Review Article

Digital Technologies in Crop Genotype Designing Methods: Scope, Limitations, and Future Perspectives

Abstract

The modern world agricultural sector has come under severe attack from several factors. These factors range from biotic to abiotic factors and they present threats to the environment and the world economies at large. If agricultural production is made more sustainable, it can be able tocombat the current food shortages.Looking into the present scenario, there is a great need to improve the traditional breeding designing methods to develop genotypes of different crops that would be able to withstand the current adverse effects brought about by persistent climate change. Central to the basis and key factor of improving the designing methods in crop productionare different digital technologies such as Artificial Intelligence (AI), Deep Learning (DL), Machine Learning (ML), Geographical Information System (GIS), Precision Agriculture (PA), and Remote Sensing (RS).The digitalization of traditional breeding strategies has its weaknesses in terms of genetic gains it could offer in improving crop production.However, improving digital technologies would result in improveddesigning methods of crop productionthat would consequently result in increasing agricultural production and productivity. Therefore, the current review highlights the gains that have been made especially by AI and ML in designing methods of crop production. In addition, the review also highlights the limitations of these digital tools and their potential incrop designing methods for future crop genetic gains and production as well.

Keywords:Artificial Intelligence,Crop design methods,Digitalization, Machine Learning,Production.

1.0 Introduction

A re-look at how productivity and production in agriculture, are addressing the issue of food shortage currently and in the future is something that cannot be argued anymore. Especially that, the world's population is expected to rise by approximately 9.6 billion by 2050[1]. Any efforts designed to overcome the current and future challenges that are affecting or have the potential to affect agricultural production and productivity negatively should be encouraged. In today's agriculture sector, there are myriad factors that affect the full potential of crop production [2]. These factors range from biotic to abiotic stress conditions that have the potential to significantly affect crop development, from breeding to the production point. Major challenges experienced by agricultural production in the recent past include bottlenecks created by climate change, the reduction of water for irrigation purposes, an exponential rise in the cost of production, and the general decrease in the workforce dedicated to agricultural production as a result of the COVID-19 pandemic among other factors [3]. Both biotic and abiotic factors present threats to the environment and also to the world economies, concerning achieving sustainability of the present and future agricultural production and supply systems.To combat and overcome the factors thatnegatively affect crop production, there is a need to significantly innovate ways and means that will help in keeping pace with the current constant climate change [4]. The seemingly unavoidable question would be, how best do we produce enough and of good quality foodmeant for the ever-growing population estimated to reach approximately 9.6 billion by 2050?

Modern crop design methods haveachieved tremendous gains at the breeding and also production levels. Way back in the 19th century, genetic gains were heavily achieved through crossing and selection which involvescombining and selecting classicalbreeding methods based on Mendel's laws, whichalso touches on experimental designs used in plant breeding [5]. During the 20th century, thegene pool enhancement that touches areas like wide crosses, pentaploidbreeding in crops such as wheat, and also doubled haploid productionwere used to advance the breeding strategies.At the dawn of the 21st century,other crop designing methods came into the picture which includesrapid generation advancement e.g., shuttle breeding, and speed breeding (Fig 1), hybrid breeding, high throughput phenotyping platforms, high throughput genotyping platforms (genomics, pangenomics, transcriptomics, proteomics), epigenetics, and genome editing technologies [6].Suffice to say, the advent of digital technologies is becoming a central point in designing methods that are promising to keep pace with the current constant and persistent climate change [7]. In the past, the development of crop designing methods was highly influenced by traditional or conventional methods.Currently, among all the digital technologies, AI and ML, have been employed on a larger scale to integrate with crop designing methods that are helping plant breeders to build genotypes that have high resilience towards climate change. Inspite of the gains made, the currently existing digital technologies have their weaknesses that if not worked on, may not be good enough for future research and crop sustainability production [9]. Therefore, this review becomes vital because it highlights the gains, limits, and potential that digital technologies (i.e., AI and ML) have in aiding crop designing methods (Fig 1) for future crop genotype designs, that could be able to overcome the current adverse effects caused by climate change, to overcome the current food shortages.

