Abstract: Crop row detection is one of the foundational and pivotal technologies of agricultural robots and autonomous vehicles for navigation, guidance, path planning, and automated farming in row crop fields. However, due to a complex and dynamic agricultural environment, crop row detection remains a challenging task. The surrounding background, such as weeds, trees, and stones, can interfere with crop appearance and increase the difficulty of detection. The detection accuracy of crop rows is also impacted by different growth stages, environmental conditions, curves, and occlusion. Therefore, appropriate sensors and multiple adaptable models are required to achieve high-precision crop row detection. This paper presents a comprehensive review of the methods and applications related to crop row detection for agricultural machinery navigation. Particular attention has been paid to the sensors and systems used for crop row detection to improve their perception and detection capabilities. The advantages and disadvantages of current mainstream crop row detection methods, including various traditional methods and deep learning frameworks, are also discussed and summarized. Additionally, the applications for different crop row detection tasks, including irrigation, harvesting, weeding, and spraying, in various agricultural scenarios, such as dryland, the paddy field, orchard, and greenhouse, are reported.

Keywords: crop row detection; navigation and guidance; machine vision; precision farming; agricultural robots; smart agriculture
controller guides the agricultural robot to operate automatically and safely without damaging the crop by adjusting the forward speed and direction of the front and rear wheels. The row detection-based navigation of agricultural machinery is widely used in different agricultural tasks such as spraying, mowing, irrigation, harvesting, fertilization, and plant protection [5]. The complexity and diversity of the agricultural environment necessitate varying requirements to be met for crop row detection and the autonomous navigation of agricultural robots. Typical agricultural scenarios include drylands, paddy fields, orchards, and greenhouses. Drylands are usually uneven, and crop growth can be messy; paddy fields have different water depths, and different crops can grow together; orchards have a dense canopy of fruit trees, and there may be other weeds and plants growing with the fruit trees; greenhouses have a variety of plants that need to be distinguished [6]. In addition, curved crop rows are common in some agricultural fields due to topography. Curved crop rows usually have complex shapes and occur not only in agricultural terraces but also in flat plots with irregular geometry. This makes it difficult to accurately detect and measure target crop rows, and the traditional line detection algorithm is difficult to cope with in this situation as it can bring certain challenges for the safe navigation of agricultural robots [7]. Therefore, in order to improve the accuracy of crop row detection, appropriate sensors, and computer algorithms need to be selected according to different application scenarios [8].

![Figure 1. Applications of agricultural robots working in row-crop fields.](image)

With the development of computer technology and intelligent equipment, various types of intelligent sensors and systems have been widely used for row detection in agricultural environments to help solve the problem of the autonomous navigation of agricultural robots [9,10]. Vision sensors have been extensively used as a reliable source of information for agricultural robots due to the advantages of a wide measurement range, rich signal information, and low costs [11,12]. Based on the detected crop row images, the information on crop row spacing, contours, and obstacle locations can be obtained in real-time for the robot to achieve row tracking and navigation [13,14]. Scholars have developed many algorithms for crop row recognition, and path extraction based on the above vision sensors and systems, including traditional methods and learning-based methods. Traditional crop row detection methods are simple to implement, widely applicable, cost-effective, and well-visualized [15]. However, environmental factors such as lighting and shading have a deep impact on the accuracy and reliability of traditional crop row detection methods in practical applications. In recent years, the development and application of machine learning and deep learning have provided strong theoretical support for vision-based crop row detection [16]. In image segmentation, feature detection, target recognition and other visual information processing and machine learning can replace traditional methods to reduce the interference of environmental noise and vegetation overlap and improve the accuracy of crop row detection [17,18]. Moreover, traditional visual inspection techniques...
are prone to occlusion and missed detection in agricultural environments with high crop density, such as fruit gardens, sorghum fields, and corn fields. In this case, LIDAR is a good alternative, with strong penetration and high accuracy. In addition, multi-sensor fusion is an important development direction in crop row detection. By integrating information from multiple sensors, multi-sensor fusion makes up for the limitations of a single sensor and improves the accuracy and robustness of crop row detection. In general, the application of different sensors and their corresponding algorithms can effectively improve the crop row detection accuracy and navigation robustness of agricultural robots and promote the transition of modern agriculture to high efficiency, automation, and precision [19,20].

Despite the increasing popularity of this topic in agricultural navigation, the related methods and applications based on crop row detection have not been summarized in detail or systematically. This is detrimental to the understanding of agricultural robot navigation methods based on crop row detection. Therefore, in order to promote the further development of crop row detection technology and agricultural robotics navigation, this paper provides a comprehensive review of the literature regarding the current state of research on crop row detection. This paper is organized as follows: Section 2 provides a comprehensive introduction to the concepts of sensors and systems in navigation systems, as well as their advantages and disadvantages. In Section 3, recognition and detection algorithms and methods of crop row are classified into two main categories: traditional methods and machine vision methods. The applications of crop row detection in robot navigation are shown in Section 4 in accordance with various perceptual conditions. Section 5 discusses the challenges and prospects of the theme.

2. Sensors and Systems for Crop-Row Detection

2.1. Monocular Cameras

Monocular vision is a fundamental building block for other vision systems, such as binocular stereo-vision and multi-vision systems [21]. The imaging principle of a monocular camera is to generate a projection onto the camera plane, reflecting the three-dimensional (3D) world in a two-dimensional (2D) form [22]. According to different signal readout processes, monocular cameras are usually divided into two kinds of image sensors: the charge-coupled device (CCD) and the complementary metal-oxide-semiconductor (CMOS) [23]. The advantages of the monocular camera include a simple structure, low cost, and low power consumption, making it a convenient tool for crop row detection. Additionally, monocular cameras can detect color, texture, and other features in agricultural scenes, providing useful information for the positioning and navigation of agricultural robots and vehicles [24]. However, due to the limited amount of information provided by a single camera, auxiliary algorithms are often required to determine the distance of the relationship between the target and the camera [25,26]. Moreover, depth information cannot be directly collected from monocular cameras because of their single-view angle.

2.2. Binocular Cameras

The binocular stereo vision technique is commonly utilized in crop row detection because it can provide precise and efficient depth information [27]. A binocular camera comprises two monocular cameras and is commonly used as a passive rangefinder. By capturing two images of an object from different positions, binocular cameras can determine the 3D geometric information of the object by calculating the position deviation between the corresponding points of the images [28]. This process is based on the principle of parallax, and it enables the camera to accurately measure the distance to the object, providing important information for crop row detection [29]. Stereo vision-based crop row detection has demonstrated superior performance in challenging field conditions such as high crop density or varying lighting [30]. Compared to monocular vision, stereo vision is less sensitive to the effects of shadows and sunlight, providing more reliable results in these environments [31]. However, the configuration and calibration of binocular cameras can be complex and requires careful attention to detail. Additionally, in the absence of texture features, stereo-matching algorithms can fail to accurately identify the corresponding points between images [32].
2.3. RGB-D Cameras

RGB-D cameras have become increasingly widespread in crop row detection due to their capacity to capture both color and depth information [33]. Structured light and Time-of-Flight (TOF) cameras, which are capable of measuring both RGB and depth information, fall under the category of RGB-D cameras [34]. Structured light systems can capture both 2D planar and 3D depth information [35]. This system is composed of projectors, cameras, image acquisition systems, and processing systems, which work together to project a particular mode of a light signal onto the surface of the object to be measured and then calculate the position and depth information according to the changes in the light signal on the surface of the object [36]. ToF cameras work on the principle of emitting a short burst of infrared light and measuring the time it takes for the light to return after reflecting off objects in the scene [37]. The camera sensor detects the reflected light and calculates the distance to each point based on the time of flight. These data are then used to create a depth map of the scene, which provides information about the distances between the camera and various objects within the field of view [38]. Unlike the passive range of binocular cameras, RGB-D sensors can actively emit signal waves and capture these waves, which are reflected back from objects [39]. The depth information obtained from RGB-D cameras provides additional geometric information that can be used to detect crop rows and estimate plant height more accurately [40]. However, the performance of RGB-D cameras may be limited in situations where the crop density is high or occlusion. In such scenarios, some crop plants may be hidden from view, or the depth of data may be noisy, leading to inaccurate detection [41]. In addition, the processing of large amounts of 3D data generated by RGB-D cameras is also a computationally intensive and time-consuming process [42].

