for OMICS studies (Schmidt et al. 2020), resulting in enhanced accuracy, sensitivity, and detecting speed (Harfouche et al. 2019).

The objective of AI is to use technology in a way that resembles certain aspects of human intelligence. Computer science and mathematical statistics form the basis of this field of study, which aims to create technological systems that can solve problems and carry out duties typically associated with the human brain (Peng et al. 2020). This field has far-reaching economic and social consequences. The capacity to rapidly analyse massive volumes of data in order to uncover unexpected connections is an example of the technical maturity that has generated an increased curiosity in artificial intelligence (AI) among the breeding community. From a breeding perspective, AI enables people to organize data that is usually available in a disaggregated form on the market, turning data into breeding decisions. This way, only tools that help with decision-making in crop breeding are considered.

Researchers have used extensive multi-omics approaches to identify crucial components in the retirement, response to stress, and yield index of commercially significant crops such rice, wheat, and maize (Veerasamy & Fredrik 2023, Peng et al. (2020), Uchida et al. (2020). This paper highlights the impact of the multi-omics transformation on improving PB effectiveness for reliable food supply. It shows how this progress has improved the amount of nutrients in plants, their ability to grow, and their ability to deal with living and non-living problems. The use of multi-omics methods will greatly improve genetic improvement and PB in the coming years. This article looks at how AI technologies can solve problems in PB techniques related to high-throughput phenotyping and gene functional analysis. It also discusses the problems that come up when you try to work with a lot of data in phenotyping and genotyping, and it suggests new ways to use envirotyping data in PB.

AI technologies for PB

More recent studies on artificial intelligence (AI) techniques, such as machine learning (ML), deep learning (DL), and predictive analysis (PA), have sought to improve planning, learning, reasoning, thinking, and action-taking capacities (Reinoso-Peláez et al. 2022). Researchers in the field of plant breeding are working on methods to better understand how plants react in different climates. To use Next-Gen AI in PB, PB databases must be analyzed intelligently and quickly using the right models and precise algorithms (Van Dijk et al. 2021). Researchers are always trying to improve and find the best ways for AI to help with high-resolution image identification and analyzing large databases. So, AI has become one of the main ways to speed up the crop development phase. Some AI methods, like Neural Networks (NN) and Deep Learning (DL), are now being used to make multi-omics data analysis more accurate and useful (Parmley et al. 2019, Niazian & Niedbała 2020, Camgözlü & Kutlu 2023). These two AI systems' inner workings are often unclear and difficult to decipher. In order to create nodes that can sort data in a manner similar to how neurons in the neurological system function, they use several nonlinear layers algorithms (Mumtaj Begum 2022).

PBs, on the other hand, are working on a Next-Gen AI system that will look at breeding principles and provide a thorough study of complex traits that change in response to changing environmental conditions (Niazian & Niedbała 2020). In addition, AI will be trained and improved to make data mining more accurate and useful (Angin et al. 2020). This will help make more accurate predictions about the factors affecting immunity and economic factors, speeding up PB processes. Many crosses and strict selection conditions have changed the genetic flexibility of farm plants in a big way (Parmley et al. 2019). Furthermore, the variety in genotypes directly impacts how genotypes interact with their surroundings, making it much harder for financially important traits to adapt and change. So, current PB projects try to make it easier for agricultural plants to handle environmental stressors by fixing the gap between genes and traits that can be seen. This is done by fixing those traits become less flexible over time. Scientists combine genetic

