

ARTIFICIAL INTELLIGENCE ASSISTED PLANT BREEDING –A WAY TOWARDS CLIMATE RESILIENT FARMING– A REVIEW

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ABSTRACT

The change in global climate pattern with increase in global population which is estimated to extend 2 billion in 2028, are putting pressure on the agriculture production with several constraints due to change in land use pattern, declining soil fertility, biodiversity loss, reduced ground water which reduces crop yield affecting global food supply. These challenges could be overcome by adopting advanced technologies coupled with sustainable solutions that are innovative. Therefore farmer's decision making capabilities can be improved by using predictive models that involve digital and data driven technologies by enhancing efficiency with growing output with minimum input resources. This review explores the capabilities of algorithms of artificial intelligence used to accelerate genomic selection, unlock genetic diversity, allow precise gene editing, and predict effects of variants at gene level on plant phenotype development. Therefore enhance the efficiency of crop improvement program by accelerating the creation and production of smart resilient and sustainable cultivars to the projected future environments.

KEYWORDS: Artificial Intelligence, machine learning, Climate resilient, crop improvement, sustainability

1. INTRODUCTION

Various challenges affecting crop production can be addressed by improving concerned traits of interest (Alotaibi *et al.*, 2023). Such improvement in crops will be done by considering observation at gene level, at phenotypic level and genotypic x interaction data. These observations are utilized for crop improvement via gene editing and epigenetic engineering. Several approaches like linkage mapping and genome-wide association studies are frequently utilized other methods include genomic selection, biometric analysis etc. (Washburn *et al.*, 2021, Jubair *et al.*, 2023). With the advancement of next generation sequencing techniques and availability of vast array of DNA markers, it becomes possible to investigate their impacts in relation to the quantity of variants and their role in trait variability across particular environments (Oliveira *et al.*, 2025). This knowledge can then be applied using CRISPR and mutagenesis in forward and reverse genetics. When population structure got changed by changing their gene frequency the success depends upon accurate phenotyping and selection according to (Chawade *et al.*, 2019). Therefore, accuracy of phenotyping and efficiency of selection depends on frequency of favourable allele. Further with the help of omic approaches along with AI and Machine learning the efficiency of methods of plant breeding can be enhanced (Resende *et al.*, 2022). Several tools are available to detect changes at phenotypic level but they are time consuming and costly. Therefore crop response linked with genotypes can be detected by linking high throughput remote sensing methods for making effective decision. As the need of the hour is the utilization of integrated approach in agriculture system that can maximize output with minimum inputs and cost of production. This can be achieved by collaborating agronomic practices, breeding with advanced technologies like sensors for sowing and spraying, use of robotics for detection and management of weeds, germplasm selection, for evaluation of physiological and photosynthetic efficiency (Thilakarathne *et al.*, 2025, Zou *et al.*, 2022, Sparrow *et al.*, 2021, Fu *et al.*, 2022, Inoue *et al.*, 2008). Further due to climate change the availability of water is unpredictable and is of huge concern affecting the crop production severely (Muzammal *et al.*, 2024). The assessment of phenotypic characters in large plant population through unmanned aerial vehicles is of huge importance as it detects variation in plant growth, resistance to diseases, response towards stress

condition which play an important aspect in accelerating plant breeding objectives. Further remote sensing assisted with machine learning and artificial intelligence algorithms help in the effective handling of large heterogeneous data as compared to done by conventional crop improvement methods can be analyzed effectively data can be analyzed (Singh *et al.*, 2016, Mahato *et al.*, 2025).

2. Smart Farming

Farming efficiency can be enhanced by adopting smart farming approach which rely on information technology. By making use of smart sensors, algorithms, robotics, analysed data using AI and machine learning it facilitates precision agriculture it collects multi spectral and thermal images using automation and drones and represents Third Green Agricultural Revolution (Assimakopoulos *et al.*, 2025). Machine learning identifies, quantifies and predicts challenges in the development cycle by increasing accuracy and problem solving approach. Algorithms in machine learning learn patterns extracting from data without being clearly programmed. The application of models of machine learning in agriculture allows decision based on data analysis. Like when data generated through sensors are analyzed using tools of Machine learning allows efficient decision or individual plant selection in the field. This helps farmers or researchers to modify his intercultural operations as per the site specific condition (Ghosh, *et al.*, 2025).