2.4. Panorama Cameras

Panoramic cameras can enable the large-scale and dead-angle-free monitoring of crops in the field [43]. Based on bionics technology, panoramic cameras work by using the spherical mirror transmission and reflection of physical optics for imaging. By rotating the camera, the photographic field can be scanned at a large angle, and the panoramic range can be achieved by stitching technology, which is enough to reach 360° [44]. The remarkable feature of panoramic cameras is that they can capture a large amount of the surrounding crop structure information in a single image, making them more suitable for large-scale farmland monitoring [45]. Fisheye panoramic cameras are one of the most commonly used types of panoramic cameras in agriculture due to their broad field of view and ability to capture rich environmental information [46]. However, the images captured by fisheye panoramic cameras suffer from large distortion and lack the details required for accurate object detection, which can limit their usefulness in certain applications [47,48]. To address these issues, deformation correction techniques, such as equidistant, stereographic, or orthographic projection models, can be used to rectify these images and remove the distortion [49].

2.5. Spectral Imaging Systems

The spectral imaging system is a combination of imaging technology and spectral information acquisition technology, which shows great potential in crop detection applications [50]. This system obtains the data cube composed of 2D spatial information and the one-dimensional (1D) spectral information of the measured object by spectral scanning [51]. According to different spectral resolution capabilities, common spectral imaging techniques can be divided into multi-spectral, hyper-spectral, and ultra-spectral [52]. Hyperspectral imaging systems provide a higher spectral resolution, enabling the more detailed and accurate identification of different objects in the field. By acquiring spectral data and analyzing the differences in their spectral reflection, this system can differentiate between crops and non-crop areas more accurately [53,54]. However, for early-growing crops, which may have similar spectral characteristics to weeds, spectral detection may not be as effective [55]. In addition, processing a large amount of imaging spectral data quickly and reliably remains a challenge for spectral imaging systems [56].
2.6. LiDAR Sensors

LiDAR, which stands for Light Detection and Ranging, is a highly advanced and reliable sensor that has been widely used in the field of crop row detection and robot navigation. This sensor is known for its high precision, wide range, and powerful anti-jamming capabilities [57]. The principle of the LiDAR operation is based on the emission of visible or near-infrared light waves by the transmitting system. These waves are then reflected off the target and detected by the receiving system. The data obtained are subsequently processed to produce parameter information, including distance [58]. LiDAR sensors have been utilized in crop row detection to provide highly accurate and detailed 3D maps of crop canopies [59]. Additionally, LiDAR sensors are able to penetrate vegetation and capture data from the ground surface, which can aid in detecting crop rows even in highly vegetated fields [60]. However, the high cost of LiDAR sensors remains a foremost drawback, limiting their use in small-scale farming operations. Additionally, LiDAR sensors require high computational power to process large amounts of data, which could be a bottleneck in real-time applications [61].

2.7. Multi-Sensor Fusion Systems

As mentioned above, both vision and LiDAR sensors have their own limitations in crop row detection and robot navigation. The multi-sensor fusion system can exploit the complementary and redundant nature of multiple sensor data to fuse different environmental information and enhance the performance of crop row detection [62,63]. Considering the variability of soil disturbance, vegetation level, and machinery speed in agricultural environments, the fusion of LiDAR and vision sensors can enable robust weed detection and crop row tracking tasks [64]. Combining the plane data given by the LiDAR with the colorful representation provided by the images, the noise of grass or leaves in the environment can be eliminated, and the detection ability of crop rows improved [65]. Since the boundaries between harvested and unharvested crops in the field are not always straight lines, the fusion of vision sensors with the Global Positioning System (GPS) is also an effective fusion scheme [66]. The use of vision sensors alone for crop row detection may result in missed detections during image processing while using a GPS device alone can produce certain errors in determining the navigation baseline. The fusion of vision and GPS improves the integrity of crop row feature information extraction and enhances localization accuracy and detection robustness. In addition, the fusion of vision sensors, encoders, and inertial measurement units (IMU) is also common in crop row detection [67]. Although multi-sensor fusion systems have additional complexities, these can be effectively mitigated by employing optimal techniques [68]. When the data are optimally integrated, the information from different sensors can give an accurate crop row detection model in the current agricultural environment.

3. Methods and Algorithms for Crop-Row Detection

3.1. Traditional Methods

3.1.1. Hough Transform (HT)

HT is a classical computer vision algorithm for crop row detection and navigation line extraction [69]. The idea behind this approach is to transform the image-coordinate space to the Hough-parameter space using the mapping relationship between points and lines, followed by detecting the target lines in the image. The HT-based detection approach is robust to image noise and outliers and performs well even in parallel structure crop fields with gaps [70]. To improve the efficiency and accuracy of these inspection results, edge detection, and image binarization are often performed prior to the HT-based detection process [71]. One limitation of the classic Hough transform is its high computational complexity, which makes it unsuitable for real-time applications. Another limitation of the classic Hough transform is its sensitivity to noise and outliers. To address this issue, researchers have proposed various modifications to HT, such as the Probabilistic Hough Transform (PHT), which uses a probabilistic voting scheme to reduce the effect of noise and outliers [72]. Other modifications include the Directional Hough Transform (DHT), which was designed to detect lines with a specific orientation [73], and the Multi-scale Hough Transform (MHT), which detects lines of different scales [74].
3.1.2. Linear Regression Method (LRM)

LRM is a widely utilized technique in detecting row crops in agriculture through image analysis. In regression analysis, one or more independent variables are studied to determine their impact on the dependent variable, with the aim of generating a hypothesis analysis [75]. The most common implementation of LRM is the least squares method, where the sum of the squared errors between the predicted and actual values is minimized to find the best-fit line. In the context of crop row detection, LRM can be used to predict the position and orientation of crop rows using image data. The goal is to find a linear relationship between the independent variables (such as pixel coordinates) and the dependent variable (crop row position or orientation). Before applying LRM to crop row detection, image preprocessing steps such as image segmentation and feature extraction can be performed to isolate the crop rows from the background and extract useful features for regression analysis [76]. One of the advantages of LRM is its simplicity and computational efficiency. However, it may encounter difficulties in handling complex data with noise in farmlands. In such cases, additional preprocessing steps, such as separating weed and crop pixels or using non-linear regression techniques, may be necessary to improve the accuracy of the model [77].

3.1.3. Horizontal Strips Method

The horizontal strips method is a reliable approach for detecting crop rows using agronomic image analysis [78]. The key concept of this technique is to divide the input image into several horizontal strips, which can serve as regions of interest (ROI). Within each ROI, feature points are determined based on the calculated center of gravity. Compared with other crop row detection methods, the horizontal strip analysis method does not require an additional image segmentation step, which improves the computational efficiency of image processing and reduces storage space [79]. Moreover, this technique was clearly superior in terms of real-time performance and precision in continuous crop rows with low weed density. Nevertheless, the horizontal strip method might not perform well in agricultural environments where crop rows are partially missing or overgrown with weeds, as these factors can affect the accuracy of feature point detection. Furthermore, the accuracy of this method is sensitive to the camera angle, which can affect the determination of feature pixel values. To mitigate this issue, the vertical projection method is often used in conjunction with the horizontal strip method to enhance accuracy [80].

3.1.4. Blob Analysis (BA)

The Blob Analysis (BA) method is a useful technique for crop row detection that operates on binarized images to group connected pixels into blobs with the same gray value [81]. The blobs that contain more than a certain number of pixels are then used to generate straight lines that represent crop rows. Unlike other machine vision techniques, BA considers features in an image as objects rather than individual pixels or lines, leading to more accurate identification of crop rows [82]. This approach leverages the unique shape and color characteristics of crop rows to accurately locate and identify them by calculating the center of gravity and principal axis position of each crop row [83]. In crop row detection, the BA technique has proven effective, particularly in situations where the crop rows have a clear definition and a distinct contrast with the surrounding field, such as in the case of newly planted crops with a different color or texture than the soil. However, BA may have limitations in fields with a high weed density or an unclear crop row definition. In such cases, the noise in the clustered blobs can lead to errors, which can affect the accuracy of the crop row detection results [84].

3.1.5. Random Sample Consensus (RANSAC)

The RANSAC algorithm is a robust and widely used technique for row detection in crops. The algorithm estimates a mathematical model and calculates the optimal solution of parameters from a dataset that may contain outliers [85]. In crop row detection, outliers can be weed points, soil points, or other objects that do not belong to the crop row. This
property makes it suitable for the centerline fitting of crop rows, even when a significant proportion of weed data points are present [86]. Furthermore, the RANSAC algorithm can optimize point cloud matching and 3D coordinate calculations for complex 3D crop row detection [87]. However, the effectiveness of the RANSAC algorithm depends on several factors, such as the number of iterations, the threshold values, and the size of the data set. In the case of crop row detection, the quality of the feature points extracted from the image data also plays a crucial role in the success of the algorithm [88]. In recent years, several variations of the RANSAC algorithm have been proposed to address some of its limitations in crop row detection, such as the Progressive Sample Consensus (PROSAC) algorithm and the M-estimator Sample Consensus (MSAC) algorithm [89].

