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Review Article

Application of computer vision in livestock and crop production—A review

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ABSTRACT: Nowadays, it is a challenge for farmers to produce healthier food for the world population and save land resources. Recently, the integration of computer vision technology in field and crop production ushered in a new era of innovation and efficiency. Computer vision, a subfield of artificial intelligence, leverages image and video analysis to extract meaningful information from visual data. In agriculture, this technology is being utilized for tasks ranging from disease detection and yield prediction to animal health monitoring and quality control. By employing various imaging techniques, such as drones, satellites, and specialized cameras, computer vision systems are able to assess the health and growth of crops and livestock with unprecedented accuracy. The review is divided into two parts: Livestock and Crop Production giving the overview of the application of computer vision applications within agriculture, highlighting its role in optimizing farming practices and enhancing agricultural productivity.

KEYWORDS: artificial intelligence; innovation; agriculture automation; computer vision; smart agriculture; smart technology

1. Introduction

The use of artificial intelligence (AI) in the livestock industry is increasing nowadays. Investment in artificial intelligence is expected to increase significantly by 2026, and computer vision is indeed a significant and growing area within the field of AI. Modern computer vision technology helps farmers collect, store, and retrieve data for livestock operations. Managing and analyzing livestock operations is much more difficult than monitoring crops because animals move from one place to another. In commercial production systems, there are barriers to the widespread adoption of computer vision although it is a promising tool for animal care[1]. Digital image analysis, together with digital image processing and computer vision, is often used as a collective term to describe similar processes and applications[2]. Digital image processing with specific algorithms was used to estimate the body length, breast ratios, height, and width of cattle. The exact yield depended on the estimation of the photographic capability of the study parameters[3]. In digital image analysis, the most important factor is image quality. Different scenarios are possible in multimodal biometric systems by using sensors, and feature sets[4]. Nasirahmadi et al.[5] describe the most advanced 3D imaging systems in combination with 2D cameras to effectively identify the behavior of farm animals and present automated approaches to monitor and study the feeding, drinking, lying, movement, aggression, and reproduction behavior of cattle and pigs. The results showed that these technologies can assist the farmer by monitoring normal behaviors and early detection of abnormal behaviors in large farms[5]. The studies showed that the use of video analysis can detect the possibility of non-intrusive animal monitoring in real time. According to Eduardo et al.[6], it was possible by video and data processing techniques after the ASF virus infection to monitor the changes in animal movement. The results showed that a significant decrease in animal movement can be detected after infection as early as four days after experimental infection with the ASF virus. Nevertheless, other technologies are also important for animal research, such as spectral and hyperspectral imaging, radiography, satellite imagery, and ultrasound. According to Patrício et al.[7], the development of precision solutions for livestock farming is one way to bring animals closer to producers in these expanding systems. Machine vision technology combined with the Internet of Things (IoT) offers benefits for precision livestock farming, such as monitoring the health status of all animals, including cattle, sheep, pigs, and poultry. On the other hand, one of the fundamental branches of agriculture (crop production) supplies the livestock industry with fodder and the human population[8]. Nowadays, with an inadequate level of management work in the field of crop production and a difficult financial and economic situation is necessary to find the best way for improving agricultural enterprises and production. Moreover, the demand for agricultural products is now growing with increasing the human population[9,10]. The intentions of development and progress in agriculture also imply that the vast majority of processes are already digitized and the volume of data. Over the past decade, it was impossible to trace over a wider geographical area, during the production season, where a specific field crop is planted. However, now with a relatively small amount of data from the field, it is possible to train artificial intelligence algorithms to recognize crops using footage. In this way, a map of the sowing structure is obtained, as well as an insight into how much arable land is under a certain culture in a given year, which is important information for state institutions. In the field of agricultural automation, the development of technology plays a key role in future development[11]. The use of the camera instead of the human eye helps in the identification, measurement, and tracking of image processing. Together with image capture by remote cameras, computer vision techniques enable non-contact and scalable sensing solutions in agriculture[12]. Intelligent systems based on machine vision algorithms are becoming an everyday part of agricultural production management, and machine vision-based agricultural automation technology is being used to increase productivity and efficiency in agriculture[13]. In addition, machine vision technology is also used for production management in crop protection, harvesting, and crop monitoring[14]. Year by year, computer vision applies in more and more scientific fields and becoming more and more popular and applicable. Therefore, the purpose of the article is to present the use of computer vision in livestock and crop production.