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and ecological knowledge with observable physical characteristics to enhance the PB program for agricultural stress resistance. The goal is to discover the most suitable genetic makeup with important agricultural qualities. Because these features are affected by things other than genetics, we need to use an advanced tracking system that can find every tiny variation in the plants. To address this challenge, scientists have developed an AI-driven biological gravimetric technique that can accurately detect even the smallest plant variations concerning soil and environment. This system is called the Soil-Plant-Atmosphere Continuum (SPAC) (Godwin et al. 2019). This technology provides botanical researchers a convenient way to observe and measure even the smallest differences in complex features throughout various plant life stages. Furthermore, consistent and thorough surveillance of these observable characteristics and their eventual examination using the Next-Gen AI method may aid in the discovery of stress-responsive quantitative trait loci (QTLs) or QTLs associated with significant agronomic qualities (Niazian & Niedbała 2020). A field phenomics package has been developed to expedite breeding efforts by offering high-quality images that facilitate the identification of superior genotypes in huge populations. The field phenomics package utilizes an ML methodology to collect large-scale phenotypic information pertinent to PB initiatives (Parmley et al. 2019). This is achieved using Unmanned Aerial Vehicles (UAVs) and ground-based hardware. The UAV and ground-based hardware have high-quality cameras and sensors to collect extensive data from many field-grown crops (Van Dijk et al. 2021). The data is then evaluated by artificial intelligence or specialized software, allowing breeders to select better genotypes that exhibit optimal economic and disease-resistant features, as illustrated in Figure 1.

Recent advancements in the science of phenomics have led to significant success in studying stress-responsive characteristics in Glycine max (Peng et al. 2020). Nevertheless, there is still a hindrance in connecting phenomic data produced via the assistance of AI to the genotype, which hampers the identification of genotypes with greater inheritance. Moreover, it is crucial to use intricate characteristics and their subsequent connection with environmental factors to overcome the abovementioned obstacle, which also presents a substantial issue. Consequently, conducting more research on developing advanced AIis crucial to bridge the gap between crops' observable characteristics (phenotype) and genetic makeup (genotype). This would enable the enhancement of crop development programs. Figure 1 illustrates the potential of AI and advanced PB to accelerate crop development and achieve significant improvements in a short timeframe. Literature of AI in plant breeding is given in the Table 1.

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Utilizing AI to Establish a Connection between Crop Genome and Phenome

Genetics and phenomics together might help make better crops that can survive in changing conditions and meet the needs of modern breeding. Expression of genes in plants and their effects on traits are closely connected and have many aspects. The directions for making proteins are stored in genes. Proteins then determine the traits or qualities that plants present. AI technology is used to effortlessly search out these features. Modern PB methods currently focus on finding a precise link between the crop's genetic makeup and visible traits. One big problem with advanced PB is combining large amounts of phenotype data with the whole genome data. Using crop phenotyping and genomics effectively is hard because of this problem (Van Dijk et al. 2021).