3.1.6. Frequency Analysis

Frequency analysis is a signal processing technique for analyzing local spatial patterns, which is widely used in crop row detection [90]. This mathematical method involves converting images from the image space to the frequency space through frequency domain filtering. By analyzing the resulting spectrum, this method can extract details from the image and enhance object detection with some simple logical operations. Common methods used in frequency-domain characterization include Fourier transform (FT), fast Fourier transform (FFT), and wavelet analysis [91]. Through these methods, the grayscale levels of weeds and shadows (tractors or crops) in field images can be attenuated, enabling the efficient detection of the position and direction of crop rows [92]. However, the frequency analysis method may not be suitable for the detection of curved crop rows with irregular crop spacing. Furthermore, the accuracy of this method may be affected by factors such as lighting conditions and the presence of noise in the image [93].

3.2. Machine Learning Methods

3.2.1. Clustering

The clustering algorithm is an unsupervised learning method that automatically groups data points into clusters according to various standard attributes or features like color, texture, or edge information [94]. This method does not require labeled data, which makes it a useful tool for detecting crop rows. The cluster-based algorithm is known for its quick detection of objects, high efficiency, and fast operation speed [95]. Data clustering methods mainly include partition-based methods, density-based methods, and hierarchical methods. Among these, the K-means clustering algorithm is the simplest and most commonly used method in crop row detection [96]. It can cluster data effectively, even when weed pixels are present between rows and are significantly smaller than planting crops. The scalability and efficiency of the K-means algorithm make it suitable for processing large datasets in cropland [97]. However, it has been noted that the K-means algorithm assumes that the clusters are spherical, equally sized, and have similar densities, which can lead to over-clustering or under-clustering in certain situations [98]. In recent years, several studies have attempted to address the limitations of traditional clustering algorithms in crop row detection. For example, some researchers have used hybrid clustering algorithms that combine the strengths of multiple clustering methods to achieve better results. Others have developed clustering algorithms that can detect irregularly shaped clusters, such as Gaussian mixture models (GMMs) or fuzzy clustering algorithms [99].

3.2.2. Deep Learning

Deep learning is a new research direction of machine learning that has been applied to crop row detection [100]. Unlike traditional shallow learning, deep learning places more emphasis on the depth and feature learning of model structures, with the goal of establishing a neural network that can analyze and learn in a manner similar to the human brain. This method has demonstrated significant improvements over traditional computer vision algorithms for identifying crop rows, especially in challenging conditions such as variable lighting, weather, and field conditions [101]. One of the main advantages of deep learning
is that it can autonomously learn from large datasets and adapt to new data distributions. This makes it well-suited for precision agriculture, where it can be used to identify crops, pests, and diseases, optimize planting patterns, and monitor crop growth and health. Object detection and semantic segmentation play crucial roles in crop row detection by enhancing the accuracy and understanding of field images. Object detection algorithms enable the identification and localization of crop rows within an image, allowing for the precise mapping and measurement of their positions. This helps when optimizing planting patterns and ensuring uniform spacing between the rows. Moreover, object detection enables the detection of other objects or obstacles in the field, such as machinery or structures, which can help to avoid potential collisions or disturbances during farming operations [102]. On the other hand, semantic segmentation goes beyond object detection by providing detailed pixel-level labeling of an image. In the context of crop row detection, semantic segmentation helps differentiate the crop rows from other objects or background elements that are present in the image. By accurately segmenting the crop rows, semantic segmentation facilitates the analysis of their spatial distribution and arrangement [103]. It enables the identification of irregularities or gaps between rows, which can indicate potential issues such as missing plants, weed infestations, or uneven growth. This information is invaluable for farmers when making informed decisions regarding subsequent farming operations. Recent studies have used deep learning techniques such as Faster R-CNN, YOLOv3, Mask R-CNN, and DeepLabv3+ to detect crop rows from images captured by drones, tractors, or robots [104]. The significant challenge of deep learning-based crop detection is a lack of annotated training data for specific crops, growth stages, and field conditions [105]. Creating such datasets requires significant time and resources, and their quality and size can significantly impact the accuracy and robustness of the models. Moreover, the computational cost of training deep learning models can be prohibitive for resource-constrained devices and systems [106].

4. Applications of Row Detection Based Navigation in Row-Crop Fields

Most crops are planted or cultivated in fields with regular parallel structures and spaced line patterns. For one thing, this structure can make full use of land and space, help crop growth and development, and increase crop yields [107]. For another, the crops grown in rows are conducive to field operations and management, improving the working efficiency of agricultural robots [108]. To achieve row detection-based navigation, various sensors, systems, and detection algorithms have been developed and applied in different agricultural scenarios such as drylands, paddy fields, orchards, and greenhouses [109]. For example, in dryland fields, visible light and near-infrared cameras have been used to detect crop rows, while in paddy fields, depth sensors and LiDAR have been utilized due to the presence of water. In orchards, stereo vision and 3D laser scanning have been employed to detect tree trunks and branches, which can be used as reference points for navigation. These technologies provide dependable crop row information, which can facilitate the implementation of precise navigation in agricultural machinery [110]. Moreover, the focus and challenges of row detection in different applications vary due to different applied objects, differences in image interpretation, and differences in weed interference [102]. In irrigation, crop row detection usually needs to identify the position of the crop row in vegetation-covered images, while in weed detection and picking, crop row detection mainly assists when distinguishing crops from weeds [111]. In terms of weed interference differences, one of the main challenges in weed detection is to accurately detect and segment weed areas, and crop row detection can help establish a frame of reference for weed distribution analysis and targeted weed control. By contrast, in harvesting, the main concern is to accurately detect and locate crop rows. The specific implementations of crop row detection in different agricultural environments and applications are detailed and summarized below [82].

4.1. Applications of Row Detection in Drylands

Dryland refers to arable land that relies on natural precipitation to grow crops, accounting for about 65% of the total arable land [112]. Water and nutrients are the main
factors affecting agricultural production in dryland. Common dryland crops include important food crops (legumes, cereals, potatoes, etc.), as well as typical cash crops (fiber, oilseeds, etc.). In drylands, complex and diverse terrain, and unstable light conditions are the main factors affecting the accuracy of crop row detection. To overcome these challenges, intelligent technology can be employed to increase the precise identification of characteristics such as the position, shape, and direction of crop rows [113,114]. This can provide technical support for the guidance and operation of agricultural robots, making agricultural production more intelligent and efficient. Table 1 details the applications of sensors for crop row detection in drylands, including sensors, scenarios, methods, and crop row detection accuracy (CRDA).