2. Computer vision in agriculture

Contributions of computer vision-artificial intelligence (AI) are generally known in areas such as analysis of weather conditions, plant health detection, monitoring, planting, and harvesting[15]. Farmers, for example, using simple tools, will receive information about the occurrence of diseases and pests before they happen. Based on the algorithms, it is possible to notice changes in plant growth and make an estimate of how much yield there will be or how much humus there is in the soil. Computer vision models are trained using datasets for processing images, for example, plants. After that, they define algorithms that help them determine the image of the diseases, pests, or weeds. These systems are particularly suitable for the evaluation of properties such as color, texture, scale, surface defects, and impurities, as well as for the classification of food into specific grades and the detection of defects[16]. Various imaging techniques are available to detect complex traits related to growth, yield, and adaptation to biotic or abiotic stress factors (e.g., diseases, insects, water stress, and nutrient deficiencies), including color imaging (e.g., machine vision), imaging spectroscopy (e.g., multispectral and hyperspectral remote sensing), thermal infrared imaging, planar imaging, fluorescence imaging and 3D imaging and planar imaging[17] (cameras, lights, and communication devices), and CV systems (image processing algorithms)[18]. In addition, since 2012 Convolutional Neural Networks (CNNs) have dominated solutions to CV tasks, showing superior performance over traditional machine-learning methods[19]. Nowadays, drone technologies, remote sensors, and satellite technology are widely used in agricultural production. The application of deep learning technology allows us to utilize the possibilities of merging computer vision and artificial intelligence in agriculture. This leads to an improvement in the yield volume of high-quality scene images that can be effectively processed for intelligent agricultural applications[20]. Computer vision automation helps farmers to achieve data about fields, or gardens, allowing them to track, and evaluate specific objects using visual elements. In addition, machine vision for detection offers numerous tools and algorithms with different performance characteristics that can be used to operate with consumer cameras[21]. The most notable contributions used today are machine learning for crop rotation, pesticide spraying, crop monitoring, phenotyping by computer vision, weed control, smart systems for crop grading and sorting, and yield analysis as well as the application of computer vision in livestock production (**Figure 1**).

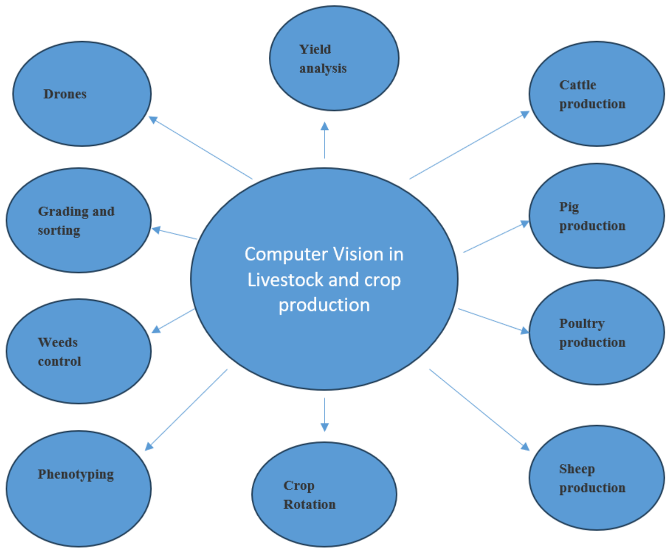

Figure 1. Computer vision in livestock and crop production.

3. Livestock production

3.1. Application of computer vision in cattle production

The Web of Science platform was searched for articles with terms such as computer vision, animal, livestock, poultry, cattle, sheep, pigs, deep learning, and any combination thereof. However, additional literature was also searched on Google and Google Scholar to find more information about livestock in general. Automation of the process of monitoring cattle behavior is becoming increasingly important, so computer vision is playing an important role in cattle production and livestock production in general. Developments in artificial intelligence and computer vision in cow production offer a wide range of solutions in the field of object detection and tracking. A recently proposed approach to cow movement or activity detection is illustrated in **Figure 2**[22]. Some of the non-computer vision solutions could be used for tracking a cow's vital signs and activity in real-time, but they use unique sensors for each cow and they are very expensive. On the other hand, the farmer could use the camera to check the video feed from his phone while trusting the system to notify him if something happens that requires his attention[23]. CVS can be exploited through breeding programs. For example, Nye et al.[24] used the catalogs of breeding programs to demonstrate a web scraper with an image segmentation algorithm for extracting images and information. They presented how the extracted information can be used to determine genetic parameters related to coat pigmentation and conformation traits in dairy cows. Similar, Moore et al.[25] reported on the use of various cattle data for the prediction of genetic parameters. The results showed that more accurate genetic parameters could be determined with the information from the CVS due to the larger amount of data. Tassinari et al.[1] conducted research on the development of a computer vision system based on Deep Learning aimed at recognizing individual cows in real-time. Results showed that the system successfully identified cows based on coat patterns, assessed their position, tracked movements, and helped understand cows' actions. An image-based model for the recognition of cow breeds was proposed by Gupta et al.[26]. The YOLOv4 algorithm of DL was used for the discriminative feature of cows with a limited training dataset. The results of the comprehensive analysis show that the proposed approach achieves an accuracy of 81.07%, with a maximum kappa value of 0.78 at an image size of 608 × 608 and an overlap over unity (IoU) threshold of 0.75 in the test dataset. However, the improvement using computer vision is achieved by several publicly available datasets: ImageNet[27], PASCAL VOC (Visual Object Classes)[28], and MSCOCO[29]. Some of the datasets developed specifically for use in cuttle computer vision systems are Holstein Cattle Recognition[30], Friesian Cattle 2017[31], Aerial Cattle 2017[32]. Currently, image classification, instance segmentation, semantic segmentation, pose estimation, tracking and object detection are public datasets for computer vision tasks or challenges[33]. Therefore, datasets and technologies for cuttle farming are important for analysis and decision-making.

