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REVIEW ARTICLE

Leveraging precision agricultural tools for enhanced crop protection in rice cultivation

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Abstract

Rice production is crucial for meeting the food demand of the ever-growing global population. However, it is impeded by biotic stressors *viz*., insect pests, diseases and weeds. Traditionally, farmers and plant protection experts rely on conventional crop protection measures to combat these challenges. These measures have various drawbacks including intensive labour requirement, higher cultivation costs, untimely pest detection and indiscriminate agrochemical use which adversely affects the consumers and the environment. Precision tools and technologies can address all these issues to benefit the farmers and agricultural ecosystem on a sustainable basis. Remote sensing technologies aid in weed mapping and detecting disease and pest incidence in rice fields by evaluating the changes in crop reflectance brought about by biotic stressors. Agricultural robotic systems are multifunctional and have attained more than 80 % correct image classification, 96 % weed control and less than 10 % crop damage. Unmanned aerial vehicles for pesticide spraying are cost-effective substitutes for manual spray and can reduce spray volume by more than 20 times besides good application efficiency and effective control. Artificial intelligence offers precise solutions for biotic stress identification and control. Biosensors have also been developed for aiding in detecting rice blast, false smut, tungro incidence and bacterial leaf blight. Apart from highlighting the utilization of precision agriculture tools and technologies for plant protection and weed control in rice, this article also reviews the challenges and prospects related to its application and its feasibility for the stakeholders utilising them to gain sustainable rice production.

Keywords

Artificial Intelligence (AI); biosensors; rice; remote sensing; robots; Unmanned Aerial Vehicles (UAVs)

Introduction

Crop protection is one of the most important aspects of sustainable rice production. Rice is grown over an area of 166.31 million hectares, with a production of 789.04 million tonnes and productivity of 4.74 t ha^{-1} worldwide (1). It entails global importance as 900 million people rely on rice as their main source of nutrition (2). Rice production is critical for all the people relying on it; however, its production is hindered by various biotic stressors which include insect pests, pathogens and weeds (3). Without proper detection and implementation of crop protection techniques against these biotic stressors, it will lead to severe losses concerning both yield and quality, hampering its global supply. These stressors pose significant challenges to farmers by degrading crop quality, lowering its economic yield and increasing the total cost of production. There are 50 main diseases causing damage to productivity, such as blast disease of rice, bacterial leaf blight, brown spot, stem rot, *fusarium* wilt, leaf streak and smut diseases (4). Globally over 100 species of insect pests infest the rice crop and out of which, 20 species can cause major monetary losses which include stemborers, leaf and plant hoppers, gall midges and a grain-sucking bug complex that feeds on developing grains resulting in an average yield loss of 20 % and 90 % of the Asia and World's rice production (5). A study conducted under the System of Rice Intensification (SRI) found that insect pests caused a yield loss of 27.9 % (6). Weeds also pose a major threat to rice cultivation. Average yield losses due to weed problems are projected to be 40-60 % and if weeds are not controlled, then yield losses may reach 96 % (7).

Farmers and plant protection personnel often resort to traditional crop protection measures to tackle the issues due to the biotic stressors. These measures, however, are associated with several constraints and poor control. The conventional methods for detecting and monitoring insect pests, diseases and weed species are often costly, time-consuming and require more labour (8). A routine inspection by the farmers in rice fields is prone to human error and may cause damage to the rice crop, ending up creating more problems (9). Labour unavailability is also a growing concern lately, resulting in untimely management of biotic stresses. The crop protection specialists carry out visual hand inspections for early detection of insect pests, diseases and weeds which are very precise and reliable, but they are time-consuming, labor-intensive and are not feasible for a large area (10). At present, agrochemicals are being used widely by farmers, due to their cost-effectiveness and feasibility and it is often observed that agrochemicals are utilised uniformly in the field, although insect pests, diseases and weeds are present as random and patchy growth (11). This results in various negative impacts, which is a serious social and ecological issue worldwide (12). According to the European Food Safety Authority, agrochemical residues were found in 98.9 % of food commodities (1.5 % above the legal limit). Additionally, in many countries, there is a threat to crop production due to plants' resistance to agrochemicals (13). More use of agrochemicals caused a decline in beneficial soil microflora emphasizing the adverse effects of their uncontrolled and long-term use on soil health and microbial activities (14).

Precision agriculture tools can be adopted to address all these issues related to crop protection. This will facilitate the farmers to use their assets more efficiently, considering the field variability while reducing the input cost incurred by them, ultimately resulting in improvement in yields and profits as well as sustainable environmental production (15). For a wide array of agricultural problems, precision tools provide a site-specific solution tailored for the particular area, rather than the indiscriminate and unscientific application of agrochemicals throughout the field (16). The amalgamation of precision tools in rice production will provide stakeholders with the necessary means for combating climate change and the shift in population and density of the biotic stressors associated with it. This article describes the applicability of precision agricultural tools, for facilitating early detection of the biotic stressors along with accurate classification and monitoring for providing precision methods and timing of weeds, disease and insect pest management in rice cultivation.

