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Title: **Predictive Artificial Intelligence for Climate-Resilient Crop Breeding: Integrating Genomics, Phenomics, and Climate Modeling**

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Predictive Artificial Intelligence for Climate-Resilient Crop Breeding: Integrating Genomics, Phenomics, and Climate Modeling

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ABSTRACT

Global food security is increasingly threatened by climate change, which intensifies both biotic and abiotic stresses on crops, leading to reduced yield stability and productivity. Conventional breeding approaches are insufficient to address these challenges due to long breeding cycles, strong genotype–environment interactions, and limited capacity to predict crop performance under future climate scenarios. Predictive artificial intelligence (AI) offers a powerful solution by integrating genomics, phenomics, environmental, and climate data to model complex traits, stress tolerance, and genotype performance across diverse agroecological conditions. This review synthesized recent advances in Machine Learning (ML), Deep Learning (DL), genomic prediction, high-throughput phenotyping, and climate modeling that collectively support the development of climate-resilient crop varieties. The application of predictive AI in plant breeding enhances selection accuracy, accelerates breeding decisions, reduces dependency on costly and time-consuming field trials, as well as improves resource-use efficiency. By enabling data-driven decision-making, AI-based approaches significantly improve the precision and scalability of modern crop improvement programs. Looking ahead, the integration of predictive AI with explainable modeling frameworks, multi-omics datasets, and genome-editing technologies holds significant promise for accelerating the development of high-yielding, resilient, and sustainable crops, thereby contributing to long-term food security under changing climatic conditions.

Keywords: climate resilient crops, crop breeding, genome prediction, machine learning, phenomics, predictive artificial intelligence

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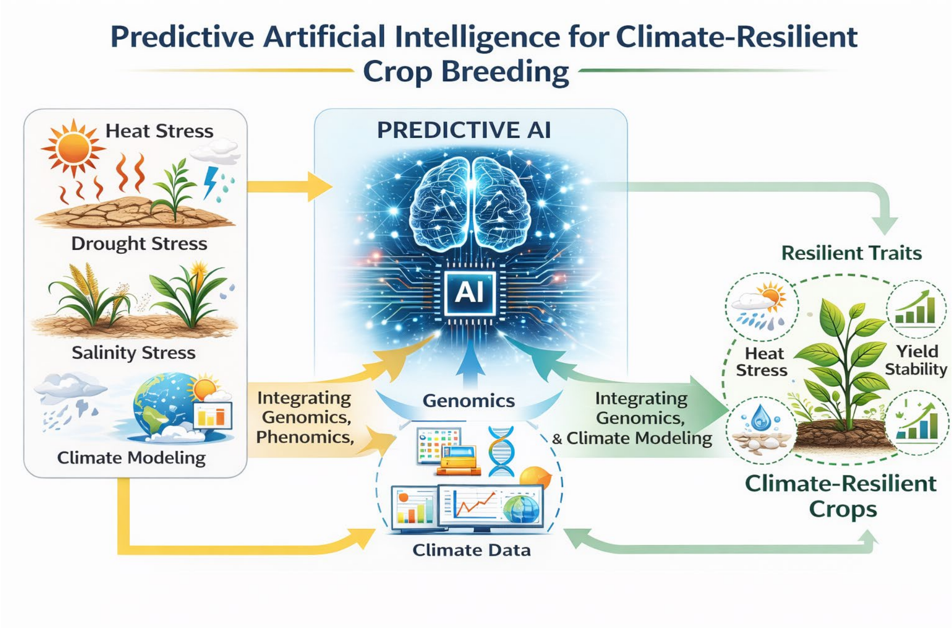
GRAPHICAL ABSTRACT



1. INTRODUCTION

Climate change is one of the major threats to global food security as increasing temperature, erratic rainfall, and degradation of soils decrease yields [1]. The agriculture sector needs to adapt even faster to unprecedented volatility of the environment with more frequent heat waves and drought conditions [2]. Several staple crops (e.g., maize, rice, and wheat) have shown yield reductions in different regions of the world due to climate stress [3]. These challenges necessitate the development of novel breeding strategies [4]. Given the protracted nature of multi-season trial work and modern environmental stress complexity, conventional plant breeding only simply cannot keep leap with the more rapid pace of climate change [5]. Growing climate variability exposes a considerable uncertainty in the interaction of genotype × environment, which highlights even greater complexity to the breeding decision making processes [6]. Predictive AI provides many new tools to overcome these limitations by simulating future environmental conditions and predicting the performance of a genotype in those projected conditions [7]. In summary, AI technologies have now been embraced as an important driving change in climate resilient crop breeding [8].

Presently, most of the literature available on these technologies is about using AI, genomics, or phenotyping in agriculture separately [7,8]. Furthermore, there is inadequate literature available as to how these technologies work together to create an overall framework for combining predictive AI with genomics, phenomics and global warming responsive breeding strategies [8]. The current study aimed to fill this gap by summarizing and critically analyzing what has recently been learned. Moreover, the study also described methodologies and explored applications of AI-assisted climate-resilient crop breeding [6,8].