<table>
<thead>
<tr>
<th>Application</th>
<th>Sensors</th>
<th>Scenarios</th>
<th>Methods</th>
<th>CRDA</th>
<th>Work</th>
</tr>
</thead>
<tbody>
<tr>
<td>Navigation</td>
<td>RGB and TOF camera</td>
<td>Corn and wheat fields</td>
<td>DBSCAN</td>
<td>-</td>
<td>[115]</td>
</tr>
<tr>
<td>Camera</td>
<td>Camera</td>
<td>Cotton crops</td>
<td>Iterative least squares method</td>
<td>-</td>
<td>[116]</td>
</tr>
<tr>
<td>Camera</td>
<td>Camera</td>
<td>Corn crop field</td>
<td>RASCM</td>
<td>97.90%</td>
<td>[117]</td>
</tr>
<tr>
<td>GNSS and color camera</td>
<td>Cabbage field</td>
<td>Pattern RANSAC</td>
<td>83%</td>
<td></td>
<td>[118]</td>
</tr>
<tr>
<td>RGB camera</td>
<td>Strawberry field</td>
<td>Convolutional neural network (CNN)</td>
<td>-</td>
<td></td>
<td>[119]</td>
</tr>
<tr>
<td>RGB Camera</td>
<td>Corn and soybean field</td>
<td>Adaptive threshold RANSAC</td>
<td>92.18%</td>
<td></td>
<td>[120]</td>
</tr>
<tr>
<td>Camera</td>
<td>Soybean seedlings</td>
<td>Least squares method (LSM)</td>
<td>90%</td>
<td></td>
<td>[121]</td>
</tr>
<tr>
<td>ToF camera</td>
<td>Corn and sorghum fields</td>
<td>Euclidean Clustering algorithm and Linear programming</td>
<td>-</td>
<td></td>
<td>[122]</td>
</tr>
<tr>
<td>Camera</td>
<td>Crop field</td>
<td>Sliding window technique</td>
<td>-</td>
<td></td>
<td>[123]</td>
</tr>
<tr>
<td>2D LiDAR</td>
<td>Cotton field</td>
<td>RANSAC</td>
<td>-</td>
<td></td>
<td>[124]</td>
</tr>
<tr>
<td>Stereo Camera</td>
<td>Strawberry fields</td>
<td>Adaptive multi-roi algorithm</td>
<td>-</td>
<td></td>
<td>[125]</td>
</tr>
<tr>
<td>LIDAR</td>
<td>Maize fields</td>
<td>LST and filter method</td>
<td>95%</td>
<td></td>
<td>[126]</td>
</tr>
<tr>
<td>RGB camera</td>
<td>Corn seedling</td>
<td>LSM</td>
<td>93.8%</td>
<td></td>
<td>[127]</td>
</tr>
<tr>
<td>Camera</td>
<td>Crop imgs</td>
<td>Luminance partition correction and Adaptive threshold</td>
<td>-</td>
<td></td>
<td>[128]</td>
</tr>
<tr>
<td>Camera</td>
<td>Corn field</td>
<td>Neural network model</td>
<td>97%</td>
<td></td>
<td>[129]</td>
</tr>
<tr>
<td>LIDAR</td>
<td>Corn crop</td>
<td>LSM</td>
<td>-</td>
<td></td>
<td>[130]</td>
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<tr>
<td>3D laser and vision camera</td>
<td>Winter canola and sugar beet plants</td>
<td>Pattern hough transform</td>
<td>-</td>
<td></td>
<td>[131]</td>
</tr>
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<td>Color camera</td>
<td>Maize fields</td>
<td>LSM</td>
<td>-</td>
<td></td>
<td>[132]</td>
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<tr>
<td>Camera</td>
<td>Cotton field</td>
<td>HT</td>
<td>100%</td>
<td></td>
<td>[133]</td>
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<td>Color video camera</td>
<td>Soybeans, wheat and cabbage</td>
<td>Improved genetic algorithm (IGA)</td>
<td>-</td>
<td></td>
<td>[134]</td>
</tr>
<tr>
<td>RGB camera</td>
<td>Maize fields</td>
<td>LSM</td>
<td>92%</td>
<td></td>
<td>[135]</td>
</tr>
<tr>
<td>3D-LIDAR Laser scanner</td>
<td>Maize rows</td>
<td>RANSAC</td>
<td>-</td>
<td></td>
<td>[136]</td>
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<tr>
<td>DFK camera</td>
<td>Maize field</td>
<td>Radial basis function (RBF) algorithm</td>
<td>95%</td>
<td></td>
<td>[137]</td>
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<tr>
<td>Color camera</td>
<td>Wheat rows</td>
<td>Vanishing point detection method based on k-means clustering</td>
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<td></td>
<td>[138]</td>
</tr>
<tr>
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<td>Cropland</td>
<td>Quadrangle method</td>
<td>-</td>
<td></td>
<td>[139]</td>
</tr>
<tr>
<td>3D Stereo camera</td>
<td>Cotton field</td>
<td>Parallax distance measuring method &amp; HT</td>
<td>90%</td>
<td></td>
<td>[140]</td>
</tr>
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</table>

Table 1. A detailed summary of applications of sensors for crop row detection in drylands.
Table 1. Cont.

<table>
<thead>
<tr>
<th>Application</th>
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<th>Scenarios</th>
<th>Methods</th>
<th>CRDA</th>
<th>Work</th>
</tr>
</thead>
<tbody>
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<td>Weeding</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RGB and NIR camera</td>
<td>Ryegrass</td>
<td>Deep neural network (DNN)</td>
<td>-</td>
<td>[141]</td>
<td></td>
</tr>
<tr>
<td>Monocular camera</td>
<td>Flaxseed fields</td>
<td>Contour algorithm</td>
<td>93.5%</td>
<td>-</td>
<td>[142]</td>
</tr>
<tr>
<td>Camera</td>
<td>Ryegrass</td>
<td>Perspective projection method</td>
<td>90%</td>
<td>-</td>
<td>[143]</td>
</tr>
<tr>
<td>Raspberry Pi Camera</td>
<td>Carrot field</td>
<td>PPHLT</td>
<td>-</td>
<td>[144]</td>
<td></td>
</tr>
<tr>
<td>Camera</td>
<td>Corn field</td>
<td>LRM</td>
<td>-</td>
<td>[145]</td>
<td></td>
</tr>
<tr>
<td>Camera</td>
<td>Maize field</td>
<td>CNN</td>
<td>85%</td>
<td>-</td>
<td>[146]</td>
</tr>
<tr>
<td>Industrial camera</td>
<td>Carrot fields</td>
<td>CNN</td>
<td>89%</td>
<td>-</td>
<td>[147]</td>
</tr>
<tr>
<td>Sequoia camera</td>
<td>Canola field</td>
<td>Design line scanner scans</td>
<td>-</td>
<td>-</td>
<td>[148]</td>
</tr>
<tr>
<td>Camera</td>
<td>Maize field</td>
<td>HT</td>
<td>93.58%</td>
<td>-</td>
<td>[149]</td>
</tr>
<tr>
<td>Camera</td>
<td>Cereal fields</td>
<td>K-means clustering method</td>
<td>94%</td>
<td>-</td>
<td>[150]</td>
</tr>
<tr>
<td>Monocular camera</td>
<td>Maize fields</td>
<td>LRM</td>
<td>-</td>
<td>[151]</td>
<td></td>
</tr>
<tr>
<td>-</td>
<td>Maize fields</td>
<td>HT and BA</td>
<td>-</td>
<td>[152]</td>
<td></td>
</tr>
<tr>
<td>RGB camera</td>
<td>Cauliflower</td>
<td>Multi-target tracking algorithm</td>
<td>99.3404%</td>
<td>[153]</td>
<td></td>
</tr>
<tr>
<td>RGB camera</td>
<td>Bean &amp; spinach</td>
<td>HT</td>
<td>-</td>
<td>[154]</td>
<td></td>
</tr>
<tr>
<td>LIDAR</td>
<td>Crop field</td>
<td>PEARL method</td>
<td>100%</td>
<td>-</td>
<td>[155]</td>
</tr>
<tr>
<td>Multispectral imaging system</td>
<td>Sugar beet field</td>
<td>HT and SVM</td>
<td>92%</td>
<td>-</td>
<td>[156]</td>
</tr>
<tr>
<td>Camera</td>
<td>Maize field</td>
<td>LRM</td>
<td>-</td>
<td>[157]</td>
<td></td>
</tr>
<tr>
<td>Color camera</td>
<td>Lettuce, cauliflower and maize</td>
<td>OTSU and median filtering</td>
<td>95%</td>
<td>-</td>
<td>[158]</td>
</tr>
<tr>
<td>Multispectral camera</td>
<td>Sunflower crops</td>
<td>HT</td>
<td>75%</td>
<td>-</td>
<td>[159]</td>
</tr>
<tr>
<td>Digital camera</td>
<td>Corn field</td>
<td>Morphological operations and stepwise discriminant analysis</td>
<td>96%</td>
<td>-</td>
<td>[160]</td>
</tr>
<tr>
<td>Camera</td>
<td>Maize field</td>
<td>Automatic threshold adjustment method</td>
<td>80%</td>
<td>-</td>
<td>[161]</td>
</tr>
<tr>
<td>CCD camera</td>
<td>Lettuce and celeriac</td>
<td>Template fitting algorithm</td>
<td>99%</td>
<td>-</td>
<td>[162]</td>
</tr>
<tr>
<td>RGB-D camera</td>
<td>Cabbage field</td>
<td>K-means Clustering</td>
<td>-</td>
<td>-</td>
<td>[163]</td>
</tr>
<tr>
<td>Camera</td>
<td>Beet field</td>
<td>ENet and LSM</td>
<td>91.2%</td>
<td>-</td>
<td>[164]</td>
</tr>
<tr>
<td>Raspberry Pi Camera</td>
<td>Maize crop</td>
<td>HT</td>
<td>100%</td>
<td>-</td>
<td>[165]</td>
</tr>
<tr>
<td>Harvesting</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stereo camera</td>
<td>Cotton field</td>
<td>Pixel-based algorithm</td>
<td>92.3%</td>
<td>-</td>
<td>[166]</td>
</tr>
<tr>
<td>LIDAR and CMOS sensor</td>
<td>Crop plantations</td>
<td>PCA Transform</td>
<td>92%</td>
<td>-</td>
<td>[167]</td>
</tr>
<tr>
<td>Binocular vision camera</td>
<td>Rice and wheat field</td>
<td>Probabilistic Hough transform</td>
<td>96.025%</td>
<td>-</td>
<td>[168]</td>
</tr>
<tr>
<td>Seeding</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ZED camera</td>
<td>Wheat field</td>
<td>Mean Shift algorithm</td>
<td>-</td>
<td>-</td>
<td>[169]</td>
</tr>
<tr>
<td>DJI H20 sensor</td>
<td>Corn crops</td>
<td>CNN</td>
<td>99.35%</td>
<td>-</td>
<td>[170]</td>
</tr>
<tr>
<td>LIDAR and camera</td>
<td>Maize fields</td>
<td>Ordinary linear regression method</td>
<td>92–94%</td>
<td>-</td>
<td>[171]</td>
</tr>
<tr>
<td>Ploughing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Digital camera</td>
<td>Rice, rape and wheat field</td>
<td>LSM</td>
<td>96.7%</td>
<td>-</td>
<td>[172]</td>
</tr>
<tr>
<td>Fertilization</td>
<td>Multi-spectral camera</td>
<td>Cabbage rows</td>
<td>CNN</td>
<td>90.5%</td>
<td>-</td>
</tr>
</tbody>
</table>

