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Digital evolution and twin miracle of sugarcane breeding

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A R T I C L E I N F O

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A B S T R A C T

Context: Sugarcane, as an important economic crop, faces challenges such as long breeding cycles, low genetic improvement efficiency, and complex breeding operations.
Method: In order to address these challenges and improve the economic benefits of sugarcane breeding, this paper proposes an innovative smart sugarcane breeding system driven by artificial intelligence (AI), blockchain and digital twin technologies.
Results: The system integrates these technologies within a Human-Cyber-Physical System framework to offer a more efficient, secure, and smart strategy for sugarcane breeding. Firstly, AI processes extensive genetic and phenotypic data to enable precise prediction and optimization of sugarcane traits, resulting in shortened breeding cycles and enhanced efficiency and accuracy in selecting elite sugarcane varieties. Secondly, blockchain technology ensures the security and traceability of breeding data, enhancing the reliability and integrity of the breeding process. Thirdly, digital twin technology enables the real-time circulation of lifelike representations of real-world data among breeding-related workers. The system architecture consists of three layers: a physical layer for data collection, a cyber layer responsible for data analysis, storage and circulation managed by AI, blockchain and digital twin, and a human layer comprised of breeders and stakeholders. This multi-layered approach allows for sophisticated interaction and collaboration between the physical and digital realms, enhancing decision-making and breeding outcomes.
Conclusion: Taken together, the system utilizes AI, blockchain, and digital twin technologies to support sugarcane breeding, offering a promising solution to overcome the limitations of traditional methods and establish a more sustainable and profitable sugarcane breeding system.

1. Introduction

Sugarcane is a major economic crop cultivated in tropical and subtropical regions worldwide, serving as the primary source of sugar production, accounting for over 70 % of the world's total sugar output (Yadav et al., 2020). It is also a significant crop for energy production and the production of by-products such as ethanol and fiber (de Morais et al., 2015). In China, approximately 60–70 % of the production costs for sugar are spent on sugarcane stalks, the raw material (Xu et al., 2021). Enhancing the yield and quality of sugarcane, which is mainly achieved by the promotion of newly bred elite varieties, is a crucial means of increasing economic returns from sugarcane cultivation.

Crop breeding, through selection and cultivation, effectively improves the agronomic traits of varieties. It is one of the oldest agricultural activities, equivalent to human civilization (Shen et al., 2022), and a primary means of increasing crop yield and improving quality. Sugarcane breeding aims to optimize growth characteristics, enhance yield, and biotic and abiotic resistance, meeting the growing global demand for sugar and improve the economic benefits of sugarcane cultivation. Through breeding, we can develop new varieties with high sugar content, high yield, good ratooning ability, pest and disease resistance, and strong adaptability, thereby increasing sugarcane yield and quality,

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contributing to the development of sugar production, energy exploitation, and other industries. Currently, mainstream sugarcane breeding methods primarily consist of two approaches: hybrid breeding and molecular breeding (Qi et al., 2022). Hybrid sugarcane breeding primarily involves creating genetically heterogeneous breeding populations by selecting superior parental lines for flowering and cross-pollination or artificial pollination, followed by selecting individuals with desired traits. At present, hybrid breeding remains the primary means of sugarcane breeding. The rapid development of genetic engineering has ushered in the era of molecular breeding. Breeders widely utilize technologies such as molecular markers, transgenics, gene editing, and genomic selection. They expedite breeding improvements and the development of new varieties by identifying and selecting genes related to target traits, inserting exogenous genes, and modifying specific portions of genes. Briefly, molecular breeding effectively shortens the breeding cycle, enhances the targeting of breeding, and increases the diversity of breeding. However, both methods have certain *shortcomings*: Hybrid breeding has reached technical bottlenecks and faces significant challenges such as long breeding cycles, low genetic improvement efficiency, and substantial time and labor consumption (Jing et al., 2021). Although molecular breeding effectively addresses some of the limitations in hybrid breeding, it encounters challenges such as high costs, complexity, and intricate steps (Zhang et al., 2021). These challenges have prompted breeders to seek more efficient and precise breeding methods, namely the emerging field of smart breeding in recent years. The process is gradually evolving from traditional breeding to modern breeding, transitioning from hybrid breeding to molecular breeding, and to smart breeding.

Smart breeding is a novel breeding approach based on high-throughput data, deeply integrating modern biotechnology and information technology, to achieve the faster and more efficient selection of new crop varieties (Chandra et al., 2024). With rapid technological advancements, it is increasingly receiving attention and promotion. Notably, the application of advanced technologies such as sensing, robotics, remote sensing (RS), artificial intelligence (AI), blockchain (Zhang et al., 2020), and digital twin (DT) (Pylianidis et al., 2021) injects new vitality and possibilities into smart breeding (see Fig. 1). Smart sugarcane breeding, through the integration of high-throughput data collection platforms comprising elements such as unmanned aerial vehicle (UAV) and a variety of sensors with AI, can precisely handle genetic and growth data of sugarcane to predict and optimize its genetic characteristics and agricultural traits. Blockchain and DT can ensure the secure storage and real-time circulation of data. These technologies enable real-time collection, analysis, storage, circulation of data during the breeding process, providing more precise and reliable decision support. This holds great promise for addressing the challenges of long breeding cycles, low improvement efficiency, labor intensiveness, and high complexity faced by traditional sugarcane breeding.

Human-Cyber-Physical Systems (H-CPS) are systems that organically integrate physical systems, network systems, and human beings (Nunes et al., 2018). In such systems, the physical system serves as the platform for data collection and task execution, the network system acts as the medium for processing, analyzing, and storing data, while humans serve as the ultimate decision-makers, transmitting decisions back to the physical system to drive device execution (B. Wang et al., 2022). In H-CPS, the knowledge base of the network system is collaboratively constructed by human beings and the self-learning and cognitive modules of the network system. This knowledge base not only includes experiential knowledge provided by humans but also incorporates reasoning knowledge learned by the network system itself, which is difficult for humans to describe and process (Bousdekis et al., 2020). The self-learning and cognitive modules enable the network system to continuously improve and optimize itself during operation (Zhou et al., 2019). H-CPS achieves highly interactive and collaborative relationships between humans, networks, and the physical world through intelligent perception, data analysis, decision-making, and execution feedback loops. This system has been applied in various fields including smart manufacturing (B. Wang et al., 2022), intelligent buildings (Li et al., 2021), and smart transportation (Taylor et al., 2023). In these areas, H-CPS has brought improvements such as increased efficiency, enhanced safety, and optimized operations. Similarly, H-CPS is poised to significantly transform breeding methods, making them more efficient, secure, profitable, and smart, just as it has done in these other domains.