Precision tools for crop protection in rice

Precision tools are cutting-edge equipment and technologies, designed to simplify and automate procedures, reduce or even replace physical labour in day-to-day work, aiding in boosting productivity while reducing farming's environmental impact and providing a sustainable farm and decision management system (17). In this review article, various precision agricultural tools have been discussed including UAVs, satellites, biosensors, artificial intelligence and robotics. UAVs have dual purpose roles as it is used as a remote sensing tool and for agrochemical spraying purposes. Satellites are applied for remote sensing purposes, while biosensors are used for detecting various rice diseases. Artificial intelligence including machine learning and deep learning aids in the monitoring, classification and mapping of the biotic stressors. Robots are used for the precise application of agrochemicals and weeding purposes. The following sections cover the application of precision tools for weed, disease and insect pest management.

Weed management

Weeds compete with crops, often lowering their yield and product quality in many circumstances and are more detrimental to the economy than the other biotic stressors. Potential and actual yield loss due to weeds in direct seeded conditions were found to be 15-66 % and 6-50 % respectively, whereas in transplanted conditions, actual yield loss was found to be 30 % (18). Many researchers also reported potential yield loss of up to 46 and 90 % in the direct-seeded rice (19, 20) highlighting the menace caused by unchecked growth and development of the weeds. Precision tools, elaborated in this section, can facilitate effective weed control through site-specific and time-specific weed management, thereby benefiting the stakeholders.

UAV-based remote sensing for weed detection and mapping

Remote sensing is used to precisely manage the different inputs and identify the weeds in the field (21). Weeds are predominantly found as patchy growth in farms and these patches can be detected by remote sensing, aiding in mapping weed densities in different crops (22). The basis of remote sensing lies in the instrument's spectral resolution and the differences in spectral reflectance between weeds and other crops, which are the two reasons behind the working principles of remote sensing techniques to map weeds (22).

UAVs are used in remote sensing applications to acquire high-resolution images (23). Various examples of UAV-based remote sensing in rice fields are described in Table 1, for weed detection and mapping. The generated weed prescription maps then can be used for precision weed management options (24) after the various steps of image processing as shown in Fig. 1.

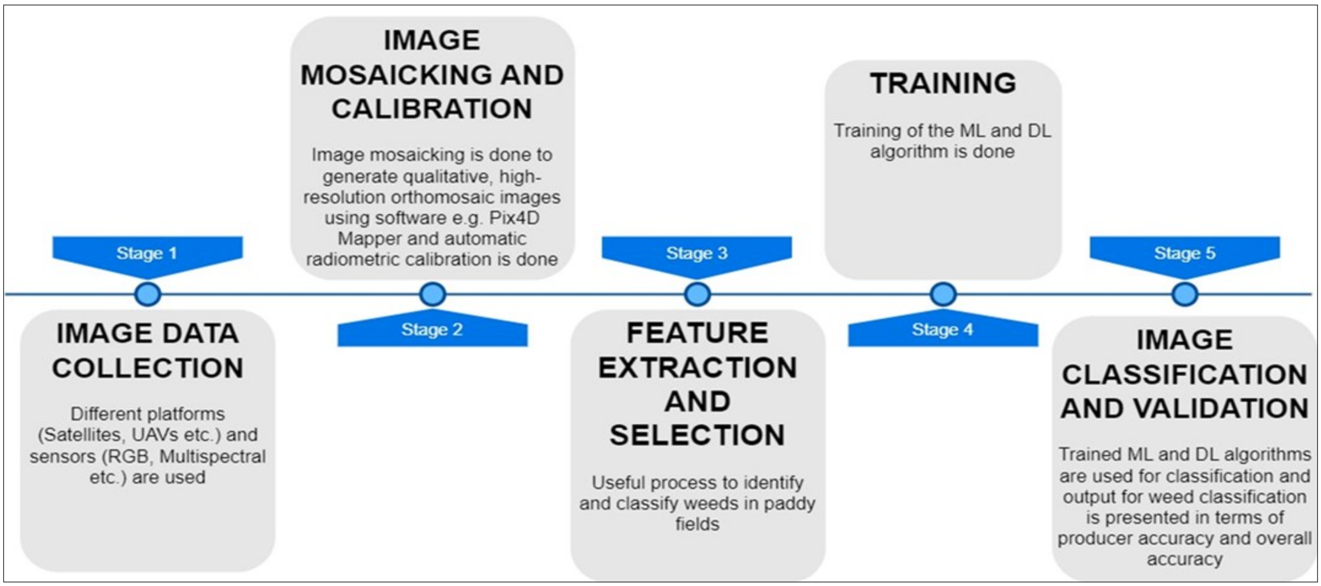

Fig. 1. Workflow of image processing for classification of weeds.

AI-based weed management options

Artificial Intelligence (AI) has initiated a great shift in the field of agriculture, particularly in weed management. To answer important agricultural problems regarding weed detection and its management, AI can provide accurate and environmentally friendly solutions (25). AI for application in weed control takes the initiative to address environmental concerns associated with herbicides by increasing their efficiency, lowering the utilization of agrochemicals and limiting the residues present in the soil (26). Artificial intelligence comprises a wide range of technologies which includes, machine learning, deep learning and computer vision each with the unique ability to address the complex issues caused by the weeds (27). For classifying Red, green and blue (RGB), multispectral and Hyperspectral images for agriculture, machine learning algorithms like Random Forest classifier, Support Vector Machine (SVM) etc., are employed for image processing (28). To achieve precision spraying, weed detection is a necessity (29), which can improve the rice yield and reduce the cost of cultivation.