4.1.1. Row Detection for Irrigation

A dryland irrigation robot is intelligent equipment that realizes dryland irrigation and has the characteristics of high efficiency, safety, and environmental protection [173]. It can
adjust irrigation quantity and irrigation time, reduce labor costs and avoid the waste of water resources [174]. Smart agricultural irrigation robots integrate unmanned driving, the Internet of Things, multi-sensor fusion, and other modern technologies. Irrigation tasks between crop rows can be performed by automatic irrigation robots in accordance with a set amount and time of irrigation, relying on positioning equipment and predefined paths [175]. Information such as the spacing of crop rows and the number of crop rows obtained by crop row detection technology, combined with navigation technology, can support the decision-making of dryland irrigation robots. Without human intervention, robots can independently judge the irrigation needs of each location, thus achieving targeted irrigation. Various approaches have been proposed in the design, development, and manufacture of irrigation robots. The flowchart of crop row detection applications in drylands is shown in Figure 2. The development of vision-based navigation in agricultural robots heavily relies on crop row detection, while machine vision technology remains a critical area that requires significant improvement. To avoid crop crushing by field machinery during irrigation, Wu et al. [176] proposed a partial differential equation (PDE)-based diffusion method that reduced the effect of local interference and strengthened the texture and detailed clarity of crop images. Considering the field variability of dryland crops, Ronchetti et al. [177] combined the threshold segmentation algorithm, classification algorithm, and Bayesian segmentation algorithm to effectively separate crop rows from soil background and weeds, optimizing the operational management of irrigation robots and improving the quality of crop yields. To solve the problem of slow visual navigation line extraction for irrigation robots, Cao et al. [163] enhanced the ENet semantic segmentation network model for the row segmentation of crop images in drylands. By designing the network structure of shunt processing and compressing the traditional ENet network, the accuracy of the beet field boundary’s location and row-to-row segmentation was improved. Faced with overwatering in irrigation systems, Singh et al. [178] designed a MAMDANI fuzzy inference method, which was applied to dryland irrigation robots to optimize the acquisition and processing of crop row information, helping to better control water flow and automate dryland crop irrigation.

Figure 2. Applications of crop row detection in drylands. (a) Flowchart of vision-based line detection in a corn field [117]; (b) Schematic of the camera position while collecting data; (c) Results of crop row detection through UAV images and the improved deep neural network [179].
4.1.2. Row Detection for Weeding

Efficient and environmentally friendly weeding robots working in drylands have advantages in saving pesticides and promoting healthy crop growth. Equipped with various sensors, intelligent control systems, and operating tools, weeding robots can integrate sensing, decision-making, and control to achieve real-time and autonomous weeding tasks [180]. The weeding robot’s sensing system, consisting of a variety of sensors such as vision and LIDAR, is used to sense environmental information and work objects in real time. With crop row detection, the robot can determine the spacing and number of rows of the crop, thus distinguishing weeds from the crop and reducing false weeding [181]. Finally, the goal of the robotic weeding robot in walking and weeding is achieved in the decision and control link. Due to the influence of illumination, weeds, and soil color, it is not an easy task for weeding robots to locate and navigate between crop rows. Wendel and Underwood [182] introduced a self-supervised training method that processed the hyperspectral imaging data of corn crop rows. This could adapt to seasonal, light or geographic variations and help distinguish confused weeds from crops, which supported the plant classification efforts of weed control robots. Louargant et al. [54] combined spatial and spectral information to detect linearly aligned maize seedlings and classified pixels within and between rows of SVM. Additionally, the weed detection rate was 89% through this method. Weeds within dryland crop rows can easily be mislabeled by crops and affect the performance of spot spraying. To solve this problem, Ota et al. [162] used deep learning and K-means clustering algorithms to detect cabbage rows and realize the automation of mechanical weeding robots. Extracting the target features of weeds or crops using traditional machine learning technology requires extensive manual feature engineering and the manual tuning of parameters, which can be solved by exploiting the powerful learning capabilities of deep learning. To minimize damage to the surrounding crops while the weeding robot is working, Su et al. [141] used a geometric position-based DNN learning method for segmentation training to improve the accuracy and speed of identifying ryegrass weeds between the rows.

4.1.3. Row Detection for Harvesting

Automatic harvesting technology for mature crops in dryland has great prospects in the agricultural robot industry [183]. The traditional manual harvesting method is time-consuming and laborious, while intelligent harvesting robots can save labor costs by virtue of their automation and mechanization. There have been many applications for harvesting dryland crops such as corn, grain, and wheat. Harvesting robots sense the terrain of the operating area and the height and location of the crop to determine the harvesting mode. Their orientation and trajectory can be generated by a positioning system installed in the vehicle, which allows for autonomous navigation and route planning. In addition, harvester selection and harvesting strategies need to vary with different crop types and characteristics. However, the image quality is easily affected by the change in outdoor lighting conditions, and errors may be caused by shadows and excessive or poor illumination through traditional color-based detection methods [184]. Considering this difficulty in the parametric navigation of the harvester at the crop boundary, Benson et al. [185] developed a new image processing method, namely an adaptive fuzzy sequential linear regression algorithm. Trials in corn fields demonstrated the accuracy of this method in crop row position and orientation, thus making the case for the more accurate navigation of the combine harvester. Pilarski et al. [186] designed a Demeter automatic harvesting system by combining a camera and GPS to solve the problem of the vision system being easily affected by light conditions and crop distribution density. It optimized the tracking and steering between crop rows and the navigation performance of harvesters. With the purpose of solving the interference caused by the tilting and omission of ramie, a U-net neural network-based method was applied by Chen et al. [187] for crop row detection to improve the navigation line fitting for harvesters. In cotton fields, a number of components and covers make it difficult to identify the track of crop rows. Therefore, Xu et al. [188]
boosted the visual navigation system performance of a cotton-picking robot following the Two-Pass algorithm, iterative method, and LSM method. Impending conditions that robots face as they work include changing environments and vibrating machines, which can make noise for navigation. Fue et al. [108] reduced the effect of environmental noise and enhanced the performance of the boll harvester by sliding window and perspective transformation algorithms to detect the left and right boll rows in 3D images. The results showed that the vision system they designed achieved 92.3% accuracy when detecting cotton rows.

4.2. Applications of Row Detection in Paddy Fields

Paddy fields means farmland with seasonal water accumulation every year; they are often planted with aquatic crops such as rice, lotus roots, and gorgonians. The autonomous navigation of farming machinery in paddy fields allows farmers to use agricultural resources more efficiently and maintain ecological sustainability. Crop row detection and robots in paddy fields can be combined to fertilize, irrigate, weed, harvest, and perform other operations. This complex water environment is a major challenge for farm machinery operating on paddy fields because water depth, water quality, and water temperature can interfere with sensor data collection and processing. There are numerous uses for crop row detection in paddy fields when paired with autonomous farming techniques, as demonstrated in Figure 3. Additionally, Table 2 lists the applications of sensors for row detection in paddy fields.

Figure 3. Applications of crop row detection in paddy fields. (a) Vision-based guidance line extraction in the paddy field [189]; (b) Schematic of the rows detected by the clustering algorithm based on dynamic search direction [190]; (c) Detection steps based on 2D clustering method [98].