The purpose of this paper is to design a more efficient and smart method for sugarcane breeding based on smart breeding technology, addressing the issues faced by traditional methods and advancing the field of sugarcane breeding. Our research method involves a literature review combined with the authors' own research to discuss the new developments and achievements in sugarcane breeding technology, particularly in smart breeding. Based on this, we propose an efficient smart breeding scheme and evaluate this new breeding approach. As a result, we firstly envisions a smart sugarcane breeding system based on an H-CPS architecture driven by AI, blockchain and DT. The innovation lies in the organic integration of the latest modern information technologies with the field of breeding, offering a novel, systematic solution for sugarcane breeding. By leveraging AI to process vast amounts of breeding data and combining it with blockchain to ensure data security and traceability, this system is poised to enhance the efficiency, precision, and reliability of breeding work. Additionally, utilizing an H-CPS architecture design endows the system with better human-machine

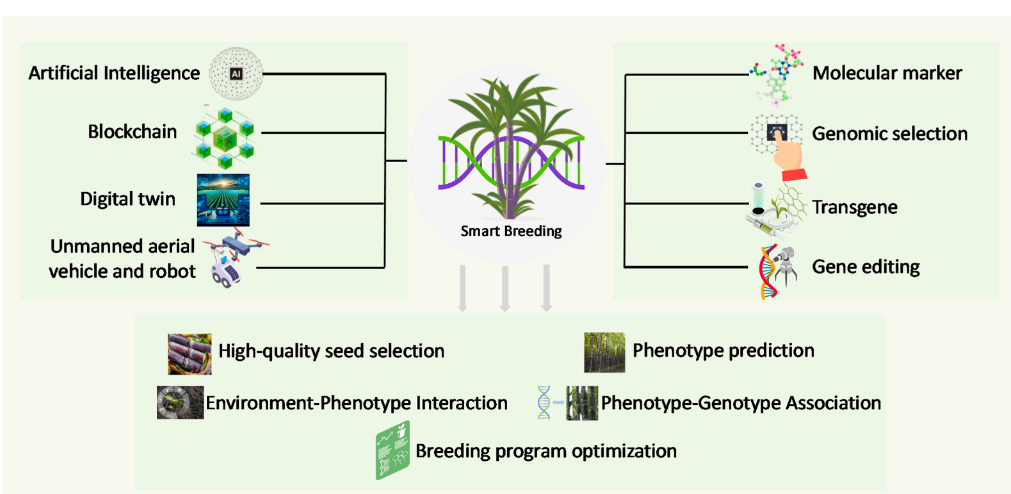

Fig. 1. A concept map for smart breeding.

collaboration capabilities, which can accelerate the development of sugarcane breeding and make positive contributions to sugarcane cultivation as well as sugar and energy production.

The main contribution of this paper lies in the conception and proposal of a smart sugarcane breeding system driven by AI, blockchain, and digital twin technologies. Additionally, it is the first to introduce the H-CPS architecture into the sugarcane breeding field, providing stronger support for human-machine collaboration and ensuring the scientific rigor and traceability of breeding decisions.

2. Sugarcane breeding has witnessed the wide application of several advanced technologies

2.1. Achievements in traditional breeding

Several studies have applied bioengineering techniques to traditional sugarcane breeding. Yang et al. developed a PCR-based diagnostic marker to assist in marker-assisted selection of sugarcane varieties resistant to leaf scald (Yang et al., 2018). Josefina et al. established a whole-genome association to find molecular markers associated with yield traits consistent across harvest seasons in breeding populations, aiming to improve sugarcane yield and sugar content (Racedo et al., 2016). Z. Wang et al., 2022 developed a sequencing-based mixed segregation strategy for polyploids to screen for candidate genetic markers associated with sugarcane leaf blight resistance. Islam et al. used genomic selection to predict breeding values, selecting ideal germplasm for disease-resistant sugarcane breeding (Islam et al., 2023). Laksana et al. discovered a method using CRISPR/Cas9 gene editing to reduce lignin content in sugarcane stems (Laksana et al., 2024). The promotion and application of techniques such as molecular markers, whole-genome association, genomic selection, and gene editing provide solid tools for smart breeding, accelerating the transition from traditional breeding to smart breeding.

2.2. Achievements in smart breeding

Smart sugarcane breeding has seen numerous beneficial attempts, with corresponding advanced technological solutions proposed for various stages of the process, such as breeding data collection, analysis, and storage. Zhou et al. utilized a logistic regression model as a decision support tool to address early selection stages in sugarcane breeding (Zhou et al., 2014). This model selects based on yield components (such as straw quantity, straw height, etc.), aiding in identifying genotypes that produce high yields during non-replication stages. Brasileiro et al. evaluated the application of Artificial Neural Networks (ANN) in sugarcane family selection (Brasileiro et al., 2015). Results showed that the optimal ANN model could successfully classify all genotypes correctly, demonstrating the ability of ANN to accurately predict the best plants. Hayes et al. employed three different genomic prediction methods, namely GBLUP based on genomic data, Genomics SS based on single-strand DNA, and BayesR based on Bayesian statistics for genomic selection, showing promising results for improving traits such as flowering time and pollen viability in sugarcane (Hayes et al., 2021). In addition to research on predicting genetic information, researchers have also investigated the measurement of sugarcane phenotypic data and environmental parameters. Using portable near-infrared spectroscopy (Sanseechan et al., 2018), sensors (Garcia et al., 2022) and sugarcane plantation mobile robot autonomous navigation systems (Xaud et al., 2019; Cardoso et al., 2020), it is possible to non-invasively track environmental changes in sugarcane fields and conduct mapping, monitoring, and image classification. Combining machine learning algorithms with RGB images collected by UAVs (Khuimphukhieo et al., 2023) or satellite-derived images (Som-ard et al., 2024) to study the direct and indirect effects of canopy characteristics, it enables effective estimation of sugarcane yield. Furthermore, UAVs equipped with multispectral cameras can accurately predict sugarcane sucrose content (Chea et al., 2022; Canata et al., 2024), nitrogen status (Hosseini et al., 2021), several other parameters such as tiller number, plant height, and stem diameter (de Oliveira et al., 2022), and create digital soil maps for predicting calcium and magnesium content in sugarcane fields (Arshad, 2020). Furthermore, research has utilized blockchain to store data during sugarcane cultivation and production processes. Deshmukh et al. employed blockchain to store data from the sugarcane production process, bridging the communication gap and enhancing transparency between sugar mills and farmers (Deshmukh et al., 2019). Ekawati et al. addressed the problem of tracking the sugarcane supply chain and real-time collection of breeding and cultivation data by proposing the design of a blockchain-based decision support system for sugar supply (Ekawati et al., 2020). Kshetri et al. used blockchain in sugarcane cultivation to assist farmers in automating the storage of sugarcane planting data in a highly trusted manner (Kshetri et al., 2023).