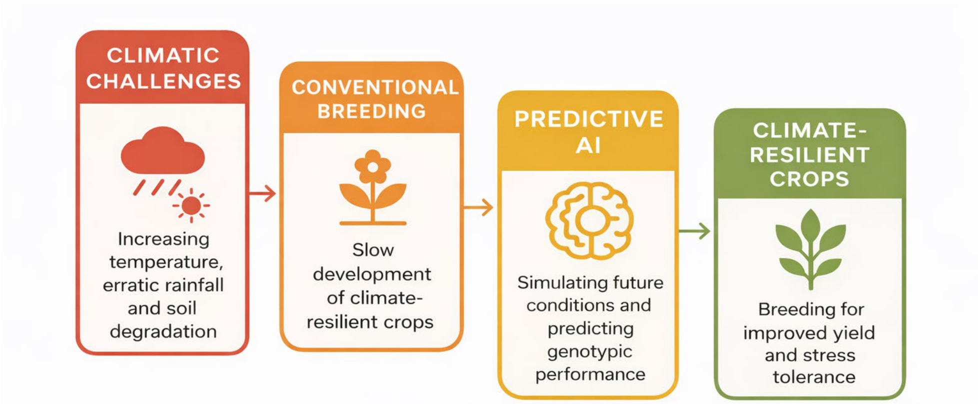


Figure 1. Systematic Approach of Predictive AI Crop Breeding

Climate stressors (heat, drought, and climate variability) are combined with genomic, phenomic, and climate data and analyzed by AI models in order to predict genotype performance and to assist in the development of crops that can withstand extreme climatic conditions.

2. PREDICTIVE AI IN CLIMATE-RESILIENT BREEDING

2.1. What is predictive AI?

Predictive AI can be defined through Machine Learning (ML), Deep Learning (DL), and statistical models that predict future events using diverse complex datasets [9]. In connection to agricultural production, predictive AI applies genomic, phenomic, climatic, and environmental factors to predict the performance of crops when planted under future stresses [10]. Predictive AI learns on its own using large data sets and finds undiscoverable hidden nonlinear relationships compared to manual approaches unlike rule-based systems [11]. The relevance to plant breeding is that predictors can provide performance predictions of genotypes with a high degree of precision across an array of climates [12]. AI can also predict breeding values, find optimal parental combinations, and simulate crop performance over the long-term under various climate scenarios [13]. Predictive AI effectively translates static breeding decisions into dynamic climate-informed breeding strategies [14].

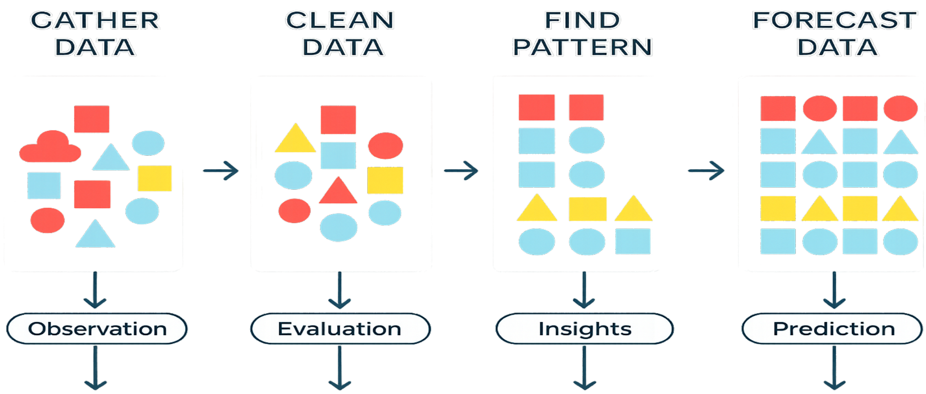


Figure 3. Image Represents the Data Analytics Pipeline, with the Process Involving Collecting, Cleaning, Identifying, and Predicting Patterns Based Upon the Data

The diagram shows the transformation of the raw data to create evidence-based predictions through statistical and ML methods, allowing for informed decisions.

2.2. Climate Challenges in Agriculture

Global warming is leading towards rising temperatures. This process tends to decrease crop productivity by impeding pollen viability, modifying grain filling, and raising plant respiration [15]. Heat stress has been known to reduce the crop yield especially of sensitive crops such as rice or wheat. Due to this reason, crops become productively inefficient when subjected to heat upsurge [16]. Heat waves interfere with phenology and also reduce the developmental cycles [17].

Drought stress is considered to be one of the most devastating limitations in the world agriculture, fleeting root growth, decreasing water-use efficiency, and senescence acceleration [18]. Salinity stresses affect approximately 20 % of the irrigated agricultural area leading towards ion toxicity and poor germination [19]. Climate change improves the movement of pests and pathogens, which prolongs the risk of disease outbreaks [20].

