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Editorial

Agricultural Unmanned Systems: Empowering Agriculture with Automation

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Automation is crucial for the advancement of modern agriculture. It plays a significant role in enhancing production efficiency and output, reducing labor costs, addressing natural disasters, and boosting sustainability. Automation utilizes big data and artificial intelligence to monitor agricultural production. It introduces new farming models that adapt to the challenges of scalability and environmental changes, achieving precise and efficient agricultural development.

In the field of smart agriculture, the emergence of unmanned systems represents a significant evolutionary breakthrough. Currently, smart agricultural unmanned systems encompass four spatial dimensions: sky (including navigation, remote sensing, meteorological, and communication satellites) [1,2], air (comprising plant protection drones, remote sensing mapping drones, long-duration solar drones, airships, and biomimetic flying robots) [3,4], land (featuring unmanned farming/harvesting machinery, biomass energy systems, soil improvement biomimetic robots, and unmanned livestock robots) [5,6], and water (including unmanned underwater vehicles, underwater operation robots, and unmanned aquaculture systems) [7,8]. These developments promise a bright future. This Special Issue, titled "Agricultural Unmanned Systems: Empowering Agriculture with Automation", focuses on sharing knowledge related to integrated and precise operational agriculture systems in the sky, air, land, and water. It explores intelligent sensing and control technologies in smart agricultural unmanned systems to advance the progress of unmanned agriculture. Establishing global demonstration sites is essential. These sites support the revolutionary advancement of smart agricultural machinery in automated, intelligent, unmanned, and cluster operations.

The following five studies explore the application of intelligent algorithms in precision agriculture. To effectively cover the canopy area of tall spindle-shaped apple trees, Wang et al. [9] developed an improved lightweight transfer learning model for citrus pest detection. They utilized networks such as ResNet50, InceptionV3, VGG16, and MobileNetV3, in conjunction with a pre-trained single-shot multibox detector (SSD). This system can classify and rapidly detect pests in citrus orchards, and can be integrated into mobile devices for quick testing and pest counting. It assists farm managers in assessing pest damage and making informed pesticide decisions in orchard management. Peng et al. [10] proposed a new method that utilizes an optimized neural network to quickly identify crop water and nitrogen content. They specifically improved a traditional backpropagation neural network by incorporating particle swarm optimization (PSO). This improved network, with a dual hidden layer structure, enhances prediction accuracy. The enhanced PSO-BPNN model demonstrates a 9.87% increase in accuracy compared to conventional BPNN models. This advancement establishes a strong foundation for precision irrigation and fertilization in modern agriculture. It offers the potential to greatly improve resource management and crop yields. Xiao et al. [11] investigated the present status of target detection and recognition technologies for fruit- and vegetable-harvesting robots, with a focus on digital

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image processing and traditional machine learning methods. They assessed how these technologies affect the robots' accuracy, speed, and robustness, identifying current challenges and future developments to enhance robotic harvesting through improved computer vision technologies. Xiao et al. [12] provided a comprehensive overview of the advancements in fruit detection and automated harvesting using deep learning, particularly through Convolutional Neural Networks (CNNs), from 2018 to the present. They detailed the challenges faced, proposed solutions, and future research directions aimed at enhancing the accuracy, speed, and robustness of visual detection systems for fruit while reducing overall complexity and costs. This work serves as a reference for future research in the field of deep learning-based automatic fruit harvesting detection and recognition. Ji et al. [13] investigated the progress of the "eye-brain-hand" harvesting system in smart agriculture. This system integrates sensor technology, machine vision algorithms, and intelligent control to simulate human functions for automated and precise fruit and vegetable picking. It explores the development of robotic arms, visual recognition, and decision systems, emphasizing technologies such as image processing and deep learning. The review also evaluates the system's application across various crops and environments. It emphasizes future challenges in algorithm optimization and mechanical device reliability.