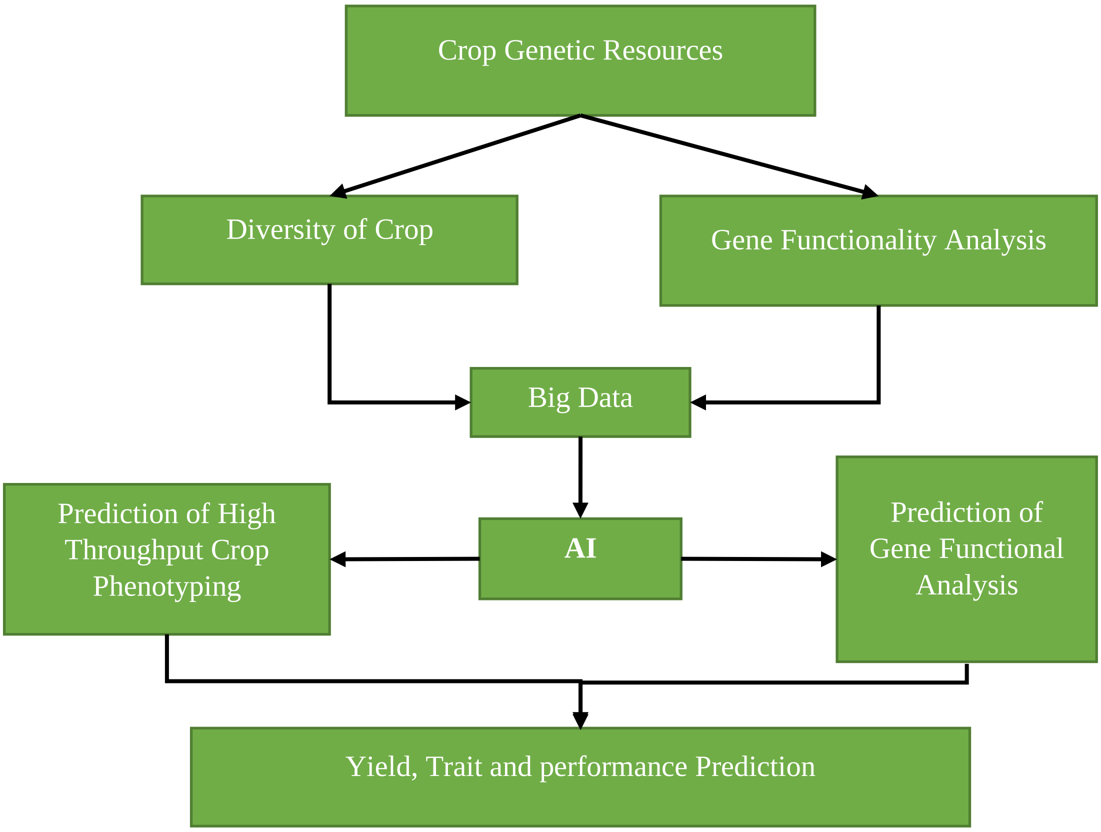

Figure 1. A comprehensive examination of the possible use of AI in enhancing PB techniques for the effortless, accurate, and early anticipation of genotypes/parental pairings for generating new varieties

Table 1. Literature of AI in plant breeding

References	Title	Method/Algorithm	Inference
(Esposito et a1. 2019)	Applications and trends of machine learning in genomics and phenomics for next-generation breeding	Machine Learning	While reporting on a case study utilizing microRNAs (miRNAs) to detect genes associated with stress situations, they go into the use of ML in handling huge data and models for prediction.
(Reinoso-Peláez et al. 2022)	Genome-enabled prediction methods based on machine learning	Machine learning	Greater resilience and predictive power were shown by various kernel, Bayesian, and ensemble techniques.
(Stergiou & Psannis 2017)	Recent advances delivered by Mobile Cloud computing and internet of things for big data applications: A survey	IoT	In order to investigate the shared characteristics and identify which of the MCC and IoT advantages enhance the usage of the Big Data applications, they combine the two previously stated technologies with the technology of the Big Data.
(El Bilali & Allahyari 2018)	Transition towards sustainability in agriculture and food systems: Role of information and communication technologies.	ICT technology survey	By raising resource efficiency, decreasing inefficiencies, cutting management expenses, and strengthening food chain coordination, ICTs may help to transition agro-food sustainability.
(Priya & Ramesh 2020)	ML based sustainable precision agriculture: A future generation perspective	ML	The basic idea of machine learning and methodical approaches to understand their use in agriculture is introduced in this work.

AI can distinguish between phenomics and genomics data across PB collections and modelling populations. To make PB methods better, AI can look at and find links between phenomics and genomics data from large datasets. The potential application of AI in training and computing models depends on its ability to reliably predict gene analysis and high-throughput crop phenotyping. AI can have enough neural network layer for data analysis and making decision. Based on the hidden layer structure it can extract the more detailed features form the incoming data and make accurate prediction. AI can also accurately predict how crops will grow and how well their traits will do (Wang et al. 2020). Combining AI with phenomics and genomics techniques speeds up the process of finding genes that are linked to agricultural phenotypes. This makes crop development projects more effective.