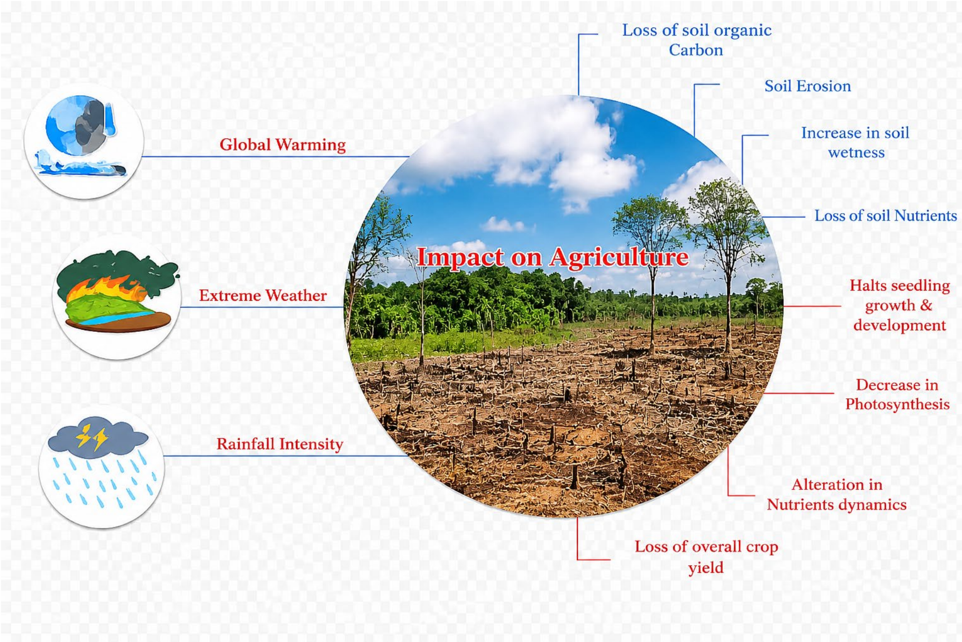


Figure 4. Effects of Climate Change

Figure illustrating how climate change affects agriculture through increased temperature, altered precipitation, and extreme weather events, leading to soil degradation, reduced plant growth, and lower crop productivity [21].

2.3. Limitations of Traditional Breeding

Conventional breeding is a process that requires 10 - 15 years, not mentioning that it may require even more. This timeframe is no longer sufficient under current climatic conditions [22]. Every cycle of selection would take numerous renewals of field testing over a variety of locations and seasons. Although this is highly scientifically true, it can easily turn out to be quiet costly and could possible slow down the speed at which a particular new variety may reach farmers [23]. Moreover, there are limited financial and human resources in many breeding programs, which might also add to the issue of attempting to move at the rate they have to [24].

Another added complication is field phenotyping, also labor-intensive, usually repetitive, and even where the best efforts have been made by the researchers, human judgment may not be consistent enough so that the same trait is measured slightly different by one individual to another, or in successive seasons [25]. Consequently, measurements such as plant height, canopy temperature, disease severity scores, and yield-related traits may vary between observers and across seasons, reducing data reliability [22, 25]. Furthermore, another problem is animal breeding since it is performed traditionally [23, 24]. This process does not actually genomic information with climate or environmental information in any significant sense, despite the fact that the latter two aspects of information could significantly enhance the strength of the selection decision [26]. Predictive AI assists in bridging this gap by combining all these datasets. Moreover, it also provides slightly quicker and enhanced evidence-based recommendations capable of assisting breeders in making improved choices in a shorter period of time [27].

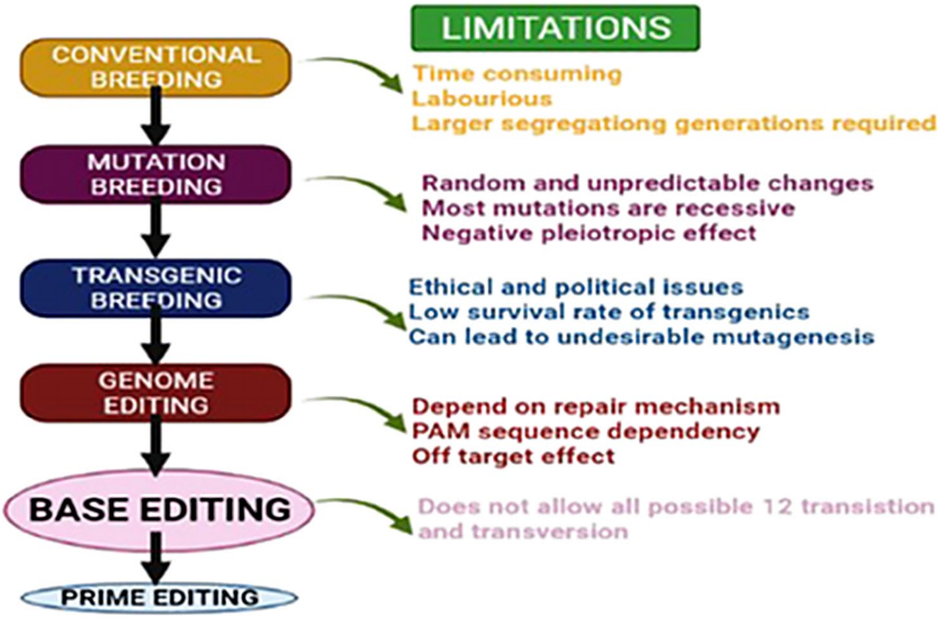


Figure 5. Plant Breeding

Advancement of plant breeding techniques has allowed for greater precision in crop improvement than traditional or mutation-based approaches. Additionally, many of these advanced techniques come with ongoing challenges including the occurrence of off-target effects and limited repair ability [28].