Rice seedling and three-leaf arrowhead weed *(Sagitattia trifolia*) differentiation were achieved in the seedling stage with the SegNet, a semantic segmentation method based on the Fully Convolutional Network (FCN). The SegNet under study resulted in a higher classification accuracy of 92.7 % (30). Researchers working on nutgrass in rice used computer vision to develop a two-classification technique to distinguish images based on weed density. Grey -level co-occurrence Matrix (GLCM) texture features were used in the first technique which performed well with SVM using the Radial Basis Function (RBF) kernel with an accuracy of 73 %. The second technique used was the moments feature set and it performed best with random forest which had an accuracy of 86 % (31). Using computer vision techniques two Multiple Classifier Systems (MCSs) were developed for classifying rice crops and three common weeds *viz.,* Sedges (*Cyperus difformis*), grass (*Echinochloa crus-galli*) and a broadleaved weed (*Monochoria vaginalis*) by using the digital images and these images were made utilizing random forest classifiers and support vector machines (32). The study concluded that with an accuracy of 91.36 %, multiple classifier systems were better than the single classifier system for weed classification. Authors developed a stereo vision system by using Artificial Neural Networks (ANNs) along with Bee Algorithm (BA) and Particle Swarm Optimization (PSO) which were the two metaheuristic algorithms for neural network optimization (33). This study was useful in differentiating rice and weeds and additionally distinguishing weeds into broad-leaved and narrow-leaved weeds. A deep learning model for identifying weeds in rice fields was developed, which gave precise real-time detection, lowering machine costs to be used widely in practice. In the study, a model WeedDet was designed based on RetinaNet to differentiate the weeds from the plants which posed a huge problem for weed detection, using a dataset containing rice and weeds (34). Their proposed model achieved an accuracy of 94.1 % with a speed of 24.3 frames per second (fps), which highlighted its effectiveness and efficiency. To combat the problem of weedy rice, researchers developed WeedyRice5, a conventional weedy rice image dataset that uses the advanced YOLOv5s method as a target detection model, with a model mean average precision (mAP@0.5) of 98.2 %. (35). To enhance the model's performance, a YOLOv5s-based new YOLOv5s-CBAM-DML Head method was proposed by the authors, which reduced the model computation and detection time. The results of the experiment showed a mAP@0.5 of 98.9 %, with an average detection time of 4 ms and reduced computational demand by 28 % compared to the original YOLOv5s model.

Robots for weed management

Advances in the field of robotics and engineering can elicit a great transformation in agriculture as robots can be employed in less mechanized aspects of weed management (36), rather than limited to conventional eradication or herbicidal spraying (22). An agricultural weeding robot consists of an independent, self-guiding platform with various weed-detecting units equipped with a variety of weeding equipment, including a spray nozzle, microwave unit, or tillage tool (37). Weed management using robots has four stages, which include navigation, detection, mapping weed species and accurate robotic weed removal (36). Decision support systems guide the effectiveness of weed-sensing apparatus, using variable rate technologies, machine vision analyses and robotic versatility where efficiency has an important role in (38) the sustenance of a weed control system. Researchers suggested using robotics to automate weed control as a hands-on pragmatic solution for integrated weed management going forward (36). Several models of robotic sprayers for precise spot-spraying techniques have been developed for single crops (39). The robots developed achieved over 80 % image classification accuracy and weed control up to 96 % while having less than 10 % crop damage (40). Robots for facilitating physical weed control have been designed which involve the use of hoeing blades, electrical energy, laser and flaming and can classify between weeds and crops, targeting the specific weed species in the intra-row space (41).

Robots are being developed and tested extensively in the rice fields. Researchers for weeding, developed K-Weedbot, (Fig. 2A) a robot which can navigate autonomously with an algorithm developed by finding the convergence point of the differently oriented leaves to form the centre of a rice plant, which provided an improved guidance line (Fig. 2B) for its mobility and performing weeding with modified wheels, between rice rows with high accuracy (42). Similarly, a paddy weeding robot was developed with a unique algorithm for aiding the robot to navigate between the complex environment of the paddy field to complete its weeding operations (43). Machine vision technology, Global navigation satellite system (GNSS) and compass were also combined to autonomously navigate the robot (Fig. 2C) deployed with cutters to perform weeding in a rice field (44). A robot with weed suppression capabilities was developed utilizing a laser range finder (LRF) for recognizing the rice crop and achieving mobility in the inter-row space of the rice rows without disrupting the plant. It utilises a robotic arm for weed removal thereby, reducing weed growth. It also included a posture control for its movement on uneven surfaces (45). Similarly, a weeding robot was introduced by researchers, which can manoeuvre independently while weeding a rice field. The weeding robot penetrates soil for weed eradication and restricts the sunlight to hinder weed growth (46). The weed robot proposed by Uchida and Funaki (47) used metal chains as a weed management tool to remove *Monochoria vaginalis*. Red rice, which is difficult to control through conventional methods can be controlled by a robot prototype. The robot consisted of a custom-made rod mechanism and control mechanisms based on sensors that can apply herbicides, precisely on the top of red rice, without damaging the commercial rice crop. The prototype was also equipped with height and slope control systems, for its efficient working even in undulating terrain (48). An adaptive cruise-weeding robot for rice fields based on improved YOLOv5 was introduced. The robot achieved an accuracy of 90.05 % for identifying rice plants in different backgrounds with 19.51 frames per second (FPS) in a realistic scenario fulfilling the requirement for the real-time weeding operation of the robot in the rice field. The robot achieved 82.4 % of weed control efficacy and a seedling damage rate of 2.8 % fulfilling the agronomic condition of weed control by mechanical means in the rice growing area (49). A commercial weeding robot for rice fields named Moondino was built by ARVAtec Srl based in Italy and was developed by a Swiss company ECO Process & Solutions. The robot could manage weeds by the action of its wheels, working as a weeding implement (50).