<table>
<thead>
<tr>
<th>Application</th>
<th>Sensors</th>
<th>Methods</th>
<th>CRDA Work</th>
</tr>
</thead>
<tbody>
<tr>
<td>Navigation</td>
<td>Industrial camera</td>
<td>Treble-classification Otsu and Double-dimensional clustering method</td>
<td>- [98]</td>
</tr>
<tr>
<td></td>
<td>Industrial camera</td>
<td>Double-dimensional adaptive clustering method</td>
<td>93.6% [191]</td>
</tr>
<tr>
<td></td>
<td>CCD camera</td>
<td>K-means Clustering</td>
<td>82.35% [192]</td>
</tr>
<tr>
<td>Weeding</td>
<td>Camera</td>
<td>Linear regression sliding window technique</td>
<td>- [193]</td>
</tr>
<tr>
<td></td>
<td>Camera</td>
<td>ESNet</td>
<td>- [194]</td>
</tr>
<tr>
<td></td>
<td>Camera</td>
<td>Sequential clustering algorithm &amp; HT</td>
<td>- [195]</td>
</tr>
<tr>
<td>Transplanting</td>
<td>Color camera</td>
<td>CNN and LSM</td>
<td>89.8% [196]</td>
</tr>
<tr>
<td></td>
<td>Camera</td>
<td>Improved Otsu method</td>
<td>- [197]</td>
</tr>
<tr>
<td></td>
<td>Camera</td>
<td>Radon transform</td>
<td>- [198]</td>
</tr>
<tr>
<td>Harvesting</td>
<td>Monocular camera</td>
<td>Probabilistic Hough transform</td>
<td>94.8% [199]</td>
</tr>
<tr>
<td></td>
<td>Color digital CMOS camera</td>
<td>CNN</td>
<td>93.22% [200]</td>
</tr>
</tbody>
</table>
Table 2. A detailed summary of applications of sensors for crop row detection in paddy fields.

<table>
<thead>
<tr>
<th>Application</th>
<th>Sensors</th>
<th>Methods</th>
<th>CRDA</th>
<th>Work</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Navigation</strong></td>
<td>Industrial camera</td>
<td>Treble-classification Otsu and Double-dimensional clustering method -</td>
<td>[98]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Industrial camera</td>
<td>Double-dimensional adaptive clustering method K-means Clustering</td>
<td>93.6%</td>
<td>[191]</td>
</tr>
<tr>
<td></td>
<td>CCD camera</td>
<td>Double-dimensional clustering method K-means Clustering</td>
<td>82.35%</td>
<td>[192]</td>
</tr>
<tr>
<td><strong>Weeding</strong></td>
<td>Camera</td>
<td>Linear regression sliding window technique -</td>
<td>[193]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Camera</td>
<td>ESNet -</td>
<td>[194]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Camera</td>
<td>Sequential clustering algorithm &amp; HT -</td>
<td>[195]</td>
<td></td>
</tr>
<tr>
<td><strong>Transplanting</strong></td>
<td>Color camera</td>
<td>CNN and LSM -</td>
<td>[196]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Camera</td>
<td>Improved Otsu method -</td>
<td>[197]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Camera</td>
<td>Radon transform -</td>
<td>[198]</td>
<td></td>
</tr>
<tr>
<td><strong>Harvesting</strong></td>
<td>Monocular camera</td>
<td>Probabilistic Hough transform -</td>
<td>[199]</td>
<td></td>
</tr>
<tr>
<td><strong>Spraying</strong></td>
<td>Color digital CMOS camera</td>
<td>CNN -</td>
<td>[200]</td>
<td></td>
</tr>
</tbody>
</table>

4.2.1. Row Detection for Transplanting

The deployment of transplanting robots in paddy field operations is essential for increasing operational effectiveness and lowering the burden of physical labor [201]. The rice transplanter is equipped with devices, including sensors and controllers, that can detect information such as crop rows, soil quality, and moisture conditions in paddy fields in real-time, which maintains the depth and spacing of rice seedlings and prevents inconsistent depth and irregular spacing [202]. Currently, complex terrain, crop growth variability, and high accuracy requirements are the main challenges facing rice transplanting robots in paddy fields. It is not easy to obtain good crop segmentation in a complex rice paddy environment. A color index-based segmentation method for rice seedlings was proposed by [203], combining the conversion from the RGB to YCrCb color space and Otsu threshold segmentation. It was applied to a visual crop row detection system to provide reliable navigation information for the transplanter, and the experimental results also verified an advanced segmentation effect and work quality. Keeping the rows of seedlings evenly spaced is beneficial to increase rice yield and reduce crop damage, yet this remains a challenge for autonomous navigation transplanters. In response, Lin et al. [196] developed a Faster R-CNN algorithm for row detection to provide the navigation parameters for rice transplanters and to control transplanting operations in rice fields in a more intelligent and automated way. In view of the poor path adaptability of rice transplanters in the paddy field, Liao et al. [197] improved previous research and designed an integrated positioning method combining GPS, INS, and VNS to reduce rice seedling pressing and improve detection accuracy.

4.2.2. Row Detection for Harvesting

Paddy field harvesting machinery can achieve the autonomous harvest of crops, which has far-reaching significance for the realization of efficient and precise agricultural automation. To assist in autonomous harvesting, paddy robots need to incorporate image processing and machine learning techniques to determine the spatial distribution and growth pattern of crop rows, as well as autonomously avoid obstacles and accidental injuries [204]. Automatic harvesters have the characteristics of high performance, multifunction, and strong flexibility and can effectively prevent over-tillage or under-tillage in complex rice environments. However, harvesting in paddy fields presents unique challenges compared to other row-crop fields due to the presence of standing water, which may cause difficulties for machines to navigate and detect crop rows accurately [205]. Research on rice harvesting has led to many applications, especially in Japan, where the technology is relatively mature. Mud and bubbles in the rice field can easily cause interference in row detection. Therefore, Tian et al. [171] first combined a custom shear
binary image algorithm and an LSM algorithm to help detect high-stubble rice plants. Their method has been proven to meet the needs of real-time processing due to a segmentation speed of 0.6s and a segmentation accuracy of 96.7%. At present, the navigation path of common harvesting robots in the market is prone to interference and is challenging to identify accurately. Li et al. [206] identified paths by analyzing the 3D spatial geometric relationships of rice fields and used an improved random sampling consistency algorithm, and perfected boundary identification by collecting boundary angles. This experiment was found to have a success rate of 94.6%. To avoid data errors caused by locally high crop in images, Wang et al. [207] realized the detection of rice rows and boundary lines through a series of conventional image processing algorithms, including morphological operations and the Sobel operator. It ensured the stability of the harvesting robot’s guidance and work in the paddy field.

4.2.3. Row Detection for Weeding

Paddy weeding robots safeguard the quality and yield of rice and other forms of aquatic crop production [208]. The distinction between the crop and weed requires that the paddy weed robot utilize sensors and algorithms to analyze the image information containing the crop and weed. According to the preset weeding scheme, the control system operates a robotic arm or spraying system to perform targeted weeding [209]. The autonomous weeding robot demonstrates a strong working ability when weeding plants in their early and late stages of growth, which helps reduce the impact of pesticide use on the environment and the human body. However, the detection of crops in the paddy fields is more challenging than in dry fields due to noise, such as green duckweed, cyanophytes, and eutrophication water. To reduce the use of herbicides, Chen et al. [210] designed a machine vision system based on passing a known point of Hough transform (PKPHT) to guide a micro-weeding robot between rows of rice seedlings. Zhang et al. [211] proposed a real-time crop row detection method based on a color model and nearest neighbor clustering, which could accurately extract features and adapt to environmental changes. To facilitate the weeding robot to weed the rice field environment without damaging the crop plants, Choi et al. [212] designed robust regression and HT algorithms to extract navigation lines based on rice morphological features. Given that weeds, duckweeds, and cyanobacteria growing in paddy fields tend to interfere with rice crop detection, Zhang et al. [213] proposed an improved sequential clustering algorithm and an angular-based image processing method.

4.3. Applications of Row Detection in Orchards

Orchards are typically agricultural lands that are planted with relatively tall trees or shrubs, which belong to a semi-structured environment. Many tasks, including monitoring, management, and harvesting, cannot be performed without the aid of orchard mobile vehicles and robotic autonomous navigation platforms [214]. Fruit tree row detection can help the robot to accurately locate the position and shape of fruit tree rows, and improve the accuracy of the robot’s autonomous navigation, thus helping fruit farmers to better manage their orchards and improve the yield and quality of fruit trees. Figure 4 shows the navigation and path detection applications under the orchard canopy. The applications of sensors for crop row detection in orchards are presented in Table 3.
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Table 3. A detailed summary of the applications of sensors for crop row detection in orchards.