2.4. Comparison: Conventional Breeding vs. AI-Driven Breeding Gains

Table 1. Comparison of Conventional and AI-assisted Methods for Crop Breeding Considering Climate Change

Aspect	Conventional Breeding	AI-Driven Breeding	References
Breeding cycle duration	Requires multiple seasons of field trials, leading to longer breeding cycles	Uses predictive models for early genotype evaluation, reducing breeding time	[26]
Selection approach	Based mainly on phenotypic selection and manual assessment	Combines genomic, phenomic, and environmental data through AI models	[10]
G×E interaction analysis	Limited ability to analyze complex genotype × environment interactions	ML effectively captures complex non-linear G×E interactions	[20]
Cost and resource use	High labor, land, and field trial costs	Reduces large-scale trial dependence and resource requirements	[9,10]
Climate change prediction	Limited prediction under future climate conditions	Simulates crop performance under diverse climate scenarios	[9]
Genetic gain	Slow and gradual genetic improvement	Faster and more accurate genetic gains through optimized selection	[10]

2.5. Role of Predictive AI in Modern Breeding

Predictive AI is becoming more of a staple among breeders [29]. This is because it has the potential to unite the data provided by genomics, field observations, and environmental data to indicate the most promising genotypes in a specific environment [30, 31]. Instead of handling these streams of information separately, the AI combines them together. This makes the prediction by the AI considerably valuable in a realistic breeding setting. Its main advantage is that it can allow writing a freer manifestation of response of different genotypes to tendencies of various environmental conditions. This thereby, aids a scientist to arrive at a better choice over parent lines and modes of choice based on actual facts rather than a sense alone [31]. Predictive AI does not merely increase the breeding procedure, however, it predicts with higher likelihood in each decision to create climate-resilient cultivars in a considerably reduced time [31].

Predictive models now contribute to hybrid prediction, trait scoring, stress detection, and even the optimization of resource use by breeders themselves [32]. A DL system, for instance, can identify minor changes in the color of leaves, canopy temperature, or growth habits indicative of drought, heat, or disease tolerance-easy to miss by the human eye, let alone over several thousand plants [33]. High-resolution information for such traits would help to significantly improve breeding efficiency and limit the reliance on slow and expensive field trials [34].

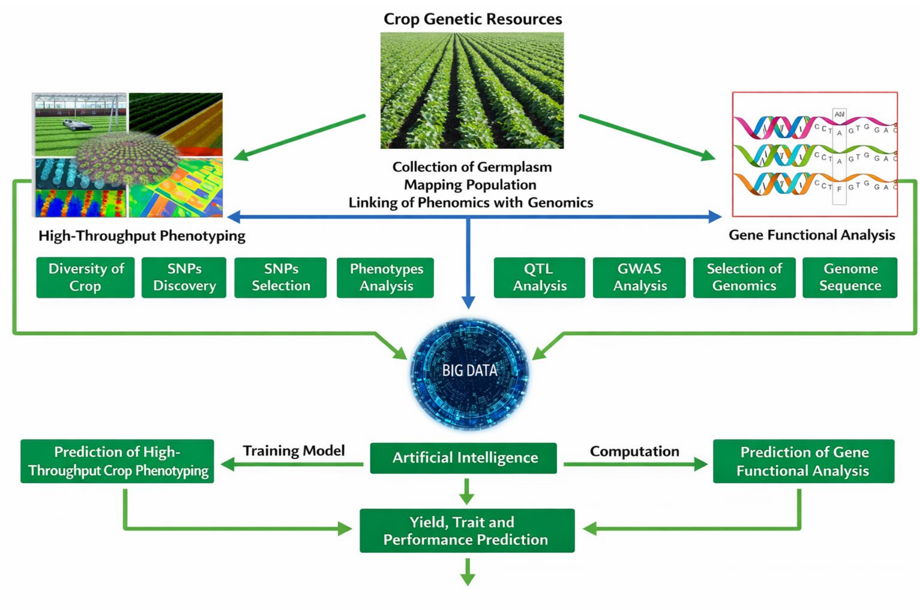


Figure 6. Farming Technologies

Methodology, based on farming technologies, incorporating genetic data, phenotypic measurements, and functional genomic methodologies. This result in prediction models which would allow breeders to find out as to increase yields, resist environmental stresses, and improve climate-resilient crops through data analysis and predictive modeling of how a given gene and trait might perform in a given environmental context [8].

3. DATA, METHODS AND APPLICATIONS

3.1. AI Methods and Technologies

ML frameworks, such as scikit-learn and related algorithms including Random Forest (RF), Support Vector Machine (SVM), and eXtreme Gradient Boosting (XGBoost) are providing support for genomic prediction [35]. The last few years have seen a massive increase in the utility of the phenotypic data gathered through drones, hyperspectral sensors, and other field-based imaging devices. This is because it has become possible to process such data through advanced DL frameworks, such as TensorFlow, PyTorch, and Keras [36,37]. These systems enable researchers to recognize early signs of plant stress at unprecedented speed and make predictions on how crops might perform under future conditions [8].