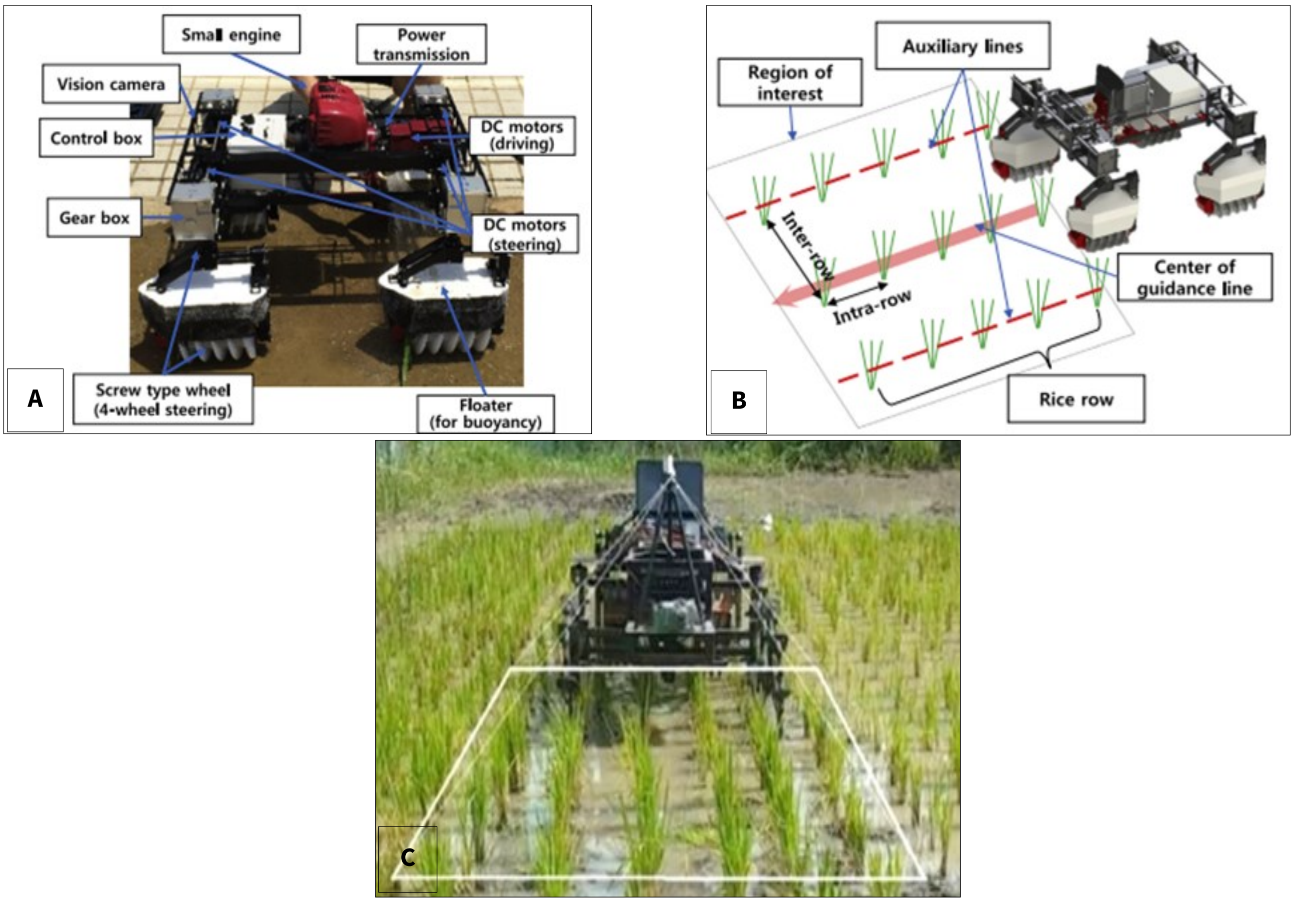

Fig. 2. Application of robots for managing weeds in rice fields. A) K-Weedbot Components, B) Navigation of the K-Weedbot and C) Robot navigated autonomously having cutters for weeding.

Disease management

Rice is susceptible to various diseases during its cultivation period which are mostly caused by bacteria, fungi and viruses. Diseases like brown spot, false smut, rice blast, sheath blight, leaf blight *etc,* cause severe damage to the crop (51) with a possible level of 15-30 % yield reduction, accounting for an annual loss of 33 billion USD (52). To combat these diseases, conventional disease monitoring approaches are used, which mostly rely on field investigations and estimations made by plant protection experts. However, this method is time-consuming, laborious and subjective with a small scope of investigation. Such traditional methods cannot meet the real-time and dynamic methods required for monitoring rice diseases (53). To minimize the losses, effective management techniques are to be undertaken and the precision agricultural tools mentioned in this section can be applied to achieve this purpose.