3. Plant Proximal Phenotyping, UAVs, and Satellite Imaging

3.1. Satellite Imaging and GIS

In agriculture remote sensing technology has been widely used to monitor agriculture activities, to observe land and water resources (Tatem *et al.*, 2008). In order to examine vegetation dynamics Geographic Information Systems proves to be a valuable tool that makes effective decisions by using observation collected from satellites, aircrafts and aerial vehicles. In addition to photo-interpretation, Geographical Information system made easier to update and modify plot boundaries and reclassify land occupation within a nation. Based on the data gathered from these resources, these initiatives help governments provide farmers with equitable subsidies (Badola *et al.*, 2019, Raihan *et al.*, 2023). This allows government agencies to provide honest subsidies to farmers on the basis of information obtained from these sources (Trivedi *et al.*, 2022). Because of their resolution power images from satellite helps to understand the impacts of changes in larger areas where utilization restriction are not a problem. Several agricultural operations have become more efficient because to the use of satellite photography. Table 2 indicates several resolution system used in agriculture for phenotyping.

Table 2: Application of High resolution satellite systems used in different crops for phenotyping (Oliveira *et al.*, 2025).

Application	Crop Used
To map leaf area index	<i>Bambusoideae and Vitis vinifera</i>
Yield prediction and monitoring	<i>Gossypium hirsutum, Helianthus annuus, Zea maize and Triticum aestivum</i>
Disease identification	<i>Triticum aestivum and Oryza sativa</i>
Observation of agronomic characters, fertilizer quantification and identification of protein content	<i>Hordeum vulgare, Zea maize and Triticum aestivum</i>

3.2 Proximal and UAV-Based Phenotyping

Satellite sensors not able to evaluate efficiently when there are more than thousands of genotypes. In that case use of unmanned aerial systems is of great choice that increases phenotyping frequency (Trivedi *et al.*, 2022). This technique is rapidly utilized in plant breeding programme and are of great advantage over satellite imaging which is affected by environmental factors like cloud coverage and spatial resolution. Different types of Unmanned aerial vehicles have been reported to use in different crops in crop improvement programmes as indicated in Table 2. In some cases effective pest monitoring and management has been done using drones with single propeller in association with techniques of machine learning (Duarte *et al.*, 2021). In order to gather data from the visual and thermal ranges, stress responsive sensors are installed in the ground and helpful in collecting observation regarding nitrogen and plant chlorophyll content, leaf area index, height of plant, date of maturity and occurrence of pest and diseases (Jin *et al.*, 2021). Mobile platforms as compared to hand held sensors analyse multiple characters thereby reducing time, cost and labour. However, technical expertise may still be necessary to achieve the greatest outcomes. An precise yield forecast of productivity with 70% accuracy in case of wheat has been reported when phenotype data are collected precisely (Rutkoski, *et al.*, 2021). Several devices like robot Oz for mechanical weeding, GUSS an automated sprayer for spraying help in effective identification and removal of weeds thereby reducing reliance on herbicides by farmers.

Table 2. Application of unmanned aerial Vehicles in different crop phenotyping (Oliveira *et al.*, 2025).

Application	Crop Used
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Determination of stage of plant growth	<i>Bambusoideae, Gossypium hirsutum,</i>
Evaluate morphological characters	<i>Hordeum vulgare, Zea maize</i>
Predict crop yield	<i>Hordeum vulgare, Zea maize, Gossypium hirsutum, Triticum aestivum, Oryza sativa, Saccharum officinarum</i>
Monitoring and evaluation of crop phenotype and stress response	<i>Saccharum officinarum, Zea maize, Triticum aestivum, Brassica napus</i>
Disease detection	<i>Gossypium hirsutum, Triticum aestivum, Musa paradisiaca</i>
Scheduling of Irrigation	Fruit trees
Flower opening	Lettuce
Estimating nitrogen	<i>Glycine max, Saccharum officinarum Triticum aestivum</i>