Table 2. AI Tools and Uses in Development of Climate Resilient Crops

AI Tool / Platform	Methodology / Use in Crop Breeding
PyTorch	DL models (CNN, LSTM) for genomic and phenotypic prediction
TensorFlow / Keras	Neural networks for trait prediction, disease detection, and yield forecasting
Scikit-learn	ML models (RF, SVM, Gradient Boosting) for genomic selection and stress prediction
Google Earth Engine	Satellite and climate data processing for environmental and crop modeling
PlantCV	Computer vision-based phenotyping for plant traits and stress detection
DroneDeploy / Pix4D	Drone-based high-throughput field phenotyping and crop monitoring
IBM Watson Studio	Big data analytics and predictive modeling for climate-resilient crop selection
QGIS + AI plugins	Spatial analysis of crop–environment interactions and geographic modeling

On a more global scale, remote-sensing resources such as Google Earth Engine provide continuous climate and vegetation information. This makes them invaluable for studies focused on climate-resilient breeding [38]. Agricultural data collected on a large scale using these platforms can then be stored, juxtaposed, and modeled within integrated analytics models, such as IBM Watson Studio or Azure ML [39]. Collectively, such a set of sensing technologies, AI systems and data-processing environments constitute a living ecosystem that is progressively supporting much of contemporary crop-breeding studies [40].

3.2. Data Sources for Predictive AI

Predictive AI models rely on genomic markers, including SNPs, whole-genome sequences, and gene annotation datasets [41]. Phenomics data includes RGB, thermal, infrared, LiDAR, and Hyperspectral imaging [42,43]. Environmental data sources include soil moisture, rainfall, temperature, and evapotranspiration [44]. In the required climate data, the essential component is from IPCC models, CMIP6 projections, and meteorological stations to simulate scenarios during the future [44]. Historical yield datasets and management records would all increase the strength of prediction [45]. The integration of these various datasets increases the strength of AI model, many folds [46].

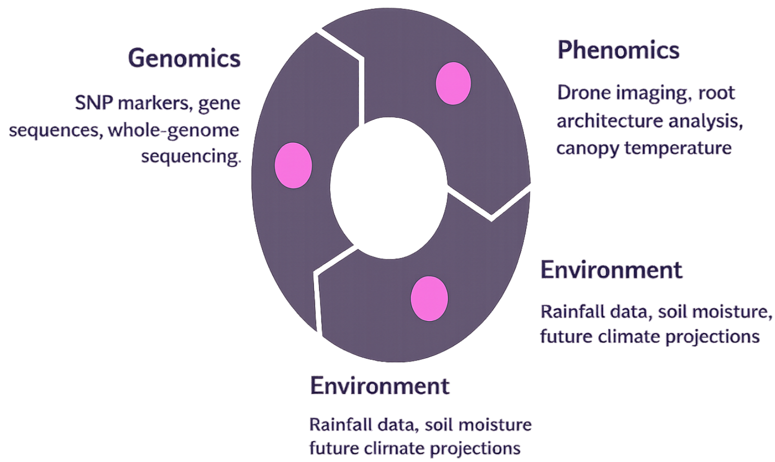


Figure 7. Integration of Genomic, Phenomic, and Environmental Data

Framework showing the integration of genomic, phenomic, and environmental data through predictive AI to analyze genotype, phenotype, and environment interactions, improving climate-resilient crop breeding.

3.3. Predictive AI Methodology

AI Breeding pipelines initiate with data accumulation which may stem from multiple genomic sequencing, drone phenotyping, and environmental climate monitoring platforms [47]. Data preprocessing involves noise removal, imputation of missing values, feature engineering, and data normalization to improve data quality and model performance [48]. This ensures that only high-quality input is trained on [49]. Training would typically comprise DL, Bayesian models, ensemble methods and statistical algorithms such as GBLUP [50]. Performance measures include accuracy, R^2, RMSE, and cross-validation measures [51]. The results from predictions may help rank genotypes which assist with decision-making in breeding [52].

Table 3. Summary of Predictive AI Algorithms Used in Crop Breeding

Algorithm	Application	Strength	Citation
CNN	Image-based phenotyping	High accuracy in stress detection	[53]
LSTM	Time-series climate modeling	Long-term forecasting capability	[54]
XGBoost	Genomic prediction	Fast and robust performance	[55]
GBLUP	Breeding value estimation	Additive genetic modeling	[56]

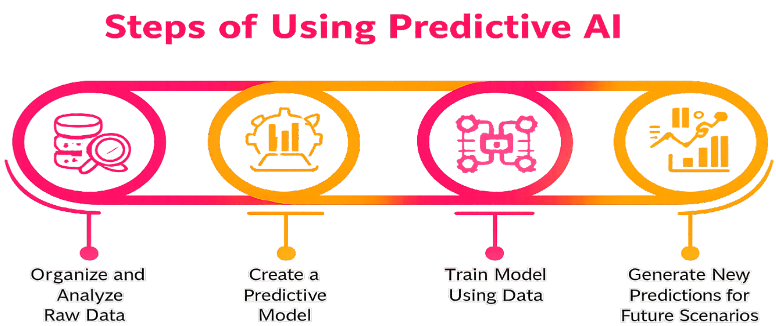


Figure 8. Steps of Using Predictive AI

3.4. Genomic Prediction Models

Conversely, genomic prediction models scan multiple thousands of markers simultaneously in estimating the breeding values [58]. With AI capabilities, genomic prediction is able to capture non-linear interactions across SNP markers [59]. The methods include GBLUP, Bayesian models and genomic prediction through DL [60]. DL models, such as CNNs and auto-encoders, detect structural patterns in raw genomic data [61]. In addition, ensemble models improvise the accuracy of predictions by combining multiple algorithms into one [62, 63]. Genomic prediction using AI has significantly expedited generations of breeding programs across the planet [63].