Remote sensing for rice disease monitoring and severity assessment

Remote sensing by UAVs is the only technical way to gather spatially continuous surface information over a wide area. Hence it has been used widely for crop disease monitoring (54). Hyperspectral remote sensing imagery provided necessary insights for assessing disease distribution of rice panicle blast, aiding in prescribing the optimum amount of fungicide required to manage the disease (55). UAV multispectral imaging coupled with machine learning, gave vital information on rice panicle blast monitoring during the critical heading stage of rice (56). A new rice blast spectral vegetation index (RBVI) in combination with machine learning models, produced higher detection accuracy using UAV remote sensing as a data source, which helped in overcoming the disadvantages of Hyperspectral detection and ultimately provided qualitative and early recognition of the blast disease in paddy fields (10). Consumer-grade UAVs equipped with RGB and multispectral cameras were used to detect the incidence of sheath blight of rice. The NDVI produced by the multispectral images produced an accuracy of 63 % for quantifying different severity of sheath blight in rice fields (57). The UAV imagery was also used to procure data for assessing the damage caused by the bacterial leaf blight in rice (58).

Hyperspectral imagery also provided means to find visible and near infra-red (VNIR) and red edge (RE) regions, that are sensitive to blast disease, assisting in evaluating the severity of the disease in the fields (8). Similarly, researchers used the leaf spectral signatures to detect and classify rice tungro, bacterial leaf blight and blast diseases. Their study highlighted that red and red-edge wavelength regions were highly associated with these diseases and concluded that on the IRRI standard evaluation system (SES) scale of 1 and 3, early diagnosis of rice BLB and blast, respectively was made possible. Also, rice tungro on (SES) scale of 5 was detected in its later stages (59). Using Hyperspectral imagery with various sensors two new spectral indices viz., rice bacterial blight difference index (RBBDI) and rice bacterial blight ratio index (RBBRI) were introduced based on spectral data gained from the rice canopy infested with BLB. The novel indices produced higher sensitivity to the disease and the resulting feature set containing the new indices and a traditional vegetation index, resulted in 90 % overall accuracy across numerous sensors used in the study, ultimately providing a tool for monitoring BLB with different remote sensing data over a vast area (60). Hyperspectral imagery was employed for monitoring false smut in rice (61). Similarly, for early recognition of sheath blight of rice, Hyperspectral imagery was used to develop a step-by-step screening method of spectral signatures and integration of the spectral features with support vector machine (SVM) was made to form a detection model which showed the accuracy of 87 % for early -stage detection of sheath blight of rice (62).

Bio-sensors for disease detection

The biosensors have now found utmost importance in agricultural development, as it has most significantly contributed to achieving the goal of precision in agriculture. To maximize productivity and achieve sustainability, an advanced method of disease detection is required, which can be used to minimize disease-induced damage during the crop period (63). The biosensor preliminary recognizes the target analytes after the application of the diseased sample to the device. Afterwards, the identification is transformed using a transducer into measurable signals to be used by the detector for processing (64). Depending on the biosensor's working principle, the analytes may be detected via magnetic, optical, electrical, electrochemical, chemical or vibrational signals. Bio-recognition compounds like enzymes, DNA, RNA and antibodies can be used to increase the specificity and nanomaterial matrices can be used as transducers to enhance the detection limit of the biosensor (65). The advantages of a biosensor in detecting diseases are given in Fig. 3.

Nano-Based Robotic Technologies have also been introduced in recent years, although they are still in the early stages of development. Nano-sensors are devices which are very tiny, about 1 and 100 nm in size and have been recently used in disease detection. These sensors utilize the nanomaterials like nanowires, nanotubes and nanoparticles. Advanced biosensors using nanomaterials are being developed with high sensitivity and specificity, aiding in early disease detection (66).

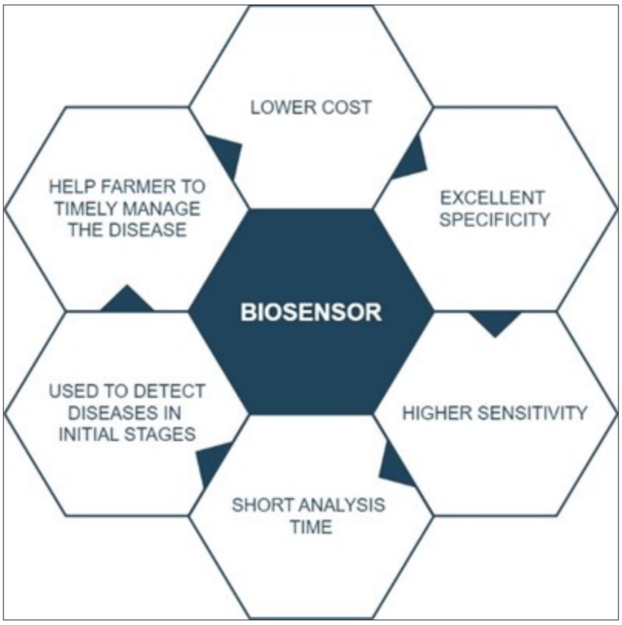

Fig. 3. Biosensor advantages for disease detection.