In the field of agricultural intelligent robotics technology and applications, Xiong et al. [14] proposed an optimized design method for an efficient dual-mechanical-arm harvesting system. For the typical spatial distribution of fruits in dwarf dense plants, a pair of vertically synchronized, three-degree-range Cartesian coordinate dual mechanical arms was designed. Through the development of a multi-objective optimization model and evaluation using the CRITIC-TOPSIS method, simulation analysis determined the optimal configuration to maximize harvesting efficiency, advancing robotic fruit-picking technology. Zhang et al. [15] implemented a mechanized picking method in trellised pear orchards by designing an integrated picker–placer end effector. They utilized the YOLOv5s object detection algorithm and a depth camera for precise fruit localization. By introducing a simulated annealing algorithm to optimize the picking order and proposing a task allocation method, the system was experimentally verified to improve picking efficiency by 30%. This study provides important references for the further development of robotic picking technologies. Shang et al. [16] addressed the issue of collisions with obstacles in unmanned agricultural machinery by proposing an obstacle detection algorithm based on two-dimensional LiDAR. This method utilizes differences between LiDAR data frames to determine collision incidents; employs preprocessing, median filtering, and DBSCAN to detect obstacles; and computes collision timing following the 6σ principle. Utilizing this algorithm, a pre-collision system was designed, integrated into agricultural navigation software, and tested on a harvester, achieving high accuracy and recall. This system enables emergency stops when farm machinery encounters obstacles during automated operation. It lays the groundwork for unmanned driving in more complex scenarios. Zhang et al. [17] investigated the application of mobile robots in agriculture, specifically emphasizing full-coverage path planning for orchard lawnmowers. They proposed a simplified motion model designed for orchard environments and enhanced the A* algorithm to optimize the lawnmower's navigation paths, reducing unnecessary turns during traversal. These improvements were validated through MATLAB 2020b simulations and field tests, demonstrating the method's effectiveness in enhancing navigation efficiency and task allocation in agricultural settings. Existing methods for controlling drive wheel slip in prototype machines have limitations, which result in suboptimal cultivation and finishing operations. To address this issue, Luo et al. [18] proposed a slip rate control method that is adjusted by both wheel speed and tillage depth. This method was validated using a New Holland T1404 power shift tractor. This method controls slip within an optimal range while ensuring maximum operational quality (tillage depth).

Additionally, the following three papers discuss and research improvements in automated agricultural equipment. Jiang et al. [19] discussed issues related to significant droplet loss, pesticide wastage, and environmental pollution caused by improper spray parameters.

They conducted a two-factor, five-level experiment focusing on power gradient and foliar area volume density (FAVD) to analyze the impact of these factors and the position of sampling points (considering horizontal distance, forward distance, and height) on droplet coverage. This research improves sprayer efficiency and establishes a foundation for future studies on precision spraying. It contributes to more sustainable agricultural practices. Liu et al. [20] developed an innovative baler feed rate detection model by utilizing power monitoring of the pickup platform. They utilized advanced signal processing techniques to mitigate the impact of machine vibration and precisely detect the feed rate of the baler. The model analyzes the dynamic characteristics of the pickup platform and utilizes frequency domain filtering to eliminate noise signals. This approach effectively correlates the power output of the pickup platform with the feed rate. Field experiments have confirmed the model's high accuracy and stability. This significantly improves the precision of feed rate measurements. The model meets the requirements of baler feed rate monitoring in field operations. Hui et al. [21] addressed low throughput and uneven treatment in plasma seed equipment. They designed a dielectric barrier discharge vibrating homogeneous material plasma seed treatment device. They systematically analyzed the structure and working principles of the vibrating homogeneous material equipment and established a mathematical model of seed force. Utilizing EDEM 2021 discrete element simulation software and a three-factor, three-level orthogonal experiment for empirical testing, the study demonstrated promising improvements in seed vitality, germination, and growth. This marks a significant advancement in seed treatment technology.

This Special Issue extends its deepest gratitude to all contributors. The papers included represent a broad range of research in the field of smart agriculture. However, there are still gaps related to 'sky', 'air', and 'water'. In the future, we anticipate more innovative research in these areas, especially focusing on how technological advancements can address current challenges and advance the holistic development of smart agriculture.

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