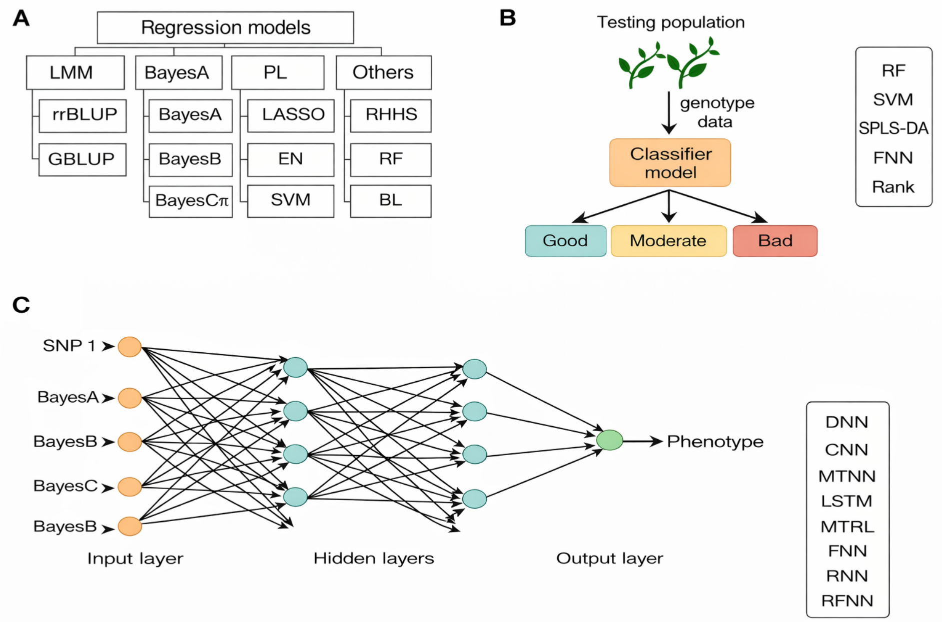


Figure 9. Illustration of AI Application to Agricultural Genetic Engineering and Predictive Genomics

This shows examples of using statistical models for predicting traits, ML for classifying genotypes, and DL networks (convolutional neural networks [CNNs], deep neural networks [DNNs], and long short-term memory [LSTM]) for predicting phenotypic characteristics [20].

3.5. Image-based Phenotyping

Recent advances in imaging have enabled AI to detect plant stresses before it can be seen by the human eye [64]. Using CNNs to diagnose drought, heat, and disease symptoms, different parameters were analyzed including plant canopy temperature, leaf color, and spectral indices [65]. High-throughput phenotyping using drone and satellite images determines phenotypic variation over larger fields [65]. Using hyperspectral imaging, biochemical traits, such as chlorophyll degradation and stomatal conductance which are absent from human sight, can be identified [64,65]. AI-based phenotyping would decrease the labor costs, increase accuracy, and speed up phenotyping of stress-resilient traits [64].

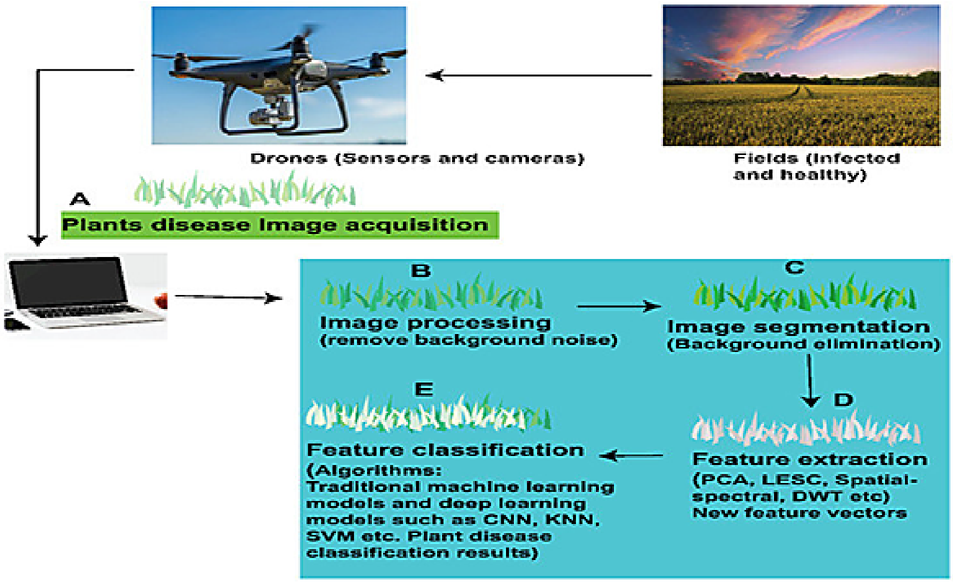


Figure 10. Automated Workflow for Real-time Plant Disease Detection

Figure 10 shows that automated workflow for real-time plant disease detection using drone imagery, image processing, feature extraction, and ML/DL algorithms such as CNNs, KNNs, and SVMs for accurate plant health classification [66].

3.6. Climate Scenario Modeling

AI incorporates global circulation models (GCMs) to model crop performance in scenarios with changing climates (2030-2100) [63]. LSTM networks assess climate time series to model drought indices, heat stress, and rainfall anomalies [65]. These predictions provide insight for long-term breeding strategies [63-65]. AI-based climate models support the breeding of stress-resilient genotypes by modeling climate scenarios to identify genotypes that can adapt to weather conditions and ensure that the new variety would be productive in the expected climate [15,20].