Prior diagnosis of Blast fungus, *Magnaporthe oryzae* can be made with a novel magnetic-controllable biosensor, which could detect even a small amount of *Magnaporthe oryzae*, because of its specificity and very-high sensitivity using *M.oryazae's* chitinases (MgChi) as a biochemical marker and Osmbl as a recognition molecule (67). A Graphene-based electrochemical DNA biosensor was developed for the detection of False smut, an important disease in rice caused by the fungus *Ustilaginoidea virens* (68). Similarly, Immunosensor-based biosensors provided rapid and simple means to detect rice tungro disease incidence (69). A biosensor based on an optical fluorescence-based immunoassay was developed for early identification of rice bacterial leaf blight (BLB) (70). Similarly, an electrochemical immunosensor strip based on a screen-printed carbon electrode (SPCE), which was tested as a portable biosensor gadget based on Android for detection of Bacterial leaf blight in hotspot regions of Malaysia such that disease diagnosis precedes symptom emergence (71).

AI, machine learning and deep learning for disease identification

To aid the stakeholders in prior diagnosis of rice diseases, Artificial intelligence (AI) and its subsets present itself as a novel solution among researchers, which has been made possible by the advancement in technologies (72). In digital image processing and recognition methods, rigorous enhancements are being made for more viable and easier detection and classification of diseases on crops (72). Some researchers propose integrating unmanned aerial vehicle (UAV) technology, cloud computing, etc. for working as a system, helping the farmers get greater yields at a lower cost as AI and ML solely are not enough (9).

A prototype system was designed to detect and classify rice diseases based on the photos of diseased rice plants and it was developed via a wide range of techniques of image processing. Major rice diseases viz., brown spot, leaf spot and bacterial leaf blight were taken into account and the images were procured with a high-resolution camera. For precise feature extraction and segmentation, a centroid feeding-based K-means clustering was proposed. Support vector machine (SVM) for multiclass classifiers was used garnering 93.3 % precision on the training dataset and 73.33 % precision on the test dataset respectively (73). Researchers utilised a Deep Convolutional Neural Network (DCNN) transfer learning-based approach that entailed a VGG19-based transfer learning method to recognise and differentiate in rice leaf diseases precisely. Detection and diagnosis of six different classes viz., leaf scald, leaf blast, brown spot, bacterial leaf blight and narrow brown spot and health can be precisely performed with this novel and improved Convolutional Neural Network (CNN) model (9). Automatic classification systems were also developed, for early detection and identification of disease in rice using AI and image processing. The researchers utilised the Kaggle data set to signify the performance of the classification system which iterated 98.1 % accuracy, 97.1 % specificity, 96.2 % sensitivity etc. and hence, the results concluded that the proposed algorithm was superior to currently utilised classification algorithms (74). A Summary of the Machine learning and deep models developed for disease identification is given in Table 2.

Insect and other invertebrate pest management

Starting from the sowing of the seeds; until its harvest, the rice crop is often infested by numerous insects. Various species of insects cause damage to the crop; however, a few of them are economically important, which causes 25-30 % of the economic loss (75). This section discusses the application of precision tools to combat the economic damage caused by insects.

Remote sensing for monitoring rice insect pests

Pest monitoring is traditionally conducted by doing surveys and assessments in fields by experts in crop protection. It takes more time, labour and is subjective with a small scope of the investigation (76). Traditional approaches have become obsolete to meet the real-time and dynamic demands for rice insect pest monitoring. To get quick continuous surface data across a wide area, remote sensing is the only technological approach available and hence it is used widely for pest monitoring (77). Hyperspectral remote sensing was utilised for detecting brown planthopper damage on potted rice plants which was observed with change in reflectance between infected and non-infected rice plants in near-infrared and visible regions of the electromagnetic spectrum (78). Similarly, hyperspectral imaging aided in the swift detection of the striped stem-borer infestation in rice seedlings (79, 80). Remote sensing approaches were also utilized for monitoring the rice leaf folder and yellow stem borer in rice. Researchers in their study used Simple ratio (SR), Green-red vegetation index (GRVI) and Normalized difference vegetation index (NDVI) as the spectral indices and their values were interpreted to get a precise assessment of damage by the pests (81). Hand-held spectroradiometer and Satellite data were also utilized for monitoring rice leaf folder damage (82). Similarly, the integration of UAV and Satellite remote sensing for data acquisition was done, eliminating the disadvantages of using satellite and UAV data. It enabled the researchers to monitor rice leaf folder damage symptoms precisely (83). Using Real-time kinematic-UAV remote sensing imagery and automatic data processing with Python and PIX4D engine SDK, a prescription map was developed indicating apple snail infestation-prone areas on paddy field. The prescription map aided the other set of UAVs in achieving precision pesticide spraying to control snail damage (84).