<table>
<thead>
<tr>
<th>Application</th>
<th>Sensors</th>
<th>Scenarios</th>
<th>Methods</th>
<th>CRDA</th>
<th>Work</th>
</tr>
</thead>
<tbody>
<tr>
<td>Navigation</td>
<td>Monocular camera</td>
<td>Apple orchard</td>
<td>CNN</td>
<td>-</td>
<td>[217]</td>
</tr>
<tr>
<td></td>
<td>RGB camera</td>
<td>Apple orchard</td>
<td>K-means clustering</td>
<td>-</td>
<td>[218]</td>
</tr>
<tr>
<td></td>
<td>RGB-D camera</td>
<td>Vineyard and pear orchard</td>
<td>Deep learning</td>
<td>-</td>
<td>[216]</td>
</tr>
<tr>
<td></td>
<td>LIDAR</td>
<td>Vineyards</td>
<td>HT 98.8%</td>
<td>[219]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Camera</td>
<td>Apple orchard</td>
<td>LSM</td>
<td>-</td>
<td>[220]</td>
</tr>
<tr>
<td>Farming</td>
<td>LIDAR</td>
<td>Vineyards</td>
<td>HT and filtering algorithm</td>
<td>-</td>
<td>[221]</td>
</tr>
<tr>
<td>Spraying</td>
<td>LIDAR</td>
<td>Vineyard</td>
<td>LSM</td>
<td>-</td>
<td>[222]</td>
</tr>
<tr>
<td>Tracking</td>
<td>Color camera</td>
<td>Vineyard</td>
<td>LS and HT</td>
<td>-</td>
<td>[223]</td>
</tr>
<tr>
<td>Pollination and</td>
<td>Monocular Camera</td>
<td>Kiwifruit orchard</td>
<td>Fully convolutional neural network</td>
<td>-</td>
<td>[215]</td>
</tr>
<tr>
<td>harvesting</td>
<td>Tetracam ADC-lite Camera</td>
<td>Vineyard</td>
<td>Hough space clustering</td>
<td>95.13%</td>
<td>[224]</td>
</tr>
<tr>
<td>PA</td>
<td>LIDAR</td>
<td>Orchards and vineyards</td>
<td>LRM 75%</td>
<td>[225]</td>
<td></td>
</tr>
</tbody>
</table>

4.3.1. Row Detection for Picking

The selective harvesting of fruits and vegetables is one of the most time-consuming and costly links in traditional agricultural production. The development of the orchard-picking robot can effectively replace the manual picking of fruit, improve picking efficiency, and reduce labor costs [226]. In the orchard environment, picking robots need to be equipped with GPS positioning or a LIDAR sensor to realize autonomous positioning and navigation and accurately move and locate the position of the fruit tree. Equipped with vision systems, robotic arms, and pickers, the picking robot can autonomously identify the location, shape, and ripeness of the fruit and accurately locate the fruit as well as complete the picking task [227]. Fruit tree row detection is the basis of the picking robot’s ability to achieve
autonomous navigation and positioning. The accurate detection of fruit tree rows can help the picking robot to identify the position, shape, and distribution of fruit trees and then determine the path and attitude of the robot, as well as the placement and expansion of the robot arm [228]. In addition, it helps the robot to identify obstacles and passable areas to avoid damage to fruit trees and other robots. However, fruit trees are diverse and complex in form, and some fruit trees also have outstretched branches and weeds, which can easily block the view of the picking robot, making it more difficult to detect fruit tree rows [229]. Lyu et al. [219] applied the naive Bayesian classifier to detect tree trunk rows and nadir points and generate a centerline by connecting these points as information for the movement path or navigation of the picking robot. This algorithm was able to effectively classify trunk points and noise points in the orchard and reduce the noise caused by small branches, soil, and ground tree shadows. In response to the random spatial arrangement of tree trunks and inconspicuous target differences in a wolfberry plantation, Ma et al. [230] proposed an autonomous navigation method for a wolfberry-picking robot based on visual cues and fuzzy control. This method extracts the trunk rows of wolfberry plants in the far field of view and dynamically tracks the navigation line by calculating a variable-slope region of interest. LiDAR can provide high-precision 3D maps for picking robots and detecting and identifying fruit tree rows, fixed obstacles, etc. Blok et al. [231] evaluated the applicability of the Kalman filtering (KF) and particle filtering (PF) localization algorithms of 2D LiDAR scanners for the in-row navigation of a picking robot in apple orchards. The results showed that for the in-row navigation of orchard-picking robots, the PF algorithm with a laser beam model had better localization performance.

4.3.2. Row Detection for Spraying

Spraying robots are becoming increasingly popular in orchards due to their efficiency and precision in applying pesticides and fertilizers to crops. Spraying robots are equipped with tanks and spraying nozzles that can hold and distribute the necessary number of pesticides and fertilizers, which reduces the labor and costs associated with manual spraying [232]. These robots use advanced sensors and mapping technologies to accurately target specific areas of a crop, avoiding obstacles and ensuring precise application [233]. Research on orchard spraying robots for fertilization, pest control, weeding management, or other controlled treatments is constantly improving. Fruit tree row detection plays an equally important role in the operation of spraying robots in orchards. Based on fruit tree row detection, spraying robots can navigate through orchard rows more quickly and accurately, reducing the likelihood of missing crops or spraying too much in one area as well as the time and resources required for spraying [234]. This can allow for the more precise and effective application of pesticides and fertilizers. Kim et al. [235] proposed an intelligent spraying system for the semantic segmentation of fruit trees in pear orchards. The system applied the SegNet model to detect fruit trees and control nozzles to accurately spray pesticides on them, which reduced the overall pesticide usage. In the framework of a vineyard or orchard, Danton et al. [222] proposed a control method that applied LiDAR to sense fruit tree row information and control the movement of the robot, and automate spraying. The horizontal LiDAR was used to guide the spraying robot to ensure the accurate positioning of the sprayer relative to the vegetation, and a vertical LiDAR was used to achieve an estimate of the vegetation covered and optimize the spraying efficiency. Liu et al. [236] used a 3D LiDAR sensor to perceive the information on fruit trees around the spraying robot and performed 2D processing on the point cloud in the region of interest. The vertical distance from the robot to the centerline of the fruit tree rows was determined using the RANSAC algorithm based on the centroid coordinates on both sides of the fruit tree rows. This method achieved automatic navigation and the precise variable speed spraying of the spraying robot, reducing the amount of pesticide application, air drift, and ground loss and effectively controlling the pollution caused by pesticides to the environment. To improve the accuracy and reliability of the orchard spraying robot, Zhang et al. [237] designed an integrated BDS/IMU navigation algorithm for the position and heading measurement
based on error Kalman filtering. Combining the kinematic model and the pure tracking model, the detection of citrus tree rows and the path tracking control of the spraying robot were realized.

4.4. Applications of Row Detection in Greenhouses

A greenhouse is a kind of agricultural application scene with environmental control equipment. Agricultural greenhouses consist of a skeleton and film covering to provide a controlled space in which to grow crops [238]. Due to the partially structured characteristics of greenhouses, their mechanization and automation are conducive to the implementation of precision agriculture. Autonomous navigation and the control of agricultural robots have a significant impact on the efficiency, productivity, and sustainability of greenhouse farming. In the greenhouse environment, the navigation precision and accuracy of the robot may be affected by the obstruction and influence of objects such as plants and equipment [239]. The robot needs crop row detection to determine plant location, growth, and health information and to better perform navigation, inspections, watering, fertilization, and other operations. The relatively enclosed environment inside greenhouses causes issues with signal interference, while insufficient lighting also impairs the accuracy of vision sensors. Therefore, reliable sensors and algorithms need to be selected to apply to crop rows in the greenhouse. Figure 5 illustrates the application of crop row detection technology in greenhouse robot navigation. In addition, reliable sensors also play an important role in the greenhouse. A detailed summary of sensors is displayed in Table 4.

Figure 5. Applications of navigation-based crop row detection in greenhouses. (a) Position of the robot relative to the crop [240]; (b) Robot motion path extraction results in a greenhouse tomato field [241]; (c) Snapshots of the robot movement in simulation; (d) Topological map for navigation [242].
Table 4. A detailed summary of applications of sensors for crop row detection in greenhouses.