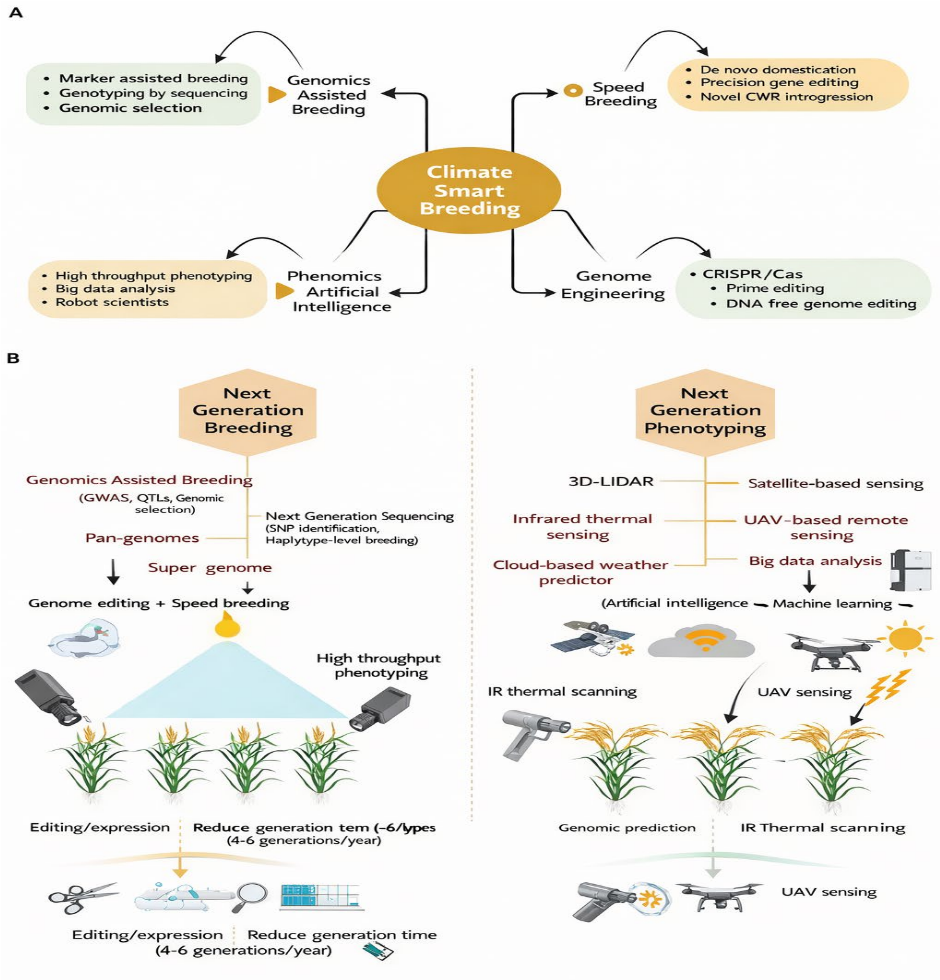


Figure 11. AI-based Conceptual Model Integrating Genomic, Phenomic, and Climatic Data

The Figure predict genotype performance, accelerate crop selection, and develop climate-resilient, stress-tolerant, and high-yield crop varieties [19].

3.7. Applications of AI in Breeding

AI provides advancements in hybrid prediction, parental selection, trait prediction, disease identification, and modeling- expected yields [67]. This discipline of ML is used to enhance multi-trait genomic selection and facilitate breeding for complex traits pertaining to climate resiliency [68]. AI is also capable to incorporate data from soils, irrigation and climate into decisions for optimized resource management [69]. Image-based AI systems detect early physiological stress symptoms, such as nutrient deficiencies, drought stress, or pathogen damage [70]. In the field of precision agriculture, AI enables prescriptive decision support, including optimized irrigation scheduling, how to space crops or apply fertilizers [71]. The incorporation of this real-time decision-making information can help resolute yield and sustainability [72].

3.8. Regional Applications of Predictive AI in Major Crops

AI has been used as a predictive tool to combat the effects of climate change and to create crops that are tailored to local conditions throughout the world. In Asia, the application of predictive AI in crop breeding programes has seen an increased use of predictive AI in breeding rice and wheat for traits such as heat sensitivity, drought susceptibility, and salt tolerance [44]. In Africa, predictive AI is also being used to breed maize, millet, and sorghum in areas with low soil fertility and where drought is common, thereby improving their ability to cope with drought and temperature fluctuations [6]. In Europe and North America, DNA testing and high throughput methods (e.g., molecular marker-assisted selection) are used as part of the breeding pipeline for crops, such as maize, soybean, and barley in order to enhance the stability of the yield and resistance to diseases [10]. In South America, the usage of predictive AI in breeding soybeans, maize, and sugar cane is increasing. This would improve the efficiency and profitability of these crops when grown under hot and variable rainfall conditions [9].