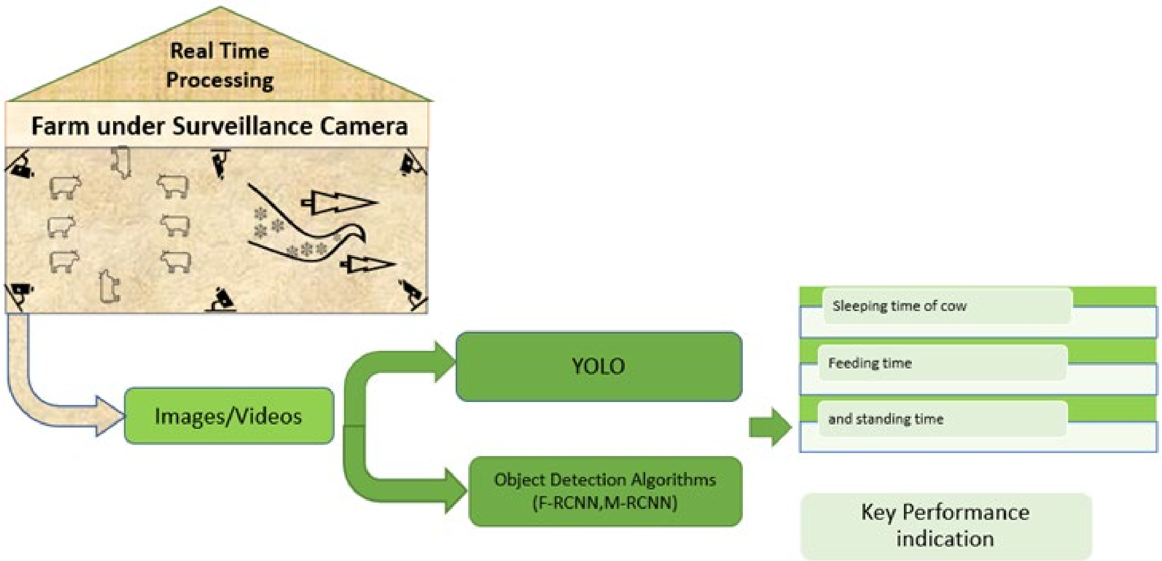

Figure 2. The proposed method for detecting cow movements and activities[22].

3.2. Application of computer vision in pig production

Pork is the meat with the second overall consumption[34] and therefore it is very important to use more advanced methods such as precision livestock management instead of conventional methods to improve production. According to Albernaz-Gonçalves at al.[35], it is currently difficult for swine production to recruit enough skilled labor to provide quality care for pigs given the economic climate and labor shortages. Rauw at all.[36] reported that more intensive care of an individual animal has a positive impact on the welfare and health of the animal. Several animal science studies have been conducted to determine pig health status[37], comfort and well-being[38], pig drinking behavior[39], posture changes in pigs[40], and live weight[41]. In pig production today, computer vision offers rapidly growing potential to improve production, resulting in improved animal care and reduced labor costs[42]. For example, precision feeding of pigs requires automated measurement devices for data collection, data processing, and calculation methods for estimating nutrient requirements[43]. Technologies such as IoT and AI to monitor the health and welfare of pigs are frequently used in pig farms. Parameters such as humidity and temperature are determined by IoT[18], while feature extraction, modeling, and data analysis are determined by AI[44]. In pig recognition based on computer vision, the importance of networks is becoming increasingly important. Some of the networks used in recognition based on computer vision in swine production are MobileNet[45], DeepLabv3+[46], Xception[47], YOLOv5[40]. AI algorithms also use deep learning models with images or videos to recognize pig behavior[18]. Chen et al.[48] applied the video-based method and obtained good results. On the other hand, for the image, researchers usually used Faster[49], Mask R-CNN[50], YOLO[51]. Although the use of new technologies improves pig production, in practice, the willingness to adopt new technologies is still in progress. Therefore, for farmers who have adopted the technology, government agencies should provide adequate subsidies, which will not only help protect farmers after adopting the risk of the new technology but also encourage more farmers to adopt the technology[44].