2.0Achievements in Designing Methods for Future Crop Genotypes

2.1 Artificial Intelligence

AI has been defined by several researchers in different ways, central to its definition is the concept of integrating human intelligence in a machine, designed to operate in the same way humans do, by imitating their behavior [9]. Furthermore, researchershave highlighted thatthe term AI is mainly applied when describing a machine that can demonstrate the characteristics of human beings. It embraces the use of sensors and instruments such as spectrometers, digital cameras, etc. to enhance the process of capturing the data, before analysis and decision-making[10].Previous strides of gains and achievements made by AI (Table 1) in the academic cycles have shown opportunities and threats, strength and weakness, for various domains in science, including crop breeding programs.To achieve desired tasks effectively and efficiently through proper machine programming, AI methods require large repositories of data. Besides, ituses algorithms that require large amounts of data to train the machine to enhance its ability in moderating the process of making decisions thereby promoting complex traits screening, such as detecting disease invasion in disease trial screening, at an early stage of crops and this, in turn, has improved the process of making decisions. In terms of developing crop designing methods, AI has made a significant contribution in the area of high-throughput phenotyping. This has been demonstrated by someresearchers[4], which demonstrated the power of AI in giving insights into complex traits such as the architectural genetics of flowering time in wheat plants. Similarly, it has allowed and helped plant breeders to expand into areas that have not been explored in the past by designing crop methods that are capable of helping breeders to develop smart climate crop genotypes [2]. Previously, measuring phenotypic crop traits has been centered on traditional methods that involve destructive means succeeded by laboratory steps to explore phenotypic traits linking them to their genetic functions.

The emergence of AI through imaging techniques has recorded achievement in this area, in that, sampling of plants can be done in a non-destructive manner, by capturing, processing, and analyzing data for observable traits of interest in different crops [5]. Moreover, its application in imaging techniques, it has been widely used, in-field phenotyping platforms and open-source devices for the collection of data and also in cyberinfrastructure for data management in different plant breeding programs to come up with better crop designing methods that have high potential in facilitating the breeding of climate-smart elite lines[10].Contrary to this, the use of AI has a high potential to create technological unemployment.AI-based models and tools used in different agricultural operations that are commercially available to ease the phenotyping, data collection, assessment of biotic and abiotic stress, and prediction of yield and quality of the products are shown in Tables 1 and 2.

Table 1: Artificial Intelligence Models Used in Different Agricultural Applications

Model	Application	Crop	Inputs	Results	Ref
DCNN	High Throughput Phenotyping	Wheat	Genotype and phenotype data	(Correlation Coefficient)>0.7	[18]
DCNN	High Throughput Phenotyping	Soybean	Genotype and phenotype data	(Correlation Coefficient)>0.4	[19]
DNN	Yield Prediction	Soybean	Unmanned Aerial System Images	R2.0.72	[20]
ANN	Yield Prediction	Wheat	Unmanned Aerial System based Vis	R2.0.7701, 0.112	[21]
RF	Yield Prediction	Wheat	Unmanned Aerial System based Vis	R2.0.7800, 0.1030	[21]
PLSR	Yield Prediction	Wheat	Unmanned Aerial System based Vis	R2.0.7667, 0.1353	[21]
DNN	Yield Prediction	Maize	2018 Syngenta Crop Challenge	Root Mean Square Error: 46%	[22]
RCNN	Fruit detection	Citrus	Unmanned Aerial System	Precision>90%	[23]
RCNN	Fruit detection	Apples	Unmanned Aerial System	R2.0.80	[24]
CNN	Weed detection	Rice	Unmanned Aerial System	General accuracy weed mapping:89% weed identifing:88%	[25]
DCNN	Disease Detection	Wheat	Unmanned Aerial System images (hyperspectral)	Accuracy: 0.85	[26]
DCNN	Disease detection	Banana	Field images	General Accuracy: >90%	[27]

RF	Disease detection	Wheat	Unmanned Aerial System images (hyperspectral)	Accuracy: 0.77	[26]
RF	Biomass Estimation	Barley	Unmanned Aerial System images	(Correlation Coefficient): 0.95	[28]
CNN	Biomass Estimation	Maize	Field images	Accuracy: 99%	[29]

DCNN; Deep Convolution Neutral Network, DNN; Deep Neutral Network, ANN; Artificial Neural Network, RF; Random Forest, PLSR; Partial Least Square Regression, RCNN; Region-Convolutional Neutral Network, CNN; Convolution Neural Network

Table 2: Artificial Intelligence (AI)-Based Tools Commercially Available for Agriculture