Artificial intelligence for insect pest management

Artificial intelligence uses advanced algorithms for analyzing data sets from different sources like UAV or satellite imagery and sensors. The output from the data enables the plant protection experts or farmers to acquire early pest detection, accurate identification and predictive modelling, helping them achieve efficient pest control with precision in pesticide application and other arbitrations (85). A Support vector machine (SVM) classifier was utilized in a rice light-trap insect imaging system. It facilitated the automatic recognition and enumeration of lepidopteran rice pests with an accuracy of 97.5 % for pest identification (86). Similarly, a four-layer deep neural network with a search and rescue optimization (DNN-SAR) method was utilized in light traps for the automatic identification of yellow stem borers and leaf folders. The method was successful as it achieved a pest detection accuracy of 98.29 % (87). A smart monitoring system was also devised using searchlight traps and machine vision. The system utilized an improved YOLO-MPNet model and was able to monitor white backed-plant hopper, brown plant hopper and rice leaf roller with accuracies of 85.82 %, 88.79 % and 94.14 % respectively (88). Rice stem borer and rice hispa were also detected using a Yolo-convolution neural network (YO-CNN) with an accuracy of 98 % (89). Similarly, a deep neural network called YOLO-GBS (GCNet, BiFPN and Swin Transformer) was developed as an improvement over YOLOv5s for the identification of rice insect pests. Seven rice pests were used in the dataset and the developed model showed a mAP of 79.8 % which was higher than the YOLOv5s, providing efficient and accurate rice pest detection (90).

Challenges and limitations in handling precision tools by the stakeholders

Precision agricultural tools have advantages over conventional practices and are becoming more prevalent nowadays. However, there are some constraints related to their acceptance and handling by the farmers. The adoption of precision agricultural tools by small and medium-sized farmers is crucial for realising the global potential of these tools, although they can be seen with a lower rate of adoption (91). PA tools require a large initial expenditure which prevents small and medium farms from accessing the innovation. The costs for adaptation and training to new technologies further add to the economic constraint (92), whereas conventional practices are relatively less costly and require minimum training. Compatibility of PA tools with the prevailing farm technologies and agricultural practical routine is also a major barrier towards adoption (93). In a study conducted by researchers, lack of technical support and training to use PA tools were the significant factors concerning the adoption by small and medium-sized farms (91). The adoption of the PA tools may be lagging among farmers due to their complexity while handling along with some technical issues (94). The complexity may arise due to the lack of knowledge of the farmers (92). Farmers' behaviour also plays a role in adoption as they are ready to embrace the innovation rapidly if they feel comfortable while handling the tools along with perceived benefits from it (95). While handling the IoT-based PA tools, a few more constraints arise which include processing, interoperability, storage and latency of the data along with power requirements, wireless communication range and higher cost (96). All these constraints should be considered for making improvements in the adoption rate of the PA tools and it should be optimised especially for the small-medium sized farms as they are in majority across the globe.

Prospects on the application of the PA tools

In the last 5 years, the research on these PA tools has increased rapidly in crop protection. It has made a significant contribution, allowing researchers and stakeholders to efficiently and precisely manage biotic stressors. However, some of the improvements are to be made by the researchers which are summarized below.

a) Remote sensing with UAVs and satellites is widely utilised for identifying, classifying and monitoring biotic stressors. Despite being an effective tool, there are several constraints to using remote sensing in rice crops. The spectral data in rice is prone to the influence of underlying water bodies making the information susceptible to errors. Rice crop has specific infestation timings based on their growth stages making the research on rice insufficient considering the enormous number of pest populations. Also, there is minimal integration of satellite data, habitat information, fluorescence and thermal imaging pertinent to pest and disease incidence. The combination of several data sources and platforms is required to enhance data information, monitoring and early detection of rice diseases and pests.

b) Artificial intelligence and its inception in agriculture, have provided significant benefits. Currently, various models have been developed for individually identifying the weed, disease and insect pests. However, there are only a few models that can identify diseases and pests simultaneously such as the YOLO-DPD model (97). Hence, developing such models is necessary as only one AI model would be required to identify the various biotic stressors.

c) UAVs are seen widely as a tool for agrochemical applications, but constraints exist. Optimization of the UAV configuration, along with ensuring consistent spray performance across varying field conditions is still to be focused upon as it may affect overall efficacy in overall crop protection.

d) Robots for managing the weeds in rice fields are still under research and developmental phase, hence are yet to be fully commercialized for consumers. The application of robots in rice fields can be enhanced with the integration of novel AI algorithms, providing higher accuracy while classifying and targeting the weeds for precision weed management.

e) From the stakeholder's perspective, future studies should focus on lowering the cost of handling the PA tools along with solving its compatibility issues with the on-farm machinery. Efforts should also be made towards providing training and technical support, which will enhance the adoption rate of the PA tools.

Conclusion

In this review, various crop protection tools are discussed and highlighted their importance in rice production and their relative advantage over conventional methods. These tools offer great efficiency in terms of precision, time and cost-effectiveness. These tools can be used in resource-constrained areas that can be trained on varying populations, densities and locations of various biotic stressors that ultimately aid in determining the symptoms and controlling measures, tailored specifically for that site rather than uniform control. These state-of-the-art tools facilitate the stakeholders to use their resources more efficiently considering the field variability thereby, lowering the input costs and ultimately aiding the sustained intensification of rice production. Tools such as UAVs, biosensors and remote sensing help to attain real-time on-site information that is then fed into suitable AI algorithms via high spectral data channels where the data is encoded into layered hierarchies.