3.9. Case Study

One breeding program utilized CNN models to analyze the data from drone-based phenotyping in order to identify drought-stressed maize [73]. The AI was able to identify relationships with resilience in the phenotypic signature faster than previous methods [74]. This improvement significantly expedited the selection of potential genotypes for future breeding cycles [75]. An additional application of AI implementation was the use of XGBoost-based genomic prediction. This improved the accuracy of drought tolerance prediction by 40–60% and reduced the time to complete one full breeding cycle by approximately 30% [22]. The program released faster and more resilient hybrid maize which is proven example of AI helping real-world applications [76].

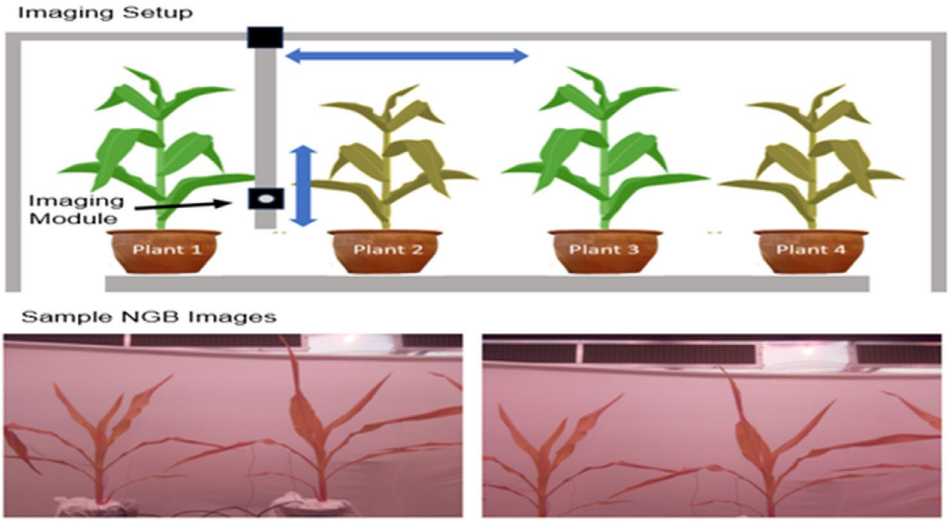


Figure 12. A High-throughput Plant Phenotyping Experimental Imaging System

Figure captures multi-angle images of individuals using an overhead imaging module to study their growth, morphology, and stress reactions. A subset of narrow green band images provides an example of how spectral data can be utilized in identifying physiological variances, allowing for automated trait extraction for AI-based phenotypic analyses [77].

4. BENEFITS, CHALLENGES, AND FUTURE DIRECTIONS

4.1. Advantages of Predictive AI

Utilizing predictive AI can decrease breeding cycle time through the rapid identification of high-potential genotypes and reduce reliance upon lengthy field trials [21]. High-throughput phenotyping not only allows for an increase in precision but also reduces staff labor [28]. AI can assimilate multiple datasets to improve decision-making [57]. Modeling climate scenarios allows breeders to create genotypes for future climates that would enhance crop stability over the long-term [78]. AI also contributes to the disease resistance process by determining the genomic markers that are important [79]. Collectively, these developments contribute towards a more food-secure world [62].

4.2. Challenges and Constraints

AI technology requires big datasets which remain limited in many developing countries [80,81]. In addition, the high computational needs of AI systems may limit uptake [35]. A number of other barriers also exist, including costs for drones, sensors, and high-performance computers [74]. There is a lack of newly-trained agricultural data scientists, which creates additional challenges for AI implementation [75]. In some regions, internet connectivity issues limit the value of real-time applications [76]. Again, if we expect equitable uptake, these issues would need to be addressed [25].

4.3. Future Directions

The current study proposed following future directions:

- Future breeding pipelines would be entirely from the field to the laboratory in real-time [59].
- Hybrid models incorporating genomic, phenomic, climatic and soil data would aid selection accuracy [60].
- Explainable AI-XAI-will make model outputs interpretable and trustworthy [21,28,57].
- AI also has the potential to guide CRISPR gene editing to discover ideal gene targets that confer climate resilience [66].
- Mobile-based phenotyping and IoT systems would democratize access, so that smallholders may also utilize AI and AI-enabled technologies. These are all advanced techniques that would define the future of sustainable agriculture [77]

5. CONCLUSION

In the world of agriculture, advances in crop breeding are being drastically impacted by new technology, such as predictive AI [5]. With this technology, breeders can now utilize much larger genomic and environmental datasets to perform more rapid, accurate, and climate-sensitive selection of traits in order to overcome many of the limitations associated with traditional breeding methods [10].

Through the use of predictive AI, breeders are able to better predict the climate, which in turn, would aid them in directing their breeding programs so that they are less risky and produce crops that are more resilient in the future [9]. The continued development of explainable AI, multi-omic integration, and gene editing technologies would further enhance breeding programs' predictive accuracy, as well as facilitate the adoption of AI-assisted breeding strategies [3].

Ultimately, predictive AI would play an important role in producing crop varieties that exhibit significant climate resilience, in addition to helping support sustainable agricultural production and ensuring global food security [6].

Author Contribution

Eizha Amir: conceptualization, data curation, writing – original draft, visualization. **Sumaira Mazhar:** supervision, methodology, writing – review & editing, validation, project administration.

Conflict of Interest

The authors of the manuscript have no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

Data Availability Statement

No new data were generated or analyzed in this study.

Funding Details

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Generative AI Disclosure Statement

The authors did not use any type of generative artificial intelligence software for this research.

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