Company	Products	Website
Trace Genomics	This product is a soil analysis system, it uses machine learning and is designed to provide a sense of the soil's strengths and weaknesses	tracegenomics.com
Harvest CROO Robotics	This product is a robot system designed for picking and packing vegetables.	harvestcroorobotics.com
Blue River Technology	The product is a smart farm machine, designed for the management of crops at a plant level and further protecting the crops from weed infestation.	bluerivertechnology.com
AGEYE Technologies	This product was specifically designed for indoor farming and it's an Artificial Intelligence-powered platform.	ageyetech.com
Fasal	This product uses affordable sensors, it's been designed to provide critical parameters to small farmers, central to this technology is Artificial Intelligence.	fasal.co
Vine View	This is the product that has aerial-based spectral sensors. It also has a cloud-based image processing service that is designed to monitor the plant health system. Its aerial-based spectral sensors are highly specialized.	vineview.com
PEAT	This is a product that is designed with a high specialization in image recognition i.e., identifying potential abnormalities and nutrient deficiencies in soils. Central to this product is deep learning.	plantix.net
HelioPas AI	This is a system developed to monitor soil moisture content and regulate the irrigation process. It is also used in the detection and management of mildew and drought.	heliopas.com
aWhere	This is the product that is designed for indoor farming.	awhere.com

	Central to this product is its Artificial Intelligence-powered platform.	
FarmShort	This is the product designed to prescribe variables and carry out integrated scouting for farmers. Its core purpose is based on images captured using drones and satellites.	farmshots.com
Root AI	This is a product that is designed for indoor farmers. Central to this product is its Artificial Intelligence-powered platform that is automated and has robotic solutions.	root-ai.com
Ibex Automation	This is a product with a robust Agric-robotic system that is autonomous. It also has an autonomous system that can detect and spray weeds.	ibexautomation.co.uk

2.2 Machine Learning

The focus of AI research has been ML since the 1970s. Different statistical models have since been developed to aid crop breeding programs, e.g., Bayesian networks, Perceptron, and support vector machines [11]. However, the challenge has been and still is that there is no single framework that works in a better way for all tasks. The determination of the best models for a given problem still poses a challenge. Despite the highlighted challenges in determining statistical models for a given task, ML models and algorithms still receive a wide and comprehensive utilization in plant breeding programs (Table 2). This may be due to the rising and successful establishment of data processing infrastructure, combined with the neutral network's establishment, high-level computational, and abundance of data [12].There have been several gains and achievements made by machine learning in plant breeding programs (Table 1) [13]. Major achievements of machine learning models and algorithms in crop breeding include the exploration of large datasets and further discovering models, that are capable of developing resolutions through the development of patterns that combine features simultaneously unlike the process that analyses the features independently and separately. The step of combining the features simultaneously instead of analyzing them separately used to be a challenge when using traditional processing methods, this may have been due to the high complexity of images of the plants and their huge quantity, which in this case, machine learning models can handle. ML has been effectively applied in the process of identification and classification of diseases that affect crops such as wheat, maize, and soybean, among other tasks [12]. To achieve this, supervised learning has been of help through the training of algorithms with images sampled from a large dataset, and in this way, algorithms can identify and classify plants that are diseased during disease screening [14]. The gains of ML regarding disease identification have been demonstrated in the research byMoshou et al., 2004 [6]. The researchers successfully used ML to automatically detect yellow rust in wheat. Though ML has the strength to detect crop diseases as demonstrated, it has one central weakness, in that, it can prevent the exploration of unexpected and novel traits that less precise unsupervised machines can be able to discover in crops [15].

The establishment, enhancement, and advancement of high-throughput phenotyping that is nondestructive in crop breeding programs have heavily been influenced positively by imaging techniques of ML. Central to this gain is the ability of ML's utilization of multiple imaging sensors that can collect the data of plants in near real-time platforms [16]. These sensors have the capability of collecting huge amounts and volumes of phenotypic data that can easily be handled by ML, since it was built and has been developed to handle big data challenges, such as those experienced when dealing with traditional breeding methods in designing crop genotypes. Large volumes of data (big datasets), still pose a challenge with regard to being sorted out, analyzed, and interpreted when using traditional processing methods but ML models and algorithms have the power to utilize ways and approaches that are effective, faster, and efficient in the process of analyzing the data collected. Through its models and algorithms, has also made some gains in utilizing the tools such as statistics, decision and probability theories, and optimization in the process of extracting features from enormous datasets, thereby creating possibilities by making it easy to identify features in tasks that are complex such as phenotyping of different forms of stress in different crops [17].

3.0 Way forward

With a lot of uncertainty that still covers today's environment due to the ever-changing climatic conditions, there is a need to optimize the utilization of digitalization, as this has a heavy bearing on the designs of breeding methods to be utilized for future plant breeding programs. The strength of artificial intelligence ranges from molecular to organismal scale, with this ability, combined with its capability to characterize complex traits in a very detailed and near real-time manner, AI still presents a ray of hope in designing crop methods that have the potential to bridge the gap between the phenotypic and genotypic traits of diverse crops.