3.3. Application of computer vision in poultry production

Today, the use of artificial intelligence can reduce losses due to premature death and the rejection of billions of chickens per year before they are processed into meat[52]. However, poultry has a higher density compared to other animals[53], which leads to limitations or a high degree of uncertainty in monitoring the behavior and distribution of groups of chickens in feeding, drinking, and resting areas. Modern broiler houses with large numbers of chickens are equipped with cameras, and the use of computer vision is one of the methods for continuous remote monitoring of commercial farms[54]. According to Okinda et al.[55], the application of computer vision in poultry farming includes recognition and identification of images, detection of objects, classification of images, segmentation, and recognition of objects. Abd Aziz et al.[56] reported that computer vision works in three basic steps: 1) acquiring an image, 2) processing the image, and 3) understanding the image. Despite the many advantages of vision systems, the performance of any vision system in monitoring livestock is greatly affected by the varying light conditions in the farm environment, color, contrast between background and foreground, and occlusion problems[55]. Recently, researchers reported the efficiency of using computer vision in poultry production, especially for monitoring chicken welfare in terms of weight, lameness, behavior, temperature, activities, and health[57–59]. Some of the Digital technologies for poultry producers are presented in the **Table 1**. The potential of computer vision algorithms using Mask R-CNN for broiler detection and monitoring resource utilization in broilers was investigated by Jerine et al.[54]. They found that in a high stocking density commercial environment, individual broilers can be detected and monitored when it comes to resource utilization. According to Karthikeyan[60], AI could be trained using computers/artificial vision to detect heat stress in birds early using thermal imaging cameras or infrared cameras. Dawkins et al.[61], used cameras to analyze the optical movement patterns of flocks of chickens as they moved around a house. The results confirmed the hypothesis that visual movement patterns of broiler flocks on commercial farms in the United Kingdom and Switzerland are correlated with two important animal welfare outcomes-mortality and fecal burn.

Table 1. Digital technologies for poultry producers.

Technology	**Description**
3D printing prosthetics	Printing of plastic or metal parts when the farm requires replacing[62].
Robots	Provide farmers to make data-driven decisions regarding broiler production that could result in a healthier, more productive growing environment[63].
Drones	Allow farmers to monitor poultry conditions from the air to keep watch for potential problems and help optimize field management[64].
Sensors	Streamlining data collection for chickens and farmers, enabling cheaper poultry production[65].
Poultry system simulation model	Simulates the water, energy, wastewater, and labor utilization of a poultry processing plant[66].
Block chain technology	Uses predictive analytics and deep learning analysis to display and forecast future performance throughout the supply chain[66].
Automation and digitalization, big data	It is possible to apply various ways to enhance poultry production by improving efficiency, productivity, and overall management[67].
Machine learning: Statistical process control	Accurate identification of changes in variables throughout the food supply chain[68].
Internet of things	Connection between sensors and smartphones or other devices in a hen house[69].

3.4. Application of computer vision in sheep production

For most sheep producers, profit is directly related to the commercial value of the flock and the cost of the bred sheep. In recent years, considerable progress has been made in the field of machine vision and machine learning[70]. Several works with sheep can be found in the literature, aiming at image processing with physiological information (skin temperature, respiratory rate, and heart rate), weight prediction, behavior recognition, sheep breed identification, etc. Fuentes et al.[71] investigated the evaluation of physiological information such as heart rate modeled with machine learning algorithms, skin temperature, and respiratory rate in sheep exposed to thermoneutral and controlled heat stress conditions by automatically tracking the regions of interest from RGB videos and infrared thermal videos of sheep. According to the results obtained, the application of automated computer vision algorithms and machine learning models was proposed to obtain critical biometric data from recorded RGB and infrared thermal videos of sheep to help in the automatic assessment of heat stress. Bhatt et al.[72] proposed an automated sheep weight estimation system for real-time operations using a smartphone. A SegNet-inspired deep network was used for segmentation, and a novel segmentation approach and neural network-based regression model were used to achieve better results for the sheep weight estimation task. A deep learning model based on the YOLO v5 network[73] was used to recognize the behavior of sheep (lying down, drinking, and eating). Nowadays the application of YOLO v7 (**Figure 3**) is becoming more popular for sheep detection behavior providing more accurate data[74].