To study crop genomics, you need to understand the biological processes that cause phenotypes and use scientific information and computer methods to look at and understand the molecular basics. AI ensures that these tasks are always done right (Altman et al. 2021). AI methodologies provide a framework for analyzing large and varied databases, such as those used in genomics and imaging, which can't be done effectively with traditional analytical methods. AI techniques have been used more recently in several areas of phenomics and genomics. This includes looking atgene-specific techniques, genetic assembly, and data mining to figure out how to deal with complex physiological problems in metabolites and proteomes. Genetics, transcriptomics, and molecular biology are some of the studied fields. The main goal is understanding transcription and finding important single nucleotide polymorphisms (SNPs) in polyploid crops. It is also possible to do high-volume agricultural stress phenotyping (Kwon et al. 2020). Researchers have used AI and its complex algorithms to control how information moves from basic DNA to genetically based traits. This is done to look at how biological populations might be different. AI will greatly help PBs when they are doing in-depth research on genetic markers to make farming more efficient (Razzaq et al. 2021).

Recently, many crop archives have added a lot of different genetic and phenotypic data, sometimes called "big data". PBs might be able to learn valuable things from this data, which could help them find possible genes linked to specific traits (Tong & Nikoloski 2021). Luckily, AI has created a new standard view of the mathematical and statistical methods used to examine large datasets in big data. A new way to sort and find genes that have not been found before is to use artificial intelligence to determine the links between possible genes and cis-regulatory elements (CREs). This could greatly improve crop production. AI techniques can also look at changes in climate, high-volume plant stress phenotyping, humidity, UV radiation, wind, rainfall, and agricultural output. To improve CRSFC (Shen et al. 2022), AI is becoming increasingly crucial for collecting, analyzing, combining, and working with genomic and phenomic data (Shen et al. 2022).

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PB for the development of CRSFC

In the present and future, climate change will significantly impact the environment and the crops grown. Along with phenotyping and genetic testing, envirotyping is a third way to sort things out and determine how PB is affected by its environment. The genotype-by-environment (GE) interface, ambient messages, reactive genes, biotic and abiotic pressures, and integrated phenotyping are some of the most essential parts of envirotyping that help crops grow and predict phenotypes.

Authors in (Cortés et al. 2022) examine the current status of the developing area of research called "GE associations" (GEAs), which integrates environmental climate information with generative genomics. The researchers propose that individuals should start gathering GE adaption values (GEAVs) for genomic forecasting (GF) and multifaceted ML algorithms to account for polymorphic Darwinian adaptation. In a recent study, Xu et al. (2022) introduced a comprehensive genomic predictive PB approach incorporating unified multiomics evidence, big data technologies, and AI (Xu et al. 2022).

The combination of extreme weather, rising populations, and disease pressure has caused significant concern over food supply worldwide. In the future, optimizing the allocation and usage of limited assets for PB and controlling land use is necessary (Resende et al. 2021). Climate-resilient crops and soils have been modified to suit ecological conditions, enhancing BP initiatives. PBs can employ this information to develop novel cropswell-suited to the changing climate. Genetic tools and high-volume phenotyping supply scientists and agriculturalists with the necessary knowledge to direct and instruct the PB techniques for climate-savvy breeding. AIis crucial in efficiently managing and analyzing a large amount of collected data. It does this by performing statistical analyses to discover specific genetic markers that are linked to versatile climate-resilient features. PBs may use such information to adapt crops to their specific habitat. They may be included using sophisticated choice or genetic modification procedures. To successfully use research findings in practical settings, combining genetic and phenomic information into broad collections and systems particular to different groups of organisms is necessary. Additionally, available resources should be developed to assist breeders in selecting climate-resilient traits.

The PB system suggested in Figure 2 combines genetic, phenotypic, and environmental data to enhance effectiveness. High-volume automated instruments capture crops' phenotypic characteristics in indoor and outdoor situations.