3.3 Precision and Comprehensive Farming

Despite appearing to have separate objectives, selection based on phenotype in precision and comprehensive farming really converge toward the same aim through various methods. Here phenotypic selection is done by systematic measurement and analysis of plant characters consideration interaction between genotype and environment while in comprehensive farming phenotypic selection is based on ideal condition, crop adaptability to get maximum yield (Chawade *et al.*, 2019). Both strategies have different goals, even though increasing agricultural productivity while lowering production costs is their ultimate goal. While precision agricultural phenotyping seeks to guarantee constant performance under varied or stressful settings, comprehensive farming aims to identify those traits that perform well in ideal condition. In order to achieve maximum economic return data should be integrated from phenotyping, genotyping, meteorological observations remote sensing using decision support platforms system. This would help farmers for making efficient decision related to farming. To enhance integration of data and decisions cost effective UAV data can be connected with international satellite remote sensing databases. Additionally, integrating observations from Unmanned Ground Vehicles (UGVs) and UAVs helps improve decision-making.

4. Identification of Loci linked with agronomic characters assisted through AI based satellite imaging and Phenotyping based on genetic algorithm

4.2 Basic fundamentals of Genetic Algorithm

For acquiring cost effective, efficient and long lasting computer based system designed to support farmers for making good agricultural decision machine learning, vehicles found to be a most trusted tool (Debangshi *et al.*, 2023). Numerous evolutionary algorithm based on single and multiple populations such as the genetic algorithm (GA) techniques, have been presented in the field of artificial intelligence (Fleming, *et al.*, 2019). Gas and classic algorithms vary in that the former use a predetermined set of criteria and logics to reach a particular solution. As a result, these are more general and might be used to describe typical algorithms that are unrelated to evolutionary principles and address everyday problems like sorting and searching. By including search fine-tuning methods like selection, crossover, and mutation, GAs aim to enhance techniques that solve problems which are depend on natural genotype selection (Alhijawi *et al.*, 2024). Genetic algorithm makes use of genetics and natural selection while crossing over and mutation explores all set of possible configuration less fit individuals are kept. Selection operates by promoting superior individuals for reproduction and eliminating inferior individuals (Singh, *et al.*, 2015). If the population become to identical individuals with less fitness are remain in the population to maintain genetic diversity. In some circumstances it is important to stop local optima if the removed individuals have good phenotype (Pandey *et al.*, Genetic algorithm identify different niches under niching technique (Li *et al.*, 2005). Therefore these algorithms utilized in problems related to optimization where chromosome population encodes solutions.

4.3 Phenotyping Based on UAV and Remote Sensing

AI technology and Remote sensing depends on characteristics of radiations captured and target object. The physical and chemical information included in this radiation or reflectance is closely linked to several bonds like oxygen-hydrogen, nitrogen-hydrogen and carbon-hydrogen (Qu *et al.*, 2015). In order to compute spectral indices using algorithms, the ultimate outcome is a unique way a particular material reflect light. The pixel intensity value can be converted into genetic algorithm to identify optimal function to find out the weight of each character observed by satellite imaging. Genetic algorithm alleles present in the individual within a population. The individual that perform best in specific environmental condition are selected as a parental line. Thereby creating new gene combinations in every generations. The outcome of algorithm using spectral indices is the specific signature of reflected light. In order to identify the actual function each image pixel spectrum values are diverted into genetic algorithm for determining weight to every trait analyzed using satellite or UAV (Costa *et al.*, 2020).

5. Application of AI in plant breeding

5.1 Generation of Genomic Data by germplasm characterization using AI

High-throughput developments in plant "omics" and remote sensing have given scientists access to sizable multi-dimensional datasets for problem-solving. It has been observed that by using machine learning algorithms in different plant breeding techniques like in selection and marker assisted selection the assessment of genetic variability and development of smart cultivars can be increased. These machine learning methods also help in accelerating the breeding program for the development of climate resistant varieties. The base of genetic gain in a plant population is the presence of genetic variability. Still the 7 million germplasm accessions present in genebanks containing landraces, wild relatives and cultivars are not being explored. Therefore genome-wide genotyping of these germplasm resources is the only valuable tool to utilize these germplasm using genebank genomics (Mohsen *et al.*, 2024). For wheat, maize and barley accessions genome-wide genotyping data has been developed that form the basis of selection of targets involving AI-driven predictive genomics in a particular environment. This involves development of reference genome that is used for comparison of individual within a species. This will help in identification and mapping of allelic mutation and enhance the breeding efficiency.