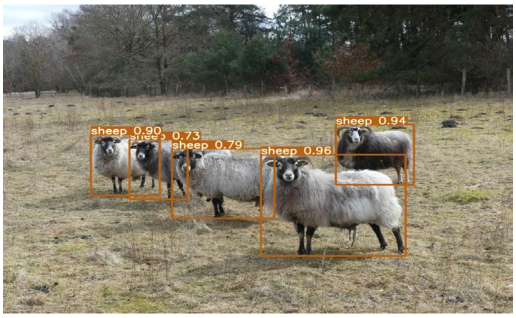

Figure 3. Computer vision to detect sheep with YOLOv7[74].

The application of a deep learning network in a structured environment of intensive farming can provide satisfactory results without the need for large amounts of data if it is ensured that the application and experimental conditions are the same. Sanibel et al.[75] presented the establishment of a prototype computer vision system in a sheep farm, the creation of a database of 1642 sheep images of four breeds taken on a farm and labeled with the respective breed by an expert with its breed, and the training of a classifier for sheep breeds using machine learning and computer vision to achieve an average accuracy of 95.8%. Sarwar et al.[76] used a combination of drone technology and deep learning algorithms to count sheep using convolutional neural networks through video streams captured by drones. They found that capturing top-view images was mainly used for free-range scenarios and could not be extended to indoor sheep rearing. According to the above-mentioned statements from different literature, it can be concluded that there is a need for the development of applications of new technologies in livestock production.

4. Crop production

4.1. Computer vision phenotyping

In the field of agriculture, the integration of cutting-edge technologies has revolutionized traditional agricultural practices. Phenotyping using computer vision is a powerful tool, providing farmers and researchers with unprecedented insights into the health, growth patterns, and overall productivity of plants. Plant phenotyping is one of the biggest bottlenecks in the field of plant science and plant breeding, and further progress requires an interdisciplinary approach and the integration of activities from fields such as plant physiology, sensing, and bioinformatics. Although some methods for phenotyping have drawbacks, such as space-time coverage and limitations in terms of cost, the plant phenotype plays an important role in sciences such as agronomy, botany and genetics[77]. The disadvantages of phenotyping include the structural characteristics of plants and their organs (leaves, fruits, roots etc.) as well as the measurement of size, growth, and 3D surface structure. However, phenotypic information with intelligent perception plays an important role in minimizing agricultural inputs without compromising crop yields and selecting new varieties of high-yielding and high-quality crops[78]. Nowadays, field experiments using aerial phenotyping with thermal and multispectral sensors help to obtain a large number of plant images for crop monitoring and are widely used in crop research[79]. Plant phenotyping frameworks include many sensors with mobile systems, such as motorized gantries[80], tray conveyors[81], and aerial and ground vehicles[82], to collect plant growth and physiology data. Bauer et al.[83] presented the results of combining AirSurf with a deep learning classifier trained with over 100,000 labeled lettuce signals and computer vision algorithms. The results show the significant value of AirSurf-L for pre-harvest plant marketability and precise harvesting strategies. Quantitative evaluation of phenotypic differences throughout the plant's life cycle helps identify genetic factors associated with growth and development[84]. In addition, researchers Choudhury et al.[85] determined stem angle using temporal analysis of plant phenotyping. They found that plant phenotyping analysis summarized the temporal patterns of stem angle into three main groups and contributed to the temporal variation of stem angle, which can be regulated by genetic variation under different environmental conditions. Mochida et al.[86] reported that useful clues for preventive interventions in farming provide a meta-analysis of the spectral signatures of crops associated in association with the environmental conditions, physiological states, and growth stage. The researchers such as Minervini et al.[87] comprehensively discussed the bottlenecks and future trends in the field of image-based plant phenotyping, Toda and Okura[88] for plant stress phenotyping, while Vandenberghe et al. for plant 3D phenotyping. Furthermore, deep learning has become more popular in phenotyping. Thus, RCNN, ZFNet, LeNet18, VGGNet, ResNet, ResNeXt, and

VGGNet[89] have been used successfully in plant phenotyping. This innovative approach leverages advanced image processing techniques to analyze visual data, offering a deeper understanding of plant characteristics that can significantly impact decision-making in agriculture. Computer vision phenotyping stands at the forefront of precision agriculture, providing a transformative approach to crop monitoring and analysis. As technology continues to evolve, the integration of computer vision will likely become a cornerstone in the pursuit of sustainable and efficient farming practices, ultimately contributing to global food security.