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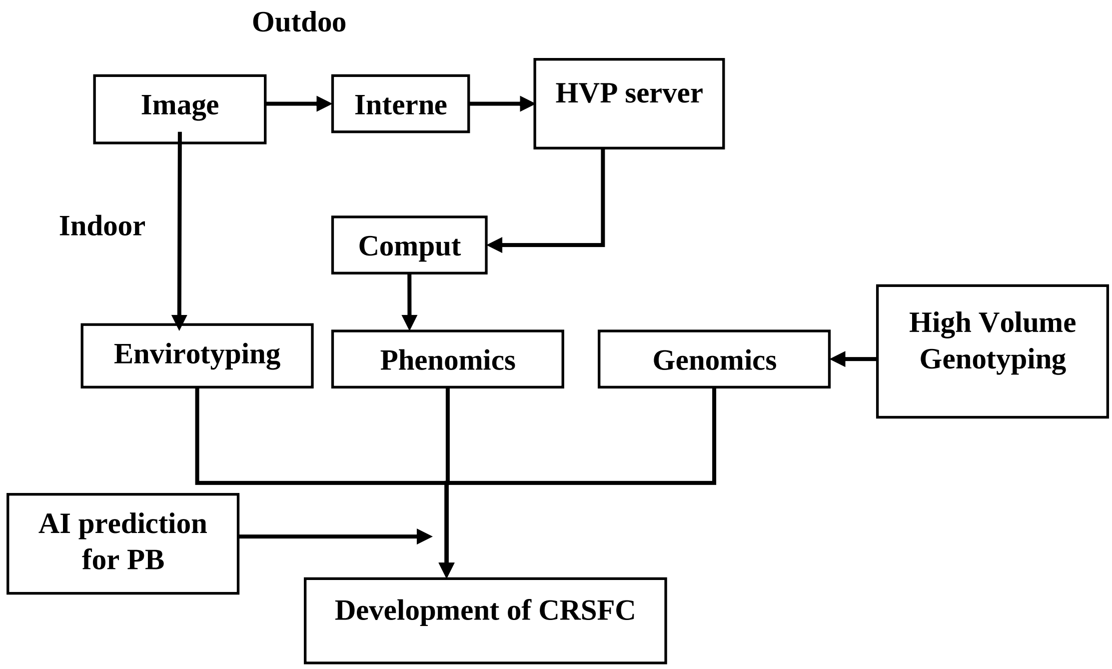

Figure 2. Use of AI to integrate and manage Genomics, Phenomics, and Envirotyping information for enhancing PB

This phenotypic data is then sent to a high-volume phenotyping (HVP) server over the global web. The genetic, phenotypic, and environmental characteristics will be combined from various databases, and the GE interaction (GEI) will be quantified across multiple settings. AI technology, namely ML and deep learning (DL), has been employed to select cultivars for single or many key habitats. This technique will allow us to make informed judgments on the chosen cultivars and their suitability for cultivation in restricted and widespread areas.

The Potential of AI-based PB for CRSFC in the Future

The ability to gather and analyse massive volumes of data is one of the most significant benefits of AI in farming for farmers. Better agricultural yields and more intelligent decision-making are necessary steps toward solving the world's food security problem. Another application of AI for farmers is to track weather patterns, crop development, and soil quality. This will allow them to detect illnesses in their earliest stages and protect crops from damage before they happen. Farmers will be able to better organize their operations and take advantage of the best planting season with the continued assistance of AI in weather predictions. On top of that, AI may assist in cutting down on resource use and waste. As an example of a sustainable and eco-friendly technique, farmers may use AI to optimize the quantity of water and fertilizer applied to their crops. Soil and water pollution is a growing worry, but this optimization will make it less likely.