5.2 Digital phenotyping

Although data collected from observable traits are crucial for crop breeding, there are several obstacles that prevent their full use. Because of their restricted ability to collect data, conventional plant phenotyping techniques observed as a crop breeding obstruction. However, this paradigm has fundamentally changed with the advent of plant phenomics (François *et al.*, 2017). Plant phenomics, which methodically examines phenotypes, has the potential to get over these restrictions. Phenomic platforms with cutting-edge imaging sensors could transform extensive phenotyping of several plant characteristics and environmental factors. Both stationary and mobile sensors may be used by these platforms. Several tools like use of digital cameras placed on phenotyping tower reported to monitor growth, content of nitrogen, leaf area index and rice bug prevalence in rice but its drawback is it provide information only within specified location (Tokihiko *et al.*, 2012). Further 3D phenotyping platform are now available that 3 dimensional data of plant, leaf structure and leaf temperature. Detectors are mounted by hands on pushed carts to overcome field coverage constraints. Using a phenocart with a variety of sensors, these platforms have effectively recorded canopy characteristics for wheat and soybeans, including plant height, temperature, reflectance spectra, remote sensing metric and red-green-blue (RGB) images. However, imaging platforms in open spaces can be affected by a number of environmental conditions, including light intensity.

5.3 AI-powered forecasts to interpret genetic data

Several research have shown how AI may be used to evaluate biochemical data and improve our knowledge of plant response to environmental challenges. For example, successful utilization of AI to locate specific DNA sequence that display high rate of mutation in maize by predicting paternal and maternal genetic crossing. Similarly AI has also been used to distinguish pseudogenes and functional genes on the basis of DNA methylation pattern in maize subjected to stress condition (Sartor *et al.*, 2019). Likewise in *Arabidopsis thaliana* and maize gene expression associated with promoter gene and cis regulatory elements are predicted by using AI algorithms (Sahra *et al.*, 2019). AI has been effectively utilized to demonstrate biosynthetic genes regulating starch biosynthesis and nitrogen use efficiency in *A. thaliana* (Li *et al.*, 2020). In a similar vein, (Meena *et al.*, 2019). enhanced biomass production using AI by employing a range varieties of plants and algal blooms to increase biofuel production. With the rapid advancement of sequencing technology, long-read sequencing has become the most used technique in crop breeding. Compared to short-read sequencing, this approach has the benefit of getting more variation in structure and data of haplotype, but it also increases mistakes and complicates variant identification. Techniques based on deep learning are put forward to improve the precision and effectiveness of identifying genetic variants through computational process. DL is distinguished by its capacity to extract significant patterns from complex data. These techniques proved to have excellent performance as compared to current tools and enable the discovery of novel variants in those regions of genome which are difficult to map by making use of haplotype-aware modeling to hold composite data in long reads and reduces the impact of error (Shafin *et al.*, 2021). The fact that these instruments are mostly trained on human somatic cells is a major disadvantage. For usage in agricultural plants, the detected variant calling needs to be thoroughly revised. The high accuracy of variant calling will improve the selection efficiency of genome as well as marker assisted selection thereby making effective decision by the plant breeder. The identification of insertion/deletion variants and single nucleotide polymorphisms through second and third-generation sequencing is very difficult. An developing answer to this problem is artificial neural networks, or ANNs. Lately, a CNN (Luo *et al.*, 2019). introduced a technique called Clairvoyante to predict zygosity, indel length, and SNP or indel variants using long-read alignments. Using information from Oxford Nanopore, PacBio, and Illumina sequencing systems, they assessed Clairvoyante, concentrating on identifying common variant locations.