4.2. Weeds control

Weed detection and control is another major problem in agriculture and, according to many growers, one of the biggest threats to crop production. Nowadays, farmers tend to use less chemical-intensive systems in order to achieve high yields with good quality. Conventional agriculture combines profitable agricultural production with environmental protection requirements by using reduced tillage, crop rotations, residues, and cover crops to control emerging weeds[90]. Traditional weed control methods often rely on manual labor or the indiscriminate use of herbicides, leading to higher costs and environmental problems. The digitalization of agriculture and new cultivation techniques are some of the possible alternatives for "smart" weed control solutions. For example, self-organizing maps (SOMs) have been used in the past[91], and today they are a powerful, unsupervised machine-learning technique that has proven to be a versatile tool in the field of data analysis. The use of self-organizing maps helps to deal with problems in an unsupervised way and independently of the data[92]. Pantazi et al.[93] used hierarchical map classifiers (SKN, CP-ANN and XY-F) to identify *S. marianum* among other plants in a field, where *Avena sterilis L.* was predominant. The results showed that the identification rates of *S. marianum* reached an accuracy of 98.64% with SKN, 98.87%, with CP-ANN, and 98.64% with XY-F. A precision farming system was proposed by Zhai et al.[94] as a multi-agent system. According to them, this system makes it possible to schedule tasks and allocate scarce resources, as well as spray pesticides only in the exact places where weeds grow. On the other hand, Zhang et al.[95] developed a weed classification model based on the YOLOV3-tiny network. Building a weed classification model based on the YOLOv3-tiny network involves several steps, including data acquisition, preprocessing, training, and evaluation. A study of weed detection and segmentation confirms that CNN shows high performance in accurately detecting and segmenting weeds. In addition, Blue River Technology has developed a robot called See & Spray, which reportedly uses computer vision to monitor and precisely spray weed plants[96,97]. Object recognition algorithms, such as YOLO or Faster R-CNN, can be used to precisely localize and identify individual weed instances.

Precision weed detection robots use advanced technologies such as computer vision, machine learning, and robotics to autonomously identify and control weeds in agricultural fields (**Figure 4**). These robots have been developed to improve efficiency and accuracy in weed detection, contributing to sustainable and precise agricultural practices. In this way, it is possible to significantly reduce weeds and the risk of contamination of crops, humans, animals, and water resources. However, growers should take long-term action to improve crop competitiveness against weeds and maintain soil fertility.

Figure 4. An example of the use of AI in the analysis of aerial images of crops for identification of weeds.

4.3. Smart systems for crop grading and sorting

Nowadays, the food industry contributes the most to the agricultural sector and the automation of vegetable sorting is the order of the day[98]. The main objective of grading in agriculture is to generate more and more income. Therefore, grading has a significant impact on agribusiness to generate more profit[99]. Smart systems for crop classification and sorting play a crucial role in increasing efficiency and accuracy in the agricultural industry. These systems use advanced technologies to automate the process of sorting and grading crops based on various parameters such as size, color, weight, and quality. For farmers sorting and grading crops enables them to separate produce into categories more accurately (**Figure 5**). Many researchers have studied the sorting of a variety of crops using artificial intelligence. Llobet et al.[100] for predicting the degree of ripeness of bananas using electronic nose sensors, Bennedsen et al.[101] for detecting surface defects in apple fruit, Zakaria et al.[102] for assessing the degree of ripeness of mangoes. Nur et al.[103] investigated agricultural products that were classified based on the shape and size of the fruit using support vector machines (SVMs) and whose quality class was determined using fuzzy logic (FL). Different types of fruit and one vegetable were used for the experiment: Oranges, mangoes, carrots, apples, and bananas. Of the five fruits selected, the results were good for three. The working model of the date fruit sorting system, including the hardware and software developed by Yousef[104], uses RGB images of date fruits. The accuracy of the system was 80%. In contrast, Nandi et al.[105] used a CCD camera and a conveyor belt to sort and classify mangoes. RGB color space, edge detection, and boundary tracking were used to determine the color quality and dimension of the mangoes. They note that experts judge the degree of ripeness by firmness and smell and not just by skin color. A new design for an autonomous fruit sorting and classification system that is portable, inexpensive, fast, and customizable by the user was presented by Hadha et al.[106]. Using a test with orange fruit, they showed that the algorithm transforms the (red, green, and blue) color space into the HSV color space (hue, saturation, and value). The size ranged from 25 mm to 75 mm, indicating good results in color classification, sizing, and sorting.