<table>
<thead>
<tr>
<th>Application</th>
<th>Sensors</th>
<th>Scenarios</th>
<th>Methods</th>
<th>Work</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spraying</td>
<td>Industrial camera</td>
<td>Cucumber greenhouse</td>
<td>Median point Hough transform</td>
<td>[241]</td>
</tr>
<tr>
<td></td>
<td>2D LIDAR and stereo camera Camera</td>
<td>Strawberry greenhouse</td>
<td>Hokuyo node production</td>
<td>[240]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Green vegetable greenhouse</td>
<td>Vertical projection method and SA</td>
<td>[243]</td>
</tr>
<tr>
<td>Picking</td>
<td>Industrial camera</td>
<td>Cucumber greenhouse</td>
<td>Prediction point Hough transform algorithm</td>
<td>[187]</td>
</tr>
<tr>
<td></td>
<td>Camera</td>
<td>Cucumber greenhouse</td>
<td>LSM</td>
<td>[244]</td>
</tr>
<tr>
<td>Inspection</td>
<td>Camera</td>
<td>Greenhouse</td>
<td>HT</td>
<td>[245]</td>
</tr>
<tr>
<td>Navigation</td>
<td>Color camera</td>
<td>Strawberry greenhouse</td>
<td>HT</td>
<td>[246]</td>
</tr>
</tbody>
</table>

4.4.1. Row Detection for Inspection

The greenhouse inspection robot is a kind of agricultural robot that is specially designed to perform inspection tasks in a greenhouse environment. Equipped with various sensors and cameras, these robots can collect data on the growing environment and health of plants in the greenhouse, detect pests and diseases, and monitor levels such as temperature and humidity [247]. The introduction of intelligent inspection robots in greenhouses can effectively improve the efficiency of greenhouse operations, reduce labor costs, and promote the transformation of facility agriculture from manual inspection to intelligent inspection [248]. With technologies such as maps, sensors, and algorithms, the autonomous navigation system can help inspection robots avoid bumping into plants and equipment in the greenhouse and plan the optimal path to optimize inspection time and energy consumption. Due to the dense growth of plants and complex environmental conditions in the greenhouse, the inspection robot needs to determine the position and growth of plants through crop row detection so as to perform inspection operations more accurately. Based on two Logitech C170 cameras mounted on the inspection robot, Mahmud et al. [249] implemented crop detection and robot navigation using the BT709 grayscale, HSL, and channel filtering algorithms. However, greenhouse crop row detection also has some difficulties, such as light and shadow changes, crop overlap, etc. In a lemongrass greenhouse environment, Mahmud et al. [245] obtained the coordinates of lemongrass using a color segmentation method based on Marxian distance and used this as a probabilistic roadmap input to achieve the navigation of the inspection robot. With an objective to achieve low-cost and non-destructive inspection of crops in a greenhouse environment, Wang et al. [250] designed information acquisition and motion control systems with a Raspberry Pi and an embedded chip as the core, respectively, to integrate a greenhouse mobile inspection robot. In the field of testing, it was found that the efficient measurement of crops and the agility of the designed robot in motion improved the efficiency of greenhouse crop research and inspection. It is a practical problem to realize the autonomous navigation of inspection robots in a greenhouse environment with obstacles. Zhang et al. [251] designed a hypervolume estimation algorithm to shorten the navigation distance and perform autonomous obstacle avoidance, solving the path-following problem between crop rows in greenhouses and improving the efficiency of inspection robots with additional cost reductions.

4.4.2. Row Detection for Spraying

The greenhouse spraying robot is intelligent agricultural machinery equipment integrating high-precision spraying technology, sensor technology, and mechatronics technology [252]. A greenhouse robot usually consists of a robotic chassis and a robotic arm that is equipped with a sprayer and a fertilizer tank, which is used to spray substances that are necessary for plant growth. The greenhouse spraying robot automatically sprays water and fertilizer based on environmental parameters in the greenhouse to ensure optimal growing conditions for plants and reduce the use of chemical fertilizers and their negative impact on the environment. Crop row detection can help to spray robots pinpoint the position and
rows of plants so that spraying and curing can be performed more precisely and production efficiency can be improved. Similar to greenhouse inspection robots, greenhouse spraying robots may also face challenges in terms of false and missed inspections, occlusion and interference, and complex environmental issues when performing crop row inspections [253]. Several studies have been proposed to develop greenhouse spraying robots. Guiding vehicles through crop rows is a challenge in greenhouse spraying applications and has become a focus of research by experts. Wang [246] successfully segmented the rows of strawberry plants from plastic film, shadow, and light using a machine vision algorithm of threshold segmentation and center point detection method. This scheme had the characteristics of strong applicability and simple operation while meeting the requirements of robustness and real-time for path detection and following greenhouse spraying robots. Targeting the low efficiency and high cost of greenhouse robot operations, Xue et al. [243] designed a multi-functional spraying robot to perform crop row detection on an RGB image information output by vision sensors. The algorithms used included vertical projection and strip division to help the spraying robot to perform path-following and spraying tasks in a greenhouse with green vegetables. Using the RGB images of tomatoes and cucumbers in a greenhouse, Chen et al. [241] innovated a crop row segmentation and detection algorithm based on LSM and traditional HT algorithms. Robustness and rapidity were demonstrated by achieving the fitting of a navigation path that took 7.13 ms on a tracked spraying robot as an experimental platform. LIDAR has also contributed to the application of greenhouse spraying robots because of their long-range and contactless advantages. Abanay et al. [240] acquired the point cloud data of strawberry greenhouse crops based on an embedded 2D LIDAR sensor and applied an estimated value approach to guide the vehicle heading and speed between rows while automating motion control through a pesticide spraying applicator system.

5. Conclusions

In conclusion, crop row detection is a critical task in precision agriculture that enables various agricultural applications, including pesticide spraying, crop health monitoring, and weed detection. Traditional image processing techniques, machine learning-based approaches, and deep learning-based methods are all viable options for crop row detection, each with its own advantages and limitations. Nonetheless, recent advances in computer vision and machine learning technologies have made deep learning-based methods, notably convolutional neural networks, the most promising option for crop row detection. Deep learning methods have demonstrated superior performance in various computer vision tasks, including object detection and semantic segmentation, which are fundamental to crop row detection. CNNs excel at learning complex features and patterns from large datasets, enabling them to automatically extract relevant information from field images and accurately identify crop rows. The ability of deep learning models to generalize well to different lighting conditions, weather variations, and field environments has further contributed to their suitability for crop row detection in real-world scenarios.

Despite the progress made, several challenges persist in the field of crop row detection. One challenge involves ensuring the robustness of detection algorithms to handle diverse lighting conditions and environmental factors, as agricultural settings can be highly variable and unpredictable. Additionally, their scalability to different crops is essential, as crop rows can exhibit variations in shape, size, and appearance across different plant species. Integrating crop row detection with other agricultural technologies, such as robotics, drones, and data analytics, also presents another challenge that requires seamless integration and interoperability.

The prospects for crop row detection in precision agriculture are promising. Researchers and industry experts are actively working on developing more accurate, efficient, and scalable methods that address existing challenges. Advancements in deep learning architectures, such as novel CNN architectures and attention mechanisms, hold the potential to further improve crop row detection performance. Furthermore, the fusion of crop
row detection with other advanced technologies, including remote sensing, the Internet of Things (IoT), and big data analytics, could enhance the overall effectiveness of precision agriculture systems.

The future of crop row detection in precision agriculture looks promising as researchers and industry experts continue to develop more accurate, efficient, and scalable methods that can benefit farmers and improve agricultural sustainability. Overall, the advancement of crop row detection in precision agriculture has the potential to revolutionize farming practices, leading to improved productivity, resource management, and agricultural sustainability. By leveraging the power of deep learning and embracing collaboration, the future of crop row detection holds great promise for enhancing crop yield, minimizing the environmental impact, and transforming the agricultural industry as a whole.

Author Contributions: Conceptualization, J.S. and Y.B.; methodology, J.S. and Y.B.; analysis, J.S.; investigation, J.S., Y.B., Z.D., J.Z., X.Y. and B.Z.; resources, Z.D. and B.Z.; data curation, J.S.; writing—original draft preparation, J.S.; writing—review and editing, J.S., Y.B. and X.Y.; visualization, J.S.; supervision, J.Z. and Z.D.; funding acquisition, B.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Jiangsu Modern Agricultural Equipment and Technology Demonstration & Promotion Project (project No. NJ2021-60), the National Natural Science Foundation of China (project No. 31901415), and the Jiangsu Agricultural Science and Technology Innovation Fund (JASTIF) (Grant No. CX (21) 3146).

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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