Table 3 AI enabled Techniques used in Crop improvement (Muhammad *et al.*, 2024).

Area	Species	Algorithm used	Application
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High-throughput phenotyping	Universal	Supervised deep learning	Minimize the amount of manual labeling Boost measurement accuracy
Integration of data from different omic sets	Universal	Neural networks with autoencoders	Create a plan for using multi-omic data in Deep Learning techniques.
Variant calling	Universal	Deep learning	Creation of quick and accurate variant calling instruments
Functional prediction and gene discovery	<i>Spartina alterniflora</i>	Deep learning	Finding potential genes that underlie particular biological processes
Genomic forecasting	Universal	Deep learning	Achieve better results using multi-omic data
Detection of transposon	Universal	Deep learning	Finding transposable elements
Enhancing genome-editing instruments	Universal	Deep learning	Finding or improving the function of proteins

5.4 AI- assisted integration of multi-omic data

Omic encompasses data generated from different sources like genomics, transcriptomics, proteomics, metabolomics and ionomics. In order to access this data by researchers it need to be gather at some platform because data generated by different omic approaches are comprehensive and invaluable to researchers in bioinformatics. So inorder to combined these all data for interpretation. Machine learning approach found to be a valuable to handle such large size and complex dataset. Besides chromatin immunoprecipitation and RNA sequencing technique for expression of genotype, a number of profiling techniques have also advanced within each omic technology. We now have unprecedented opportunities to understand the fundamental biological basis of phenotypic diversity on systems biology exploring single genetic element to regulatory networks. However, incorporation of observation from different source and linked them to environmental responses and accurately modeling the entire system remain difficult tasks for accelerating crop development. ML has been useful in identifying different kinds of genomic areas, for example. For example, an ML model trained on DNA methylation characteristics can distinguish between live genes and dead pseudogenes in maize (Sartor *et al.*, 2019). To forecast the likelihood of a crossover along a chromosome, an ML-based technique has also been devised (Demirci *et al.*, 2018). Furthermore, ML is beginning to be used in population genetics, but primarily in humans (Tobias *et al.*, 2018). Using machine learning complete fixation of mutation conserved during natural selection in plants was reported (Yann Bourgeois *et al.*, 2018). Therefore it proves that how helpful is machine learning approach in predicting function of a genome (Yip *et al.*, 2013).

5.5 Bridging the genotype-phenotype gap with AI

The use of AI for accurate, non-destructive agricultural trait estimate and genetic research has gained popularity. Genetic advancements through the discovery of new alleles and genomic assisted selection are important in the development climate resilient high yielding cultivars. Several scientist have successfully employed hyperspectral and RGB datasets AI-based techniques to project yield and genetic analysis of quantitative traits in wheat (Li *et al.*, 2023). Enhanced Precision and idea of Faster R-CNN model was reported by employing auto matic spike-counting system using quantitative genetic analysis with RGB images (Lei *et al.*, 2022). Using Deep learning based identification of sudden death syndrome (SDS) in soybean via genome-wide association studies addressed the importance of accurate disease screening for the development of disease-resistant cultivars and found significant SNPs close to potential SDS genes. Multimodel based deep learning algorithms were used to predict wheat yield by using support vector regression for phenotypic observations (López *et al.*, 2014). Therefore omics assisted with AI will help in accelerating the efficiency of crop improvement programme and develop climate resilient crop.

5.6 AI-based gene mining and functional genomics

By making use of function of a specific gene or by analyzing protein interaction, mixing gene annotation with sequence variation several genes related to agronomic traits have been identified using all the mention machine learning approaches. For example researchers have explained how genes linked with metabolism have identified in less characterized species by employing information from well annotated species (Lin *et al.*, 2019) demonstrated that in case of rice and *Arabidopsis thaliana* transcription factors help in identifying genes associated with specific traits in these species. Similarly DNA sequence and shape are predictive for crossover frequency in certain crop species like in rice, maize, tomato and *A. thaliana* (Demirci *et al.*, 2018). Genes associated with abiotic stress tolerance also identified using techniques of machine learning (Huang *et al.*, 2024). Testable hypothesis on identification of candidate genes, genomic regions are created using data obtained from