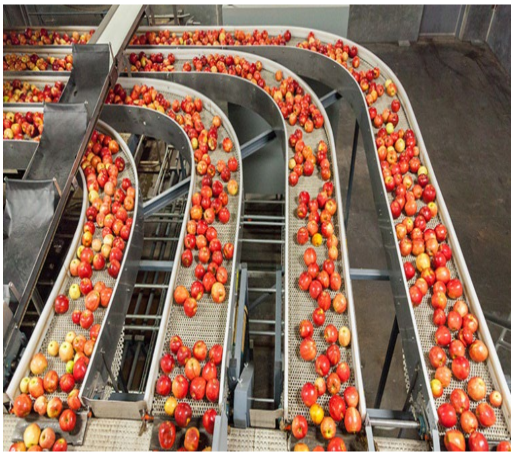

Figure 5. Example of sorting and grading tomato fruit by application of AI[107].

Researchers Paymode et al.[108] used the CNN model with an accuracy of 97.59% for the training images and an accuracy of 92.45% for the test images to determine the size, quality, and shape of the onions. The classification and sorting of dragon fruit were also performed using machine learning algorithms (CNN, ANN, and SVM)[109]. The functioning of these algorithms was based on the shape, size, weight, color, and diseases of the dragon fruit. The use of advanced computer vision algorithms and machine learning models enables the automatic recognition and classification of plants based on various parameters such as size, color, and quality[110]. While the introduction of intelligent crop sorting systems offers many benefits, ongoing research and development is essential to overcome challenges and further refine these technologies. Interdisciplinary collaboration between agronomists, engineers, and technologists is critical to realizing the full potential of smart systems, promoting sustainable agriculture, and ensuring food security in a rapidly evolving global landscape. The use of smart systems for crop sorting increases productivity, reduces labor costs, and ensures a consistently high-quality crop. These technologies contribute to the overall efficiency of the agricultural value chain.

4.4. Using drones in crop production

Drones, also known as Unmanned Aerial Vehicles (UAVs) or Unmanned Aircraft Systems (UAS), are becoming increasingly popular in agriculture, including crop production. They offer various benefits and applications that can improve efficiency, precision, and overall crop management. Spray drones are used for the application of fertilizers, herbicides, pesticides, fungicides, and seeds as they are cheaper, faster, and more accurate compared to traditional methods. In some countries, popular methods for precision agriculture include photogrammetry and remote sensing[111,112], crop monitoring[113] and soil and field analysis[114]. The use of drones in agriculture is useful for monitoring plant growth, increasing yields, and spraying pesticides and fertilizers in the field[115]. Drones equipped with spraying systems can precisely apply fertilizers, pesticides, or herbicides to specific areas, minimizing waste and reducing environmental impact. Today, the ability of unmanned aerial vehicles (UAVs) to, for example, fly over crops and quickly collect crop management data is crucial for precision agriculture, which requires real-time data[116]. Hogan[117] reported that flight duration, ease of use, the ability to better utilize cameras, and reliability through the Global Positioning System (GPS) and customizable apps for smartphones and tablets. According to El Bilali et al.[118] the use of drones together with other information and communication technologies (ICT) opens up a new phase in agriculture, in which we speak of digital agriculture, smart agriculture, e-agriculture, and precision agriculture. Mogili and Deepak[119] have studied the use of drones for crop monitoring and pesticide spraying. They concluded that the UAV spraying system automatically navigates with the GPS coordinates to spray the pesticides on the infected areas where there is no vegetation identified by the Normalized Difference Vegetation Index (NDVI). NDVI maps created using drone imagery can help farmers identify areas of the field that may be under stress, allowing for targeted interventions. The use of drone-generated variable rate application (VRA) maps makes it possible to determine the level of nutrient uptake in the field. In this way, the farmer can apply 300 kg/ha of fertilizer to problematic areas, 200 kg/ha to medium-quality areas, and 150 kg/ha to healthy areas, thus reducing fertilizer costs and increasing yields[120]. Drones create 3D maps to help farmers analyze the soil. To achieve better plant growth, the use of drones provides data useful for irrigation and nitrogen management via soil analysis[121]. In addition, drones can create detailed topographic maps of fields that help farmers understand the terrain and plan irrigation systems more effectively. Drones with hyper-spectral, multi-spectral, or thermal sensors can be used to count plants and assess their health, allowing farmers to detect areas of lower plant density or signs of disease early[122]. According to Ayamga et al.[123], drones play a critical role in decision-making and the management process by providing plant health imaging, integrated GIS mapping, and minimizing the need to physically enter the field, thus contributing to higher yields and lower costs. In addition, information expert Gerard Sylvester said that drones will help farmers adapt to climate change and tackle other challenges to improve the efficiency of overall farming operations[124]. The data collected by drones can be processed with specialized software to gain actionable insights. This information can support decision-making and enable farmers to make informed decisions about how to manage their crops. While drones offer numerous benefits for crop production, it is important that farmers undergo appropriate training and comply with regulations to ensure safe and effective use. Furthermore, ongoing advances in drone technology are likely to bring even more opportunities and improvements in precision agriculture.