Likewise, inspiteof the gains and achievements made bycrop designing methods using ML models and algorithms, there is a need to still explore ways of making it more effective and efficient to improve the development of climate-smartcrop genotypes. Some of the strong points of MLare its ability to handle large volumes of data (big datasets),creating possibilities for developing and advancingML approaches to a level where a single framework will beable to handle multiple tasks simultaneously and precisely which would otherwise enable futurecrop researchers to create crop designing methods that would have high accuracy, great precision and easy to execute.Furthermore, as feature identification of complex traits,it provides a platform to design cropswith great precision and less time-consuming, and has the potential to reduce breeding cycles of cropsto increase the genetic gains.Below is the chart describing the impact and potential of digital agriculture with a focus on AI and ML and their contribution in optimizing crop genetic improvement if efficiently and effectively used.

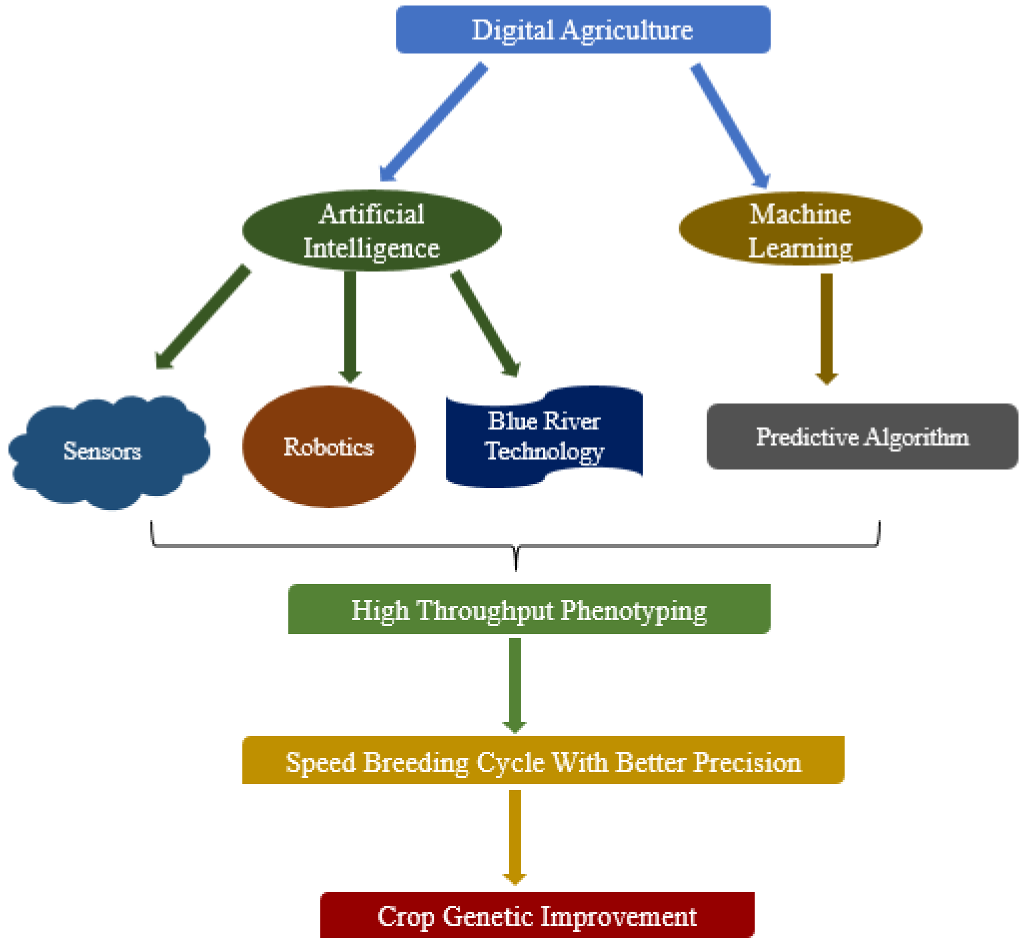

Fig 1: Digital Agriculture for Crop Genetic Improvement

4.0 Conclusion

Innovations that can help us produce food sustainably,more effectively, and efficientlyare no longer a question to be debated. Digital technologies such as AI and ML, present a promising platform for designing methods that have a high potential to make crop production operate at an optimal levelwhere food production is concerned. Moving forward, there is a great need to improve the weaknesses that still exist in AI and ML if the current challenges and future needs are to be addressed. Improving digital technologies would result in an improvement in designing methods of crop production which would consequently increase agricultural production and productivity.

8.0 References

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