models of machine learning. 16 *Spartina alterniflora* (Sa)HKT genes were detected by (Yang *et al.*, 2023) expressing different patterns and K⁺ ion transport linked with tolerance to salt by employing deep learning algorithm. Co-evolutionary information about genes is being utilized in machine learning to identify genes associated with salt stress (Shang *et al.*, 2023). These studies help in the identification of over-represented set of specific genes associated with ion transporters and detoxification pathway. These studies provide insights into functional genomics and mechanism of salt tolerance in *S. alterniflora*'s by interpreting the mechanism at molecular level. And explained how helpful is deep learning and machine learning approach in identifying important genes involved in providing tolerance to abiotic stress in plants.

5.7 Gene editing assisted with AI

Plant breeding approaches involving hybridization to modern breeding approaches including mutation breeding, recombinant DNA technology have proved as a valuable tool for developing high yielding and improved quality cultivars. However they face several disadvantage like screening require more time, high randomness, frequency of precision is low and extended breeding cycle (Labroo *et al.*, 2021). The advancement of genome sequencing technology has enhanced the efficiency of molecular breeding procedures and gained popularity among plant breeders. Similarly several varieties developed using CRISPR/Cas9 technology provide advancement in improving quality parameters in crop (Wang *et al.*, 2021). Further the progress in breeding approaches accelerated by gene editing technology where several site directed nucleases like homing endonucleases (HEs), mega-nucleases (MNs), zinc-finger nucleases (ZFNs), transcription activator-like effector nucleases (TALENs), and CRISPR/Cas9– played an important role. Homing endonuclease and mega nuclease target large sequence of DNA but fail to identify the target sites (Rasheed *et al.*, 2021). As compare to homing and mega nucleases zinc finger nucleases make use of zinc ion to allow selective DNA binding. Likewise both FokI DNA cleavage domain and TALE module ZFNs, combined to make more effective domain TALEN (Christian *et al.*, 2010). In order to characterize protein structure and function Alpha Fold 2 proved to be a effective AI tool in predicting protein structure and function (Jumper *et al.*, 2021). Gene editing through AI has opened advancement in crop improvement by developing ideal plant type. Successful utilization of AlphaFold2 in revealing new cluster of deaminases enzymes which was utilized to develop base editors of high efficiency (Huang *et al.*, 2023). Recently OpenCRISPR-1 first de novo gene editor was designed that opened a new beginning for producing designer proteins (Ruffolo *et al.*, 2024). Improved efficiency and precision during genetic modifications achieved by developing genome editors with compact structures. This will be done more precisely by using AI tools. Different approaches used to predict protein structures are helpful in redesigning proteins with important agronomic functions. However it require expertise for protein optimization but AI driven protein engineering will help in developing designer crops with protein of interest leads to future crop improvement.

6. CONCLUSION

Plant breeding projects in the public sector, such those run by the One CGIAR (Consultative Group for International Agricultural Research) program, could undergo a revolution thanks to AI technologies. These kinds of data-driven decentralized breeding strategies can forecast crop performance more accurately than traditional GS (de Sousa *et al.*, 2021). Ai- driven plant breeding procedures using sophisticated methods for analysis thereby accelerating the process of crop improvement. AI approaches well demonstrated in discovering specific genes and in mining allele but their role in developing resilient cultivars that perform well in specific environmental condition is a challenge. Further problems are characterization of genetic diversity from gene banks for a particular condition to intro-gress new traits without introducing undesirable genes. Similarly the availability of experts that can use the AI assisted computational breeding tools is another concern. Provide training to plant breeders on AI tools and techniques and constructing cyber infrastructure inspite of data islands. Prediction of suitable cropping pattern and system by integrating data from different platforms like by using sensors, UAV platform under different genotype, environment and management condition are possible (Jung *et al.*, 2021). Therefore the required rate of genetic gain can be achieved by assisting plant breeding with artificial intelligence which will serve as a promising tool to meet the demand of food and nutritional security in the upcoming decade globally.

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Conflict of Interest

There is no conflict of interest to declare.

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