Recently, there has been a substantial proliferation of discourse around the significance of AI, which has sparked arguments over the many uses of AI worldwide. It is essential to modernize PB to capitalize on the digital era (Van et al. 2021). To achieve fulfilment in their future endeavors, academics and breeders must assess digitally produced recommendations in light of the requirements and expectations of farmers. Implementing and effectively using AI technologies have increased revenue and significant economic development rates in several industries worldwide, including PB (Van et al. 2021). In addition, AI will prioritize developing innovative methodologies based on human needs while evaluating the potential use of automated systems in many global sectors and enterprises. AI will revolutionize global business expansion and competition by introducing innovative manufacturing methods to drive higher revenue. In future with the use of AI in farm management software, farmers may improve their decision-making at every step of crop cultivation, leading to increased yield and profitability. Agricultural producers and breeders may input information into wireless AI applications through handheld gadgets, aerial vehicles, and agro-equipment systems, increasing the accessibility of AI applications. The phenomics and genome data acquired using ML and DL techniques are precise; however, it is insufficient to entirely depend on the technology for expediting PB, which remains challenging, laborious, and costly.

Application of AI

Both current and future generations will feel the effects of climate change on the environment and agricultural output. To further understand the role of environmental factors in crop breeding, the idea of envirotyping has been proposed up as a third "typing" tool to complement phenotyping and genotyping. Modelling crops and predicting their phenotypes rely heavily on envirotyping and its effective components, which include biotic and abiotic stressors, responsive genes, environmental signals, and genotype-by-environment interaction (GEI). For genomic prediction (GP) and multi-dimensional ML models to account for polygenic evolutionary adaptation, the authors urge the community to start collecting genomic estimated adaptive values (GEAVs). A recent proposal used integrated multiomics data, big data technology, and artificial intelligence to develop a genomic-enviromics predictive breeding system.

The world's food supply is under concern because to climate change, population growth, and disease pressure. Strategies for making the most of few resources in areas like crop breeding and land management will have to be devised in the near future. In order to improve breeding programs, researchers have developed crops and soils that are more resistant to climate change. With this new information, they can create even more climate-smart crops. The data needed to

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inform and direct breeding approaches for climate-smart breeding is being made available to academics and farmers via genomic technologies and high-throughput phenotyping. By doing association studies to discover genetic targets associated with adaptive climate-resilient features, AI plays a crucial role in integrating and managing this rapidly growth of data. In order to develop bread drought-tolerant cultivars, a strategy to use multi-trait gene editing, genetic polymorphism, and machine learning to identify and isolate new variations in abiotic stress tolerance in wild crop relatives has been introduced. This information may be used by breeders to make environmental adjustments to crops via genome editing or sophisticated selection. To successfully apply studies in the field, genomic and phenomics data must be combined into thorough clade-specific databases and platforms. Breeders should also have access to tools that may help them select for traits that are well-suited to different climates.

Conclusions: Plant breeders have made some ill-advised attempts in recent decades to create cultivars with high yields and resistance to both biotic and abiotic stressors. To reduce the time, space, and money needed to create, distribute, and sell new or enhanced cultivars with more precision and predictability, speed breeding has recently arisen as a promising option. When it comes to adapting to new environments, plant performance is heavily dependent on elements like growth and development. One method to speed up this process is the speed breeding procedure using AI based feature detecting and prediction model. To further support crop improvement initiatives, this study should instead focus on creating public and private businesses to help with capacity development, knowledge transfer, speed breeding, and AI-driven research. Together, the public and commercial sectors can provide the groundwork for ground breaking plant breeding research and innovations that include artificial intelligence (AI) to benefit people, animals, and the environment.

Acknowledgement: The author declares that no funds, grants, or other support were received during the preparation of this manuscript.

Conflict of Interest: There is no conflict of Interest.