Table 1. UAV-based weed detection in rice

S. No.	UAV Type	Sensors	Major Weed Spp. Detected	Image gathering stages	Technique	Accuracy	Inference	Reference
1	3D Robotics SOLO Quadcopter drone	Multi-spectral sensor	*Echinochloa spp.* and *Portulaca oleracea* L	Early growth stage (10-15 cm plant height)	Vegetation indices (VI) and ISODATA classification	96.5 %	Spectral indices comprising GSAVI and SAVI outperformed others producing a weed map	(98)
2	Multi-rotor UAV (Phantom 4, SZ DJI)	Red-green-blue (RGB)	*Leptochloa chinensis* Nees and *Cyperus iria*	Early tillering stage	Pre-trained ImageNet CNN with the residual framework in an FCN form and transferred to a dataset by fine-tuning.	94.45 %	Semantic labelling approach gave accurate mapping of weeds	(99)
3	Multi-rotor Phantom 4 UAV	Red-green-blue (RGB)	*Leptochloa chinensis* Nees and *Cyperus iria*	Early growth stage	Fully convolutional networks (FCN)	>94 %	Successful weed map and prescription map generation resulting in 58.3% to 70.8% herbicide saving	(100)
4	Multi-rotor UAV	Red-green-blue (RGB)	*Leptochloa chinensis* Nees, *Cyperus iria, Digitaria sanguinalis (L)* and *Echinochloa crus-galli*	Field 1- Tillering stage Field 2- seedling stage	Convolutional neural network (CNN)	80.2 %	VGGNet-based FCN outperformed OBIA classification providing key information for precision application of herbicides	(101)
5	DJI P4 Multispectral UAV	Red-green-blue (RGB)	*Echinochloa crus-galli, Leptochloa chinensis* Nees and other spp.	Tillering stage	Deep learning semantic segmentation networks BiSeNetV2 and U-Net and their improved structures FFB-BiSeNetV2 and MobileNetV2-UNet	93.09 %	Real-time identification of weeds in rice fields provides the opportunity for subsequent drone spray	(102)
6	Small consumer UAV, DJI Phantom 4	Red-green-blue (RGB)	*Digitaria ciliaris* and *Ageratum conyzoides* L.	9 and 29 days after sowing of rice	Random forest (RF) classifier and simple linear iterative clustering (SLIC) algorithm	90.4 %	Consumer-grade UAV imagery provides satisfactory accuracy in rice and weed differentiation	(103)
7	Quad-copter Phantom 4 RTK UAV	Multi-spectral sensor	*Echinochloa crus-galli* and *Monochoria korsakowii* Regel & Maack	Tillering stage	Weed identification index ($WDVI_{NIR}$) based on RE, G and NIR and utilization of confusion matrix accuracy verification method to verify the result of weed identification vector	93.47 %	A novel method of detecting weeds in rice fields was achieved to facilitate Site-specific weed management	(104)
8	DJI M300 RTK UAV	Red-green-blue (RGB)	*Echinochloa crus-galli*	Tillering and panicle initiation stage	Multi-scale featured enhanced DETR Network - RMS-DETR	79.2 %	Accurate weed detection in rice fields in complex real-life scenarios for precise herbicide application	(105)

Table 2. Disease identification in rice using machine learning and deep learning approaches

Approach	Models	Diseases	Accuracy	References
MACHINE LEARNING	Support vector machines (SVM)	Rice leaf blast	82 %	(106)
	Random forest (RF)	Blast disease of rice	97.21 %	(107)
	Learning Vector Quantization (LVQ) Neural Network	Rice panicle blast	91.6 %	(108)
	Support vector machine (SVM) for multiclass classification	Bacterial leaf blight, brown spot and leaf smut	93.33 %	(73)
DEEP LEARNING	DenseNet169- MLP	Leaf blight, Brown spot, Leaf smut	97.68 %	(109)
	Convolutional Neural Networks based Deep Learning (CNN-based DL)	Blight, blast, brown spot	96.4 %	(110)
	Multiscale YOLOv5	Rice leaf disease	94.87 %	(111)
	Customized CNN	Brown spot, blast, leaf smut, blight and tungro	91.4 %	(112)
	EfficientNETB0 and capsule network	Narrow brown spot, brown spot, leaf blast, leaf scald, bacterial leaf blight	97.86 %	(113)

This data is then classified via neural networks for the detection, identification and classification of various biotic stressors. This helps to mitigate the stress even before any economic loss occurs. Tools/Techniques such as ML and DL not only detect present biotic stressors but can also predict patterns of future outbreaks. This leads to improved efficacy of UAVs and robotic systems that are used to attain site-specific management of yield-reducing bio-agents albeit pathogens or pests. UAVs comprehend these datasets via prescription maps and execute site-specific mitigation of biotic stress often via agrochemical application leading to increased efficacy both spatially and temporally thereby, drastically reducing total input costs. Robotics employ both chemical and physical methods of control reducing human drudgery and labour costs. This automation presents itself as a necessity in impending climate change to deal with inconsistencies and challenges associated with it. These precision tools help eliminate agrochemical overdose, reducing carbon footprint and environmental pollution. Therefore, precision tools possess the potential to alter the face of farming aiding in the conservation of biological resources leading to sustained intensification of productivity to meet the food security.

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Authors' contributions

SS was responsible for conceptualization, Visualization, writing the original draft and writing - review and editing. GP as the Corresponding author, led the manuscript writing, editing, conceptualization and supervision. MS, MG, VBRP and VM were involved in supervising the manuscript. PMA was involved in conceptualization of the manuscript. PD and PB were involved in Writing - review and editing. All authors read and approved the final manuscript.

Compliance with ethical standards

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