In summary (see Table 1), advanced technologies such as sensors, UAVs, robots, and AI have been widely applied in the field of smart sugarcane breeding. Although there have been some examples on blockchain solutions in the sugarcane supply chain, the research on how to apply blockchain to sugarcane breeding is scarce. Therefore, exploring and developing novel solutions that combine blockchain with sugarcane breeding are of significant importance. The organic integration of AI, blockchain and DT can lead to more efficient data management in sugarcane breeding, providing breeders with richer and better recommendations.

3. A smart sugarcane breeding system driven by AI, blockchain and DT

We envision a smart sugarcane breeding system driven by AI, blockchain, and DT (see Fig. 2). As for the H-CPS architecture, it includes three layers: (1) Physical Layer: Comprises devices like ground sensors, UAVs, robots, and communication devices to collect data from the breeding environment. (2) Cyber Layer: Involves cloud servers, 5 G networks, blockchain, AI, and DT. Data from the physical layer is processed here, structuring it for AI algorithms and blockchain storage. AI models analyze this data to provide critical insights such as yield prediction, disease detection, growth parameter monitoring, phenotype prediction, high-quality seed selection, and breeding improvement decisions (Zhou et al., 2014; Khuimphukhieo et al., 2023; de Oliveira et al., 2022; Sharma and Punhani, 2023). Blockchain ensures data security and traceability, allowing for model semantics deployment and governance via smart contracts (Zhu et al., 2019). Federated meta-learning trains both personalized and global breeding models from multiple regions (Fallah et al., 2020; Jiang et al., 2019), with data circulating in real-time on DT platforms. (3) Human Layer: Breeders contribute additional data and expertise to the system, enhancing AI model reliability. They use DT to access and utilize stored data for decision-making. This collaboration under the H-CPS architecture enhances machine perception and efficiency, leveraging both physical and human resources to significantly improve breeding efficiency.

The smart sugarcane breeding system addresses complex breeding challenges by processing large-scale data. It integrates genotype, phenotype, and environmental data, alongside multiple omics, next-generation biotechnologies, and information technologies, to analyze extensive datasets and generate smart breeding decisions. This system rapidly identifies superior hybrid combinations or high-quality parents, shortens breeding cycles, improves efficiency, reduces costs, and produces elite sugarcane varieties with desirable traits. The breeding workflow under this framework includes four key steps (see Fig. 3): collection, analysis, storage, and circulation. The first step involves collecting sugarcane genetic resource data, environmental data, and growth condition data. The second step utilizes emerging technologies such as deep learning (LeCun et al., 2015), reinforcement learning (Kaelbling et al., 1996) and large language model (LLM) (Zhao et al., 2023) for data processing, prediction, and decision-making. The third

Table 1
Corresponding technical solutions proposed at different stages of the breeding process.

Process	Breeding data	Technology
data collection	phenotype, environment type	sensors (Garcia et al., 2022)
	phenotype, environment type	portable infrared spectrometers (Sanseechan et al., 2018)
	phenotype	robots (Cardoso et al., 2020)
	phenotype, environment type	robots (Xaud et al., 2019)
	phenotype	satellites (Som-ard et al., 2024; Canata et al., 2024)
	phenotype	UAVs (Khuimphukhieo et al., 2023; Chea et al., 2022; Hosseini et al., 2021; de Oliveira et al., 2022)
	environment type	UAVs (Arshad, 2020)
data analysis	phenotype	AI (Zhou et al., 2014; Som-ard et al., 2024; Chea et al., 2022; Canata et al., 2024; Hosseini et al., 2021)
	genotype	AI (Brasileiro et al., 2015; Hayes et al., 2021)
	environment type	AI (de Oliveira et al., 2022; Arshad, 2020)
data storage	phenotype	blockchain (Deshmukh et al., 2019)
	phenotype, environment type	blockchain (Kshetri et al., 2023)
	genotype, phenotype environment type	blockchain (Sharma and Punhani, 2023)

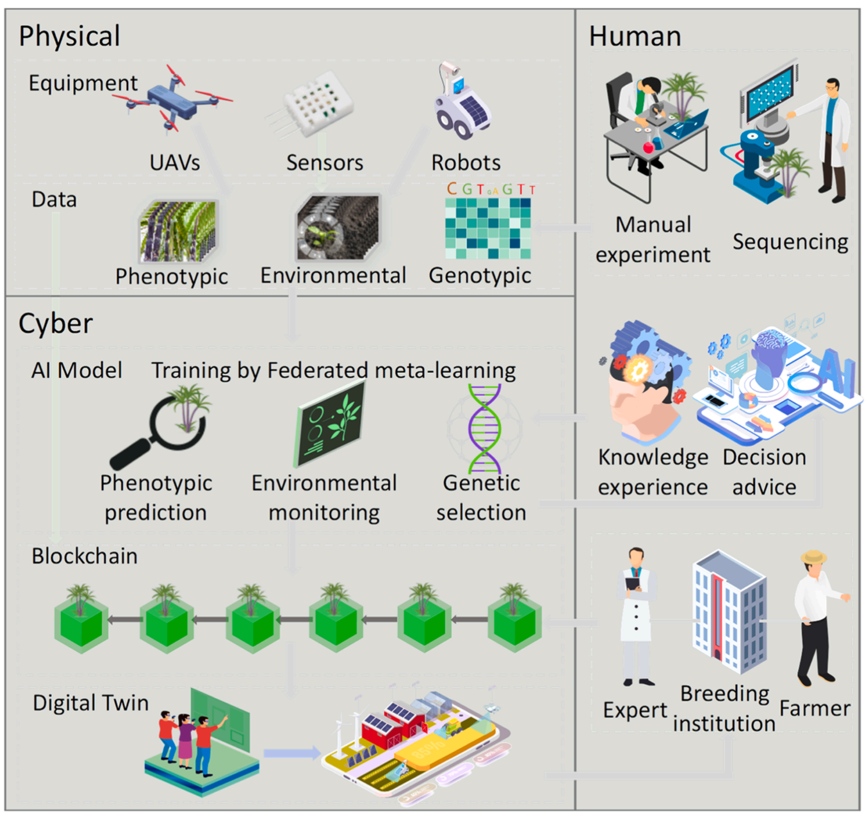

Fig. 2. The architecture of a smart sugarcane breeding system driven by AI, blockchain and DT.

step leverages blockchain to ensure the secure storage and traceability of breeding data. In the final step, employing the DT approach, the data is visualized and rendered in a lifelike manner, circulating among various stakeholders in breeding-related fields. The following sections will sequentially introduce these four aspects in detail and discuss the roles of each element in these processes.

3.1. Data Collection

Data collection is a crucial step in sugarcane breeding (see Fig. 4). Genotype data provides information about the plant genome, including but not limited to genotype, genotype frequency and genetic diversity. Collecting genotype data can help assess the genetic background and genetic diversity, aiding in the selection of superior germplasm resources, thereby improving breeding efficiency and success rate. After obtaining high-quality DNA samples (Li et al., 2013), breeders use molecular marker to obtain more detailed genotype data (Erlich, 1989; Ganal et al., 2009). In addition, genome sequencing can also be used to directly obtain DNA, RNA and protein sequence information of plant genomes (Shendure et al., 2017). In this process, the incorporation of AI can monitor the working status and data output of experimental instruments and equipment in real-time and automatically identify and correct errors or abnormalities in the data, thereby improving the quality and accuracy of breeding data. For example, AI algorithms can detect PCR deviations and anomalies during the amplification process, thereby reducing error introduction and improving data reliability (Villarreal-González et al., 2020). Through the above steps and methods, genotype data can be effectively collected, providing important genetic information and data support for smart sugarcane breeding.

All breeding ultimately needs to be implemented in field population testing. The field-testing is also the process of collecting plant phenotype data, enabling breeders to accurately measure the traits of sugarcane

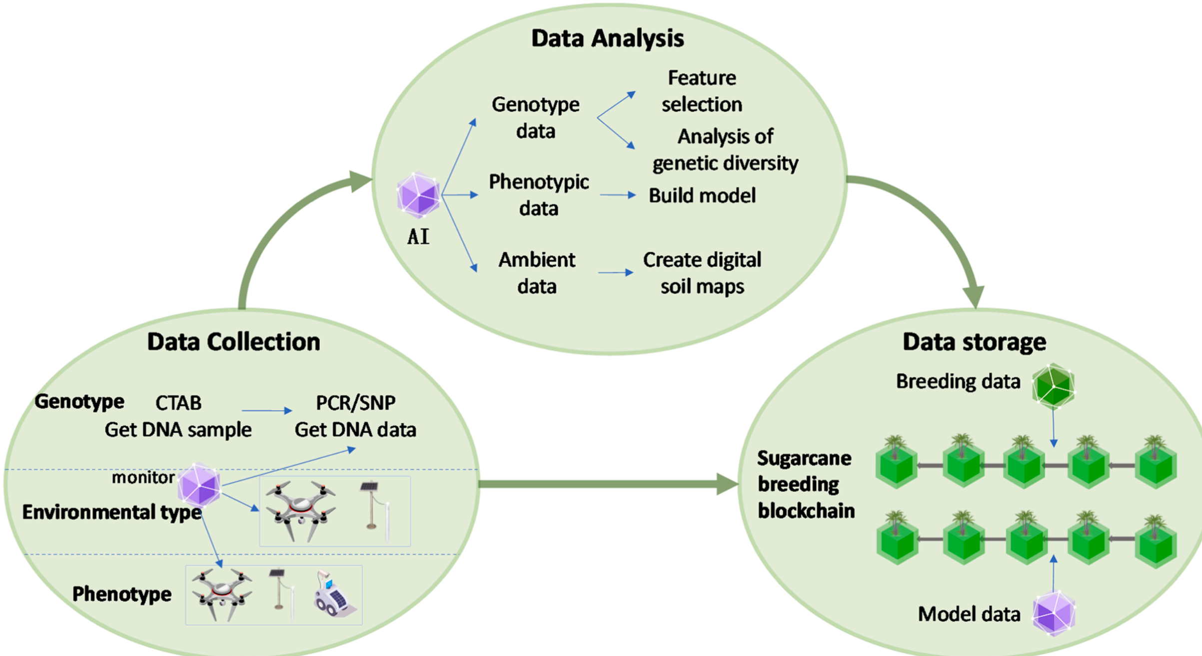

Fig. 3. The detailed workflow of sugarcane breeding using AI, blockchain, and DT.

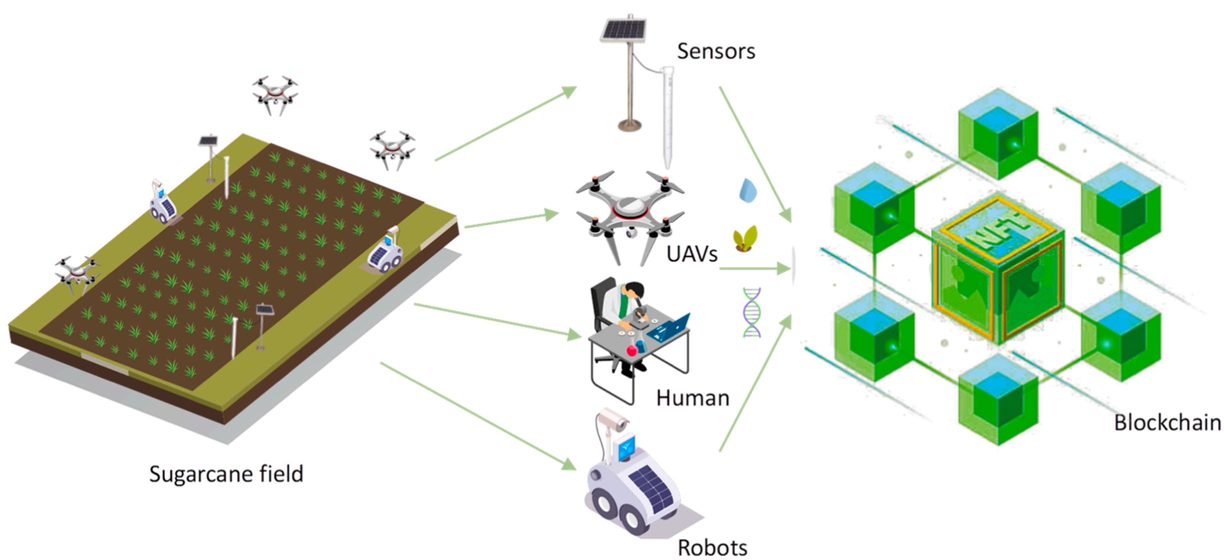

Fig. 4. Data collection for sugarcane breeding.

varieties, such as sugar content, height, biomass, disease resistance and tolerance, and helping breeders discover the intrinsic relationship between genotype and phenotype and make the wiser breeding decisions (Fountas et al., 2022). In breeding work, there is still a large amount of phenotype collection work being carried out in the traditional "eye measurement, hand touch" manner. Can traditional phenotype measurement methods keep up with the pace of biological breeding? The answer is optimistic. This requires the introduction of technologies such as sensors, UAVs, and agricultural robots. Currently, a series of sensors optimized by AI algorithms have been used to achieve real-time, rapid, and efficient plant phenotyping (Feng et al., 2021; Lv et al., 2022). Sensors can automatically perceive and record relevant growth information of sugarcane seedlings, such as leaf color and stem height. These data can be used to analyze plant growth characteristics and trait performance, providing important references for breeding work. In addition to the basic sensor system, agricultural robots can serve as practical platforms carrying various imaging devices for efficient and accurate phenotypic data collection, such as RGB, thermal imaging, multispectral, and hyperspectral cameras. Agricultural robots need to be sufficiently intelligent to perform complex tasks, such as moving between rows, identifying target areas, and avoiding obstacles in the field. Therefore, the use of AI technologies, such as YOLO and deep reinforcement learning (Yan et al., 2021; Ibarz et al., 2021), can help robots make autonomous decisions and path planning, learn and optimize target detection and obstacle avoidance strategies, accurately locate detection areas, and avoid collisions with obstacles. In addition to agricultural robots, another popular platform is UAVs. Unlike agricultural robots that collect phenotype data in close proximity on the ground, UAVs equipped with various imaging devices can perform large-scale and efficient data collection from the air. Since sugarcane is much higher than that of general crops, some phenotypic data measurements (such as plant density and growth trend) require the aerial advantages of UAVs. Similarly, AI algorithms can be deployed for UAVs to enhance their image recognition capabilities and optimize flight routes. The combination of sensors, imaging devices, and platforms such as robots and UAVs constitute a high-throughput sugarcane phenotyping platform, realizing real-time, large-scale, automated, high-precision, high-resolution non-destructive measurement of sugarcane phenotypic data.

Moreover, sugarcane has a high demand for water and nutrients, including nitrogen, phosphorus and potassium, and the amount of these elements in the soil affects the yield and quality of sugarcane. Environmental factors such as temperature and climate also affect the growth of sugarcane. Even in the same variety, sugar content and stem height will vary with the environment. Therefore, the collection of environmental data is also an indispensable part of breeding work. By using various sensor arrays, mapping UAVs, we can promote environmental typing and effectively measure and characterize physical and environmental variables, draw digital soil maps. This enables us to simulate the relationship between crops and the environment and unlock the genetic variation hidden in potential features (Mir et al., 2019). By understanding these environmental impacts, breeders can select and develop sugarcane varieties that are more resilient to specific conditions, ensuring optimal growth and yield under different environments.

3.2. Data Analysis

Breeding data possess a critical characteristic: accessibility to breeders. Ensuring accessibility means relieving breeders from the burden of analyzing vast amounts of genetic, phenotypic, and environmental data, allowing them to focus on the in-depth exploration of analyzed data and the breeding issues themselves. In recent years, with the advancement of large-scale datasets, powerful computing capabilities, and improved algorithms, AI has made significant strides in crop breeding (Khan et al., 2022). Methods like machine learning and deep learning can assist breeders in managing large multidimensional datasets of genotype-phenotype-environment, thereby efficiently selecting and cultivating superior, multi-resistant varieties (see Fig. 5). Genotypic data typically contain numerous features, some of which may be redundant. AI can automatically filter out important data that have a significant impact on sugarcane trait using feature selection algorithms. Feature selection algorithms evaluate the importance of each feature to identify those that significantly affect sugarcane traits, thereby improving the accuracy and efficiency of prediction models. With these data, predictions of sugarcane trait can be made using well-trained models. Furthermore, AI can analyze the genetic regulation networks based on genotypic data, helping breeders better understand the genetic background and diversity of germplasm resources. By combining genotypic and phenotypic data, AI can uncover the intrinsic connections, aiding in identifying key genes and understanding how these genes influence phenotype, thereby guiding breeding strategies and selecting excellent genotypes. Genetic variation is the basis of genetic improvement and one of the main driving forces behind breeding work. Deep learning methods can fit the correlation between gene expression and regulatory sequences, thereby uncovering various sites that affect gene expression, helping breeders understand the genomic variation of terminal phenotypes. Breeders can selectively breed new varieties based on this understanding, thereby improving and optimizing sugarcane traits.

The processing and analysis of phenotypic data form the foundation of AI breeding. The ultimate goal of sugarcane breeding is to cultivate varieties with high sugar content, strong ratooning, lodging resistance, high yield, strong disease resistance, and wide adaptability. Selecting seedlings with these characteristics requires the evaluation of phenotypic data. By collecting spectral features, root system structures, root densities, stem structures, and other growth information using physical layer devices and combining them with machine learning and deep learning algorithms, we can construct prediction models for sugar content, ratooning ability, and lodging resistance. This enables effective prediction of large-scale sugarcane phenotypic traits and the selection of high-quality seedlings, thereby improving breeding efficiency. In most cases, yield is the primary factor considered in crop breeding, and sugarcane breeding is no exception. By using machine learning and deep learning methods to extract, construct, and select features from collected image and growth data, features relevant to sugarcane yield can be extracted, and yield prediction models can be constructed, enabling high-precision prediction and facilitating the selection of high-yield sugarcane lines. During sugarcane growth, diseases are one of the main factors affecting yield and quality. Some diseases such as smut, rust, and leaf scald pose significant challenges to disease control. Breeding for disease resistance is a fundamental way to control these diseases. Deep learning and target detection algorithms can be used to identify diseased plants in sugarcane fields. By deploying these algorithms and models to robots and UAVs, efficient disease identification

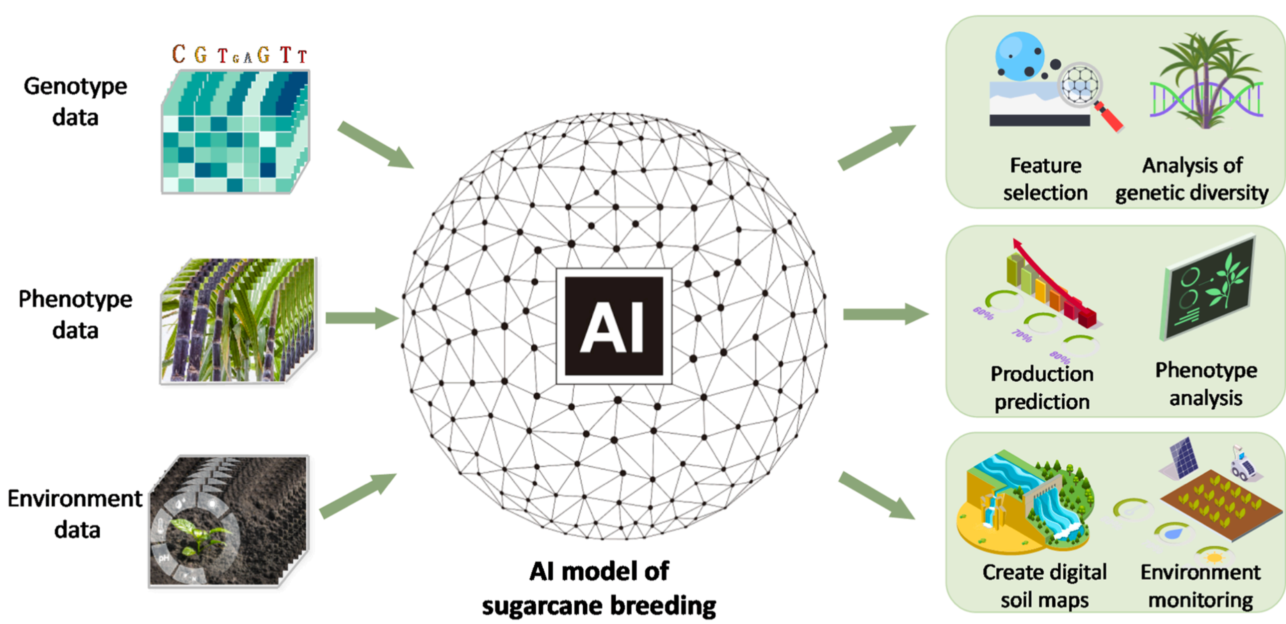

Fig. 5. Data analysis for sugarcane breeding.

can be achieved, enabling breeders to make early decisions and accelerate the selection process of superior varieties. Of course, during the growth of sugarcane, any phenotypic trait is influenced by the environment. Therefore, we cannot simply judge the quality of varieties based on collected phenotypic data. A rigorous approach is to use AI to process and analyze environmental data, draw digital soil maps, analyze the correlation between environmental data and sugarcane phenotypic traits, and reveal the variation patterns of sugarcane phenotypes under different environmental conditions, further guiding breeding work.

It is worth noting that sugarcane varieties vary greatly in different regions. For example, in high-altitude areas, with increasing temperatures, sugarcane tends to grow faster, increase in height, decrease in stem diameter, increase in lodging, and increase in humidity, while in low-altitude areas, with increasing ultraviolet radiation, sugarcane tends to have shorter heights, thicker stem diameters, reduced flowering, and decreased lodging. Therefore, a model that performs well in one region may perform poorly in another. Therefore, training a global breeding model using federated meta-learning is adopted. The global breeding model is jointly trained by network centers from different regions and can be applied to sugarcane varieties in multiple regions. Federated meta-learning trains models collects locally across multiple data sources and aggregates model updates on a central server, thereby protecting data privacy and enhancing the generalization capability. This approach avoids the transmission of raw data to central servers and effectively ensures the security of breeding data. Furthermore, a LLM on breeding can be trained using federated meta-learning. This model enables the interpretation of complex agricultural knowledge in simple language, distilling key information from literature so that breeders can access the latest knowledge in botany or sugarcane breeding (Tzachor et al., 2023). By integrating genotypic, phenotypic, and environmental data, AI can provide comprehensive and systematic analysis and prediction for sugarcane breeding, providing breeders with scientific and accurate decision support and promoting the development of sugarcane breeding towards more smart and efficient directions.

3.3. Data Storage

After collecting breeding data, it is essential to record and store the data for subsequent tracking, analysis, and decision-making. Traditional methods of sugarcane data management relied on manual recording of data on paper, which was then transferred to Excel spreadsheets or databases on computers. It required specialized personnel for management. However, this approach had several drawbacks, especially consuming significant time and effort during the data recording and input process. Additionally, human errors during data entry could compromise the accuracy and integrity of the data. Therefore, introducing a more efficient, accurate, and secure digital recording method becomes necessary to address these concerns associated with traditional sugarcane data recording methods. The introduction of blockchain provides an innovative solution for storing and recording breeding data, making the process automated, decentralized, and tamper-proof. This enhances the credibility and reliability of the data (Namasudra et al., 2021), laying a solid foundation for further development and application of sugarcane breeding. Here, we refer to the blockchain deployed in this system architecture as the Sugarcane Breeding Chain (see Fig. 6), as it spans the entire sugarcane breeding cycle. It significantly simplifies the process of breeders handling and recording breeding data, allowing them to focus on analyzing processed, information-rich data during breeding. Stakeholders can also easily trace breeding data on the Sugarcane Breeding Chain.

In terms of the most basic breeding data storage records, sugarcane breeding chain can provide a highly secure data storage and transmission mechanism to ensure that important data generated during the sugarcane breeding process is not tampered with or leaked. During breeding, data collected from platforms such as sensors, robots, and UAVs are automatically stored in the Sugarcane Breeding Chain via

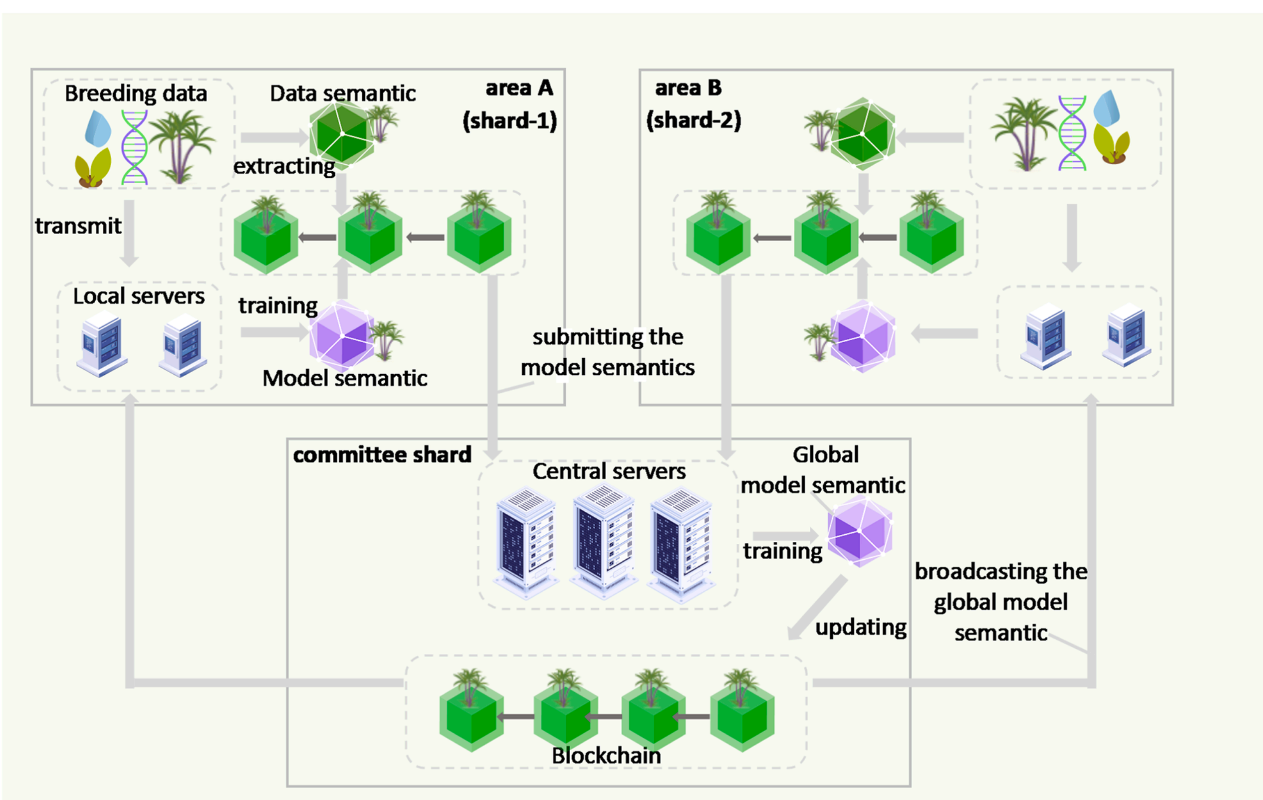

Fig. 6. Blockchain structure for sugarcane breeding based on semantics and sharding.

servers. Due to the decentralized nature of blockchain, breeding data is stored on multiple nodes, making it difficult for attackers to modify or sabotage, thereby ensuring data integrity and security. Furthermore, blockchain records timestamps and detailed information for each operation, enabling full traceability of the sugarcane breeding process. This aids in tracking the growth and breeding history of sugarcane, identifying potential issues and risk factors. Smart contracts are programs on the blockchain that can execute pre-programmed logic without third-party intervention (Zheng et al., 2020). In that chain, smart contracts can automate contract execution in the breeding process, such as automatically distributing breeding outcomes or paying breeders' rewards. Through the Sugarcane Breeding Chain, different breeding institutions, farmers, and researchers can upload and share sugarcane breeding-related data, accelerating breeding research progress and improving breeding efficiency.

Furthermore, we can store the semantic representation of breeding models on the Sugarcane Breeding Chain, allowing the models to run and process data automatically under the supervision of smart contracts. The parameters of sugarcane breeding models trained from massive genotype, phenotype, and environmental breeding data are extensive, and their model sizes are substantial. As blockchain is not suitable for storing very large data, the semantic representation of models needs to be compressed and stored on the blockchain to reduce data volume. Semantic data models capture the meaning of data attributes and relationships, providing a higher-level representation of knowledge (Zhu et al., 2019). By introducing semantic features, the intelligence, interpretability, and interoperability of the Sugarcane Breeding Chain can be enhanced, while reducing storage pressure. To further strengthen the scalability, we implement sharding (Zamani et al., 2018), which improves the performance and processing capacity of the Sugarcane Breeding Chain network. Sharding solves performance bottleneck issues caused by handling large volumes of transactions through dividing the entire sugarcane chain network into small, independent fragments. This method significantly increases parallelism, thus enhancing the throughput of the entire network. With the help of semantic data models and sharding technology, breeding data from different regions can be transformed into semantic representations and stored on different shards. Additionally, expert knowledge about sugarcane pedigree relationships (a kind of knowledge graph) can be transformed into semantic representations and stored on the Sugarcane Breeding Chain. Since we adopt a semantic sharding-based blockchain architecture, pedigree relationship graphs of sugarcane from different regions can be stored on dedicated blockchain shards. AI algorithms related to knowledge graphs (Rožanec et al., 2022) are used to merge pedigree relationship graphs of sugarcane from different regions, generating a more comprehensive and accurate large-scale knowledge graph, and this process involves removing redundant, erroneous, and inaccurate graph data. This allows breeding experts from different regions to accurately query crop knowledge graphs for their own and other regions, facilitating subsequent breeding research. It is worth noting that the above solution is dynamic, meaning that with the addition of pedigree relationship graphs of crops from new regions, the structure of the Sugarcane Breeding Chain will also dynamically adjust. Similarly, the above solution is also applicable to the storage of excellent gene data. Based on the semantic sharding-based Sugarcane Breeding Chain architecture, the semantics of breeding models from each region can be used to generate shards for that region. The shards playing the role of committee members (selected based on some strategy with higher permissions) aggregate the semantic breeding model stored in different regional shards (Zhang et al., 2022), forming a global semantic breeding model. Once deployed, breeders from each region can directly use the sugarcane breeding models and global models of their region on the Sugarcane Breeding Chain, and can also request sugarcane breeding models from other regions.

3.4. Data Circulation

Recent years, DT has demonstrated remarkable capabilities in simulating, analyzing, and visualizing the real world (Liu et al., 2021; Liu et al., 2023). It holds promise as a novel way of data circulation, offering a fresh perspective and methods for sugarcane breeding work. In the Smart Sugarcane Breeding System, DT serves as a three-dimensional representation of data, aiming to construct a sugarcane data circulation system from a multidimensional data visualization perspective, supported by technologies such as sensors, robots, UAVs, AI, and blockchain. DT utilizes updated data from collection devices, AI models, and blockchain to map physical entities in virtual space, thereby reflecting the life cycle process of physical entities anywhere and in real time (Ding et al., 2019). Physical devices such as sensors, robots, and UAVs can collect breeding information about sugarcane, and when combined with DT, can become a real-time visualization tool, automatically updating data on the physical devices themselves and breeding data. Information derived from AI breeding models can also circulate on DT, enabling breeders as well as stakeholders to engage in human-machine dialogues with the models through DT, thereby providing useful insights. Blockchain offers potential unified standards and protocols to ensure the security, reliability, and collaborative improvement of circulating data generated by DT. In our envisioned smart sugarcane breeding system, DT provides monitoring and optimization services for breeders and stakeholders, allowing them to simulate their ideas and conduct virtual tests before implementation in the real world to determine their impact. This integrated circulation of breeding models and multiple information resources results in practical applications. For example (see Fig. 7), breeders or stakeholders can use DT to view current growth information of specific sugarcane plants and their surrounding environmental condition anywhere and in real time, presented in a lifelike manner, facilitating the revelation of environmental impacts and their interactions under controlled genotype effects.

4. Discussion

Compared with traditional breeding, the biggest advantage of this smart breeding system is that it can make full use of the feature extraction capabilities of AI to achieve rapid and precise selection effects that cannot be achieved by manual selection, thus greatly shortening the breeding cycle to develop elite sugarcane varieties. In addition, equipment such as UAVs and robots can automate breeding work and reduce the workload of breeders; while blockchain can automatically store information on the breeding process and provide information traceability, which will undoubtedly bring benefits to breeders. It provides unprecedented convenience, and the real-time and virtual reality features of the DT platform can support efficient collaboration between different collaborators. Although this study primarily focuses on technologies that shorten the breeding cycle, the potential benefits of their long-term application in perennial crops like sugarcane are equally promising. Smart breeding technologies, particularly AI-driven data analysis and digital twin technologies, can accumulate and optimize large amounts of data across each generation of breeding, enabling continuous improvement over multiple generations. Over time, these technologies can enhance the stability and adaptability of sugarcane varieties by identifying and preserving optimal genotypes. Moreover, the precise prediction and real-time feedback capabilities provided by smart breeding can continually optimize breeding strategies throughout the lifecycle of perennial crops, ensuring that each generation's improvements are directed towards the best possible outcomes. Therefore, smart breeding technologies not only accelerate the breeding process but also hold significant potential to enhance the overall performance of crops in multi-generational breeding, leading to long-term improvements in sugarcane yield and quality.

Despite the significant advantages of this smart sugarcane breeding system, we still need to consider some of its challenges. For example, the

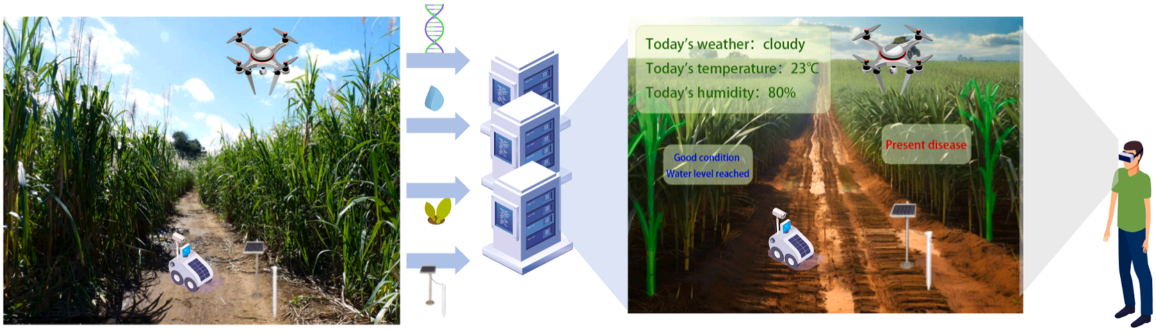

Fig. 7. A scenario of sugarcane breeding in the DT context.

training of AI models requires a large amount of high-quality data, which places higher requirements on the collection and processing capabilities of data collection equipment, while data interoperability and collaborative work between different technologies face compatibility between different technology platforms. Furthermore, the traditional concepts and habits of breeders will also cause the system to encounter resistance or even refusion in the promotion process. These require in-depth research and resolution in the future. Nowadays, technologies such as UAVs, AI, and blockchain are developing rapidly. We have confidence that in the coming years, data collection devices such as UAVs will collect data more intelligently and accurately, and the deployment and implementation of technologies such as AI and blockchain will also become easier in the future.

5. Conclusions

As an important economic crop, optimizing sugarcane breeding is crucial for enhancing sugar and energy production. Currently, sugarcane breeding mainly utilizes conventional hybridization and molecular breeding techniques, however both methods face technical bottlenecks and inefficiencies. Smart breeding, promising to overcome challenges unresolvable issues, is a novel approach integrating high-throughput data, modern biotechnology, and information technology. In the present study, we envision a new smart sugarcane breeding system aimed at addressing the inefficiencies, long cycles, and high complexity observed in traditional breeding by precisely processing genetic and growth data, predicting and optimizing the genetic traits and agronomic characteristics of sugarcane. We also introduce here a H-CPS to guide the system architecture of smart sugarcane breeding, an integrated framework of physical systems, network systems, and human decision-makers that enables high interaction and collaboration through intelligent sensing, data analysis, and execution feedback loops. The system comprises three layers: the physical layer, including ground sensors, UAVs, robots, and other devices for sensing and collecting breeding information; the cyber layer, including cloud servers, AI, blockchain, DT and so on for data transmission, processing, storage and circulation; and the human layer, consisting of breeders, farmers, and breeding institutions, which provide genetic data and breeding expertise and participate in AI model training and decision-making.

Taken together, this system provides more accurate and reliable decision support for the sugarcane breeding process. It integrates AI, blockchain, and DT to enhance efficiency and precision, shorten the breeding cycle, reduce costs, and cultivate high-quality sugarcane varieties. Nevertheless, in order to fully leverage its advantages, it is necessary to further optimize the technical details and continuously improve and perfect them in practical applications. We believe that the present study can offer new directions and possibilities for sugarcane breeding and the broader field of agricultural technology.

Compliance with ethics requirements

This article does not contain any studies with human or animal subjects.

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CRediT authorship contribution statement

Xiaoding Wang: Writing – original draft, Visualization, Software, Formal analysis. **Qibin Wu:** Writing – original draft, Visualization, Software, Formal analysis. **Haitao Zeng:** Writing – review & editing, Resources. **Xu Yang:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Xuechao Yang:** Visualization, Resources. **Xun Yi:** Visualization, Resources. **Ibrahim Khalil:** Visualization, Resources. **Youxiong Que:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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