4.5. Computer vision and machine learning for crop rotation

Crop rotation is one of the plant production systems that represent a regular spatial (crop rotation) and temporal (crop rotation) change of crops. Proper crop rotation plays an important role in the production of field crops. The application of crop rotation is important because the continuous cultivation of crops puts a lot of stress on the soil, and since it is the most important resource in agriculture, we must do everything we can to restore it. Nowadays, most methods are used to work only one year compared to annual crop rotations. Many researchers have studied crop classification and have come to the conclusion that PSE + LTAE (Pixel Set Encoder and Lightweight Temporal Attention) is one of the most modern methods[125–127]. Machine learning models can analyze historical data on crop performance and soil conditions to predict the best crop rotation plans for optimal yields. Satellite observations and past reports help classify perennial crops to improve the crops grown in agriculture[128]. Liu et al.[129] proposed a hybrid convolutional neural network (CNN) and long short memory (LSTM) architecture for crop rotation mapping (CRM) to combine the time series of synthetic aperture radar (SAR) and optical data in a crop rotation mapping. According to Shiraly[130], the visual features—such as plant boundaries, plant types, soil texture, etc.—are represented as vectors by neural convolutional networks. These vectors are then fed into the time series prediction model. Algorithms such as random forests, XGBoost, recurrent neural networks, or even transformer networks are then used to predict the new soil variables. Stanhope et al.[131] investigated a webcam-based system to augment mechanical guidance systems for row crop cultivation in the early stages of plant growth, combining computer vision and machine learning. They used a low-cost CCD camera and the Python OpenCV platform. The results show that the system was successfully tested for driving speeds up to 6 km/h in several corn and soybean fields under different ambient light and growing conditions. Braeger and Foroosh[132] proposed a voxel CNN method that proved successful when applied to the latest voxel CNN Octnet architecture, achieving a 1% increase in overall accuracy on the ModelNet10 dataset. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), can be used in the context of crop rotation to model temporal dependencies and make predictions based on historical data[133]. However, according to Niall et al.[134], some of the traditional CV techniques (SIFT, SURF, BRIEF) are still useful and collaboration with agronomists and professionals is essential to ensure that the model's recommendations are consistent with practical farming considerations. Today, a combination of computer vision and machine learning provides farmers with data-driven decisions that improve the efficiency and sustainability of crop rotation practices, resulting in higher yields and long-term soil health.

4.6. Yield analysis

Yield mapping is a precision agriculture technique that involves collecting and analyzing data on crop yields in a field. A yield mapping system in precision agriculture measures and records the number of crops harvested at different points in a field and simultaneously records the position of harvesting machinery[135]. Assessing the quality and quantity of specialty crops during harvest is critical for several reasons, including achieving higher yields and improving overall farming practices[136]. In the 1990s, image classification functions were used to detect fruit moving along the packing line to distinguish between acceptable features (e.g., a stalk and blemishes)[137]. However, Raphael et al.[138] concluded that the application of RGB-recorded images in orchards is associated with difficulties, e.g. the different sizes and colors of apples and the non-diffuse natural light causing strong shading. The integration of computer vision, chemical markers (such as Marker M-2), and other accessories can indeed provide a powerful and efficient solution for determining the location of cold and hot spots after microwave sterilization. This approach combines real-time visual data with chemical indicators to increase accuracy and speed in identifying temperature variations[139]. Patel et al.[140] have looked at the localization of fruit on trees as one of the requirements for an effective fruit harvesting system. The ability to accurately identify the location and ripeness of fruit enables the automation of harvesting processes, reducing waste and optimizing the use of resources. Color and shape analysis was used to segment the images of different fruits taken under different lighting conditions. The results show that the proposed method can accurately segment the occluded fruits with an efficiency of 98%. In addition, it was found that based on the data obtained from the hyperspectral camera at the full pod development stage, the yield of soybeans can