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

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

استفاده از هوش مصنوعی برای افزایش اثربخشی اصلاح نباتات برای توسعه محصولات غذایی هوشمند مقاوم در برابر آب و هوا

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تاریخ دریافت: ۱۴۰۳/۰۵/۰۵ تاریخ دریافت فایل اصلاح شده نهایی: ۱۴۰۳/۰۷/۰۲ تاریخ پذیرش: ۱۴۰۳/۰۷/۰۳

چکیده

هدف: کشت محصولات همیشه هدف اولیه عملیات کشاورزی است. با این حال، سیستم‌های کشاورزی در سراسر جهان به دلیل تغییرات آب و هوایی و تعداد فزاینده افرادی که در سراسر جهان به غذا نیاز دارند، تحت فشار فزاینده‌ای قرار دارند. مقابله با تغییرات اقلیمی، تولید محصولات بیشتر، حفاظت از محیط زیست، و سازگاری با شرایط متغیر برای اطمینان از ادامه رشد جمعیت جهان دشوار شده است. محصولات غذایی هوشمند مقاوم در برابر آب و هوا (CRSFC)، که بخش مهمی از حفظ محیط زیست در سطح جهانی است نیز برای کنترل خروجی زیست توده مورد نیاز است. انتخاب‌های خالص، انتخاب انبوه، اصلاح مجدد متقابل، انتخاب مکرر برای بهبود CRSFC کشاورزی محدود و زمان بر هستند. برای رشد انواع محصولات جدید و بهتر به فرآیندهای انتخاب دقیق نیاز است. نیاز فوری به تسریع فرآیند پرورش CRSFC با استفاده از هوش مصنوعی برای تکرار برخی از ویژگی‌های هوش انسانی با استفاده از فناوری وجود دارد. هوش مصنوعی به دلیل آموزش شبکه عصبی و ماژول طبقه بندی، قابلیت‌های محاسباتی قابل توجه و طیف گسترده‌ای از ابزارها و روش‌های جدید را برای اصلاح گیاهان (PB) ارائه می‌دهد.

نتایج: این بررسی استفاده از فناوری هوش مصنوعی را در شیوه‌های اصلاحی فعلی برای رسیدگی به چالش‌ها در فنوتیپ‌سازی در مقیاس بزرگ و تجزیه و تحلیل عملکرد ژن مورد بحث قرار می‌دهد. الگوریتم‌های هوش مصنوعی بررسی سریع داده‌های ژنتیکی، یافتن روندهای پیچیده و ساخت مدل‌های پیش‌بینی‌کننده را برای محققان آسان می‌کند که به اصلاح محصول و انتخاب سودمندترین

ویژگی‌ها کمک می‌کند. همچنین بررسی خواهد کرد که چگونه پیشرفت‌ها در فناوری‌های هوش مصنوعی با ترویج استفاده گسترده از اطلاعات محیطی، فرصت‌های جدیدی را برای پرورش بعدی ایجاد می‌کنند. یافتن همبستگی ژن با صفت با روش‌های اصلاحی که اکنون داریم دشوار است. این کار استفاده موثر از فنوتیپ، ژنومیک و محیط زیست با حجم بالا را دشوارتر می‌کند.

نتیجه گیری: این مقاله استفاده از هوش مصنوعی را به عنوان روشی ارجح برای بهبود قابلیت اطمینان فنوتیپ، ژنوتیپ و اطلاعات محیطی با حجم بالا مورد بحث قرار می‌دهد. علاوه بر این، روش‌ها و موانع در حال ظهور در ادغام داده‌های محاسباتی مالتی‌اومیکس بزرگ را بررسی می‌کند. از این رو، ترکیب هوش مصنوعی با اومیکس ممکن است کشف سریع ژن را تسهیل کند و در نهایت ابتکارات بهبود کشاورزی را تسریع بخشد.

واژه‌های کلیدی: اصلاح نژاد، ژنوتیپ، کشاورزی، هوش مصنوعی، CRSFC

نوع مقاله: مروری.

استناد: دیویا، یالاکالا دینش کومار (۱۴۰۳) استفاده از هوش مصنوعی برای افزایش اثربخشی اصلاح نباتات برای توسعه محصولات غذایی هوشمند مقاوم در برابر آب و هوا. *مجله بیوتکنولوژی کشاورزی*، ۱۶(۳)، ۱۷۱–۱۸۸.

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