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SHORT COMMUNICATION

Stress phenotyping in plants using artificial intelligence and machine learning

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ABSTRACT

The global population is rapidly increasing and is expected to exceed 9 billion by 2050, resulting in significant challenges for agriculture due to factors such as industrialization, reduced farmland, and biotic and abiotic stresses. To address these challenges and ensure future sustainability, the agriculture system needs to become more productive, efficient, and resilient. Artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools to transform the agricultural sector. Agricultural productivity is greatly influenced by biotic and abiotic stresses, and developing climate-smart crops through conventional breeding techniques is time-consuming and challenging. Plant phenotyping, which involves measuring specific plant features related to function, is crucial in breeding for target traits. However, traditional phenotyping methods are laborious, error-prone, and less accurate, particularly under stress conditions. To overcome these limitations, researchers have focused on developing high-throughput phenotyping technologies. State-of-the-art imaging techniques, such as light detection and ranging (LIDAR), remote sensing, and RGB imaging, combined with autonomous carriers like unmanned aerial vehicles (UAVs) and ground robots, enable real-time and high-throughput phenotyping of morphological, physiological, and stress-related traits. ML tools can compartmentalize big data, identify related traits, classify them, quantify their expression, and predict their function within the plant system. AI and ML offer multidisciplinary approaches for analyzing big data accumulated over time, leading to the discovery of patterns and systematic data of interest, such as stress phenotypes. Using these technologies, researchers worldwide can expedite agricultural research and develop climate-smart crops. The future of AI and ML in agriculture is promising, as they can lead to new scientific discoveries and help overcome the challenges of limited resources in food production.

KEYWORDS

Stress phenotyping; Artificial intelligence; Machine learning; Climate-smart crops

ARTICLE HISTORY

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As per the statistics of the Food and Agriculture Organization (FAO) of the United Nations, the population of the world is increasing rapidly and is expected to reach beyond 9 billion by 2050 [1]. Exaggerated population bursts, rapid industrialization, decreased farmland, biotic/abiotic stresses, and shrinking natural resources are catastrophically affecting agriculture productivity [2]. To meet the future demand for food, feed and fuel, there is an urgent need to push the present agriculture system into a new zone so that it can become more productive, efficient, and resilient against biotic/abiotic stresses, thus ensuring its sustainability for future generations [3,4]. Artificial intelligence (AI) and machine learning (ML) are the most obvious candidates for addressing the challenge of the new zone [5]. Agricultural productivity is inherently affected by various biotic/abiotic stresses. Nonetheless, plant breeders have managed to significantly reduce the damaging effect of plant stresses by incorporating resistance genes to develop climate-smart crops [6,7]. Development of climate-smart crops through conventional/molecular breeding techniques is time-consuming, and the success dramatically depends upon the accuracy and precision of plant phenotyping for the target trait [8]. Phenotyping refers to the measurement of specific features in plants, either morphological, cellular, or canopy level, related to plant function that can be exploited to achieve their research goals [9]. The traditional method of phenotyping involves the phenotyping of a large plant population of plants for multiple traits till the complete life-cycle of plants, which requires extensive sampling from growing replicated trials [9]. Furthermore, the traditional methods of phenotyping, i.e., manual and anatomical, are more error-prone and less accurate and thus are the major bottleneck for plant phenotyping under stress conditions [8].

To overcome this challenge, intensive efforts have been made by the scientific community to develop and adapt new high-throughput technologies in the field of plant stress phenotyping [8]. For instance, several high-throughput imaging technologies are now being exploited that have enabled real-time phenotyping not only for morphological traits in plants but also for physiological biotic and abiotic stress traits [10]. State-of-the-art imaging techniques like light detection and ranging (LIDAR), remote sensing, spectroradiometers, 3D laser scanning, and trichromatic (RGB) imaging in conjunction with autonomous carriers have genuinely unlocked the possibility of high-throughput stress phenotyping [9]. Additionally, the inclusion of unmanned aerial vehicles (UAVs) and ground robots retrofitted with the above sensors record real-time images at frequent intervals throughout the experimental setup or up to the life cycle of the crops [10]. Phenotyping of traits using an AI-imaging approach results in the accumulation of a large amount of

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data, which is subsequently stored and analyzed to make practical interpretations for its application in a breeding program [11]. Interestingly, one of the most effective ways of making sense of all the collected data is by integrating ML tools with AI [12]. The exploitation of ML tools is new in the plant stress phenotyping is employed to compartmentalize big data into small units by identifying related traits, classifying them into specific groups, quantifying according to their relative expression, and finally, predicting their overall function within plant system [13].

AI and ML are integrally multidisciplinary approaches that perform big-data analysis, which has been accumulated gradually over time to produce systematic data of interest, i.e., stress phenotype [14]. The exploitation of AI in conjunction with the ML approach has enabled plant breeders, pathologists, physiologists, and biologists to analyze largely to discover patterns by using combinations of factors simultaneously instead of analyzing all the combinations individually [13]. AI coupled with ML exploits probability theory, decision statistics, visualization of patterns, and optimization to create a holistic model that includes genetic, agronomic, environmental, and anthropogenic factors to unravel the effect on plant stress response and, ultimately, yield [9]. In addition, plant scientists have performed high-throughput phenotyping using AI-fitted sensors to measure morphological traits at different growth stages in *Gossypium hirsutum, Zea mays*, and triticale [8]. Further, researchers have corroborated that complementing AI/ML-driven high-throughput phenotyping of plant stress-related traits with a next-generation sequencing platform may reveal novel quantitative trait loci (QTLs) associated with the query stress [9,15]. The integration of high-throughput phenotyping data with QTLs obtained can be used to bridge the genotype-phenotype gap and can be used as a model for other stress-related traits in plants [10,15]. Additionally, combining real-time phenotypic data with real-time gene expression data obtained through AI-driven platforms such as UAVs and ground robots is integrated with a viable ML approach that can provide new insight into the cellular and molecular mechanism underlying stress tolerance in plants [8].

AI-coupled with ML, gives a realistic transformation of phenotyping and big data visualization that will reform the pattern and limit of traditional agricultural systems. These AI and ML will pave the way for another agricultural revolution to produce more food using limited resources in these trying times. Scientists worldwide are employing AI/ML technologies around the globe to expedite their agricultural research for developing climate-smart crops by performing high-throughput phenotyping for stress resistance/tolerance. Several notable instances of artificial intelligence and machine learning applications within the field of plant stress phenotyping encompass the i-Plant initiative and an integrated analytical platform. These technologies hold promise for facilitating the execution of multifaceted research endeavors. The future of AI/ML technologies is beneficial in agriculture, which, if executed accurately employing curated pipeline and its crucial ingredient, i.e., big-data analysis, can lead to new scientific discoveries.

Disclosure statement

No potential conflict of interest was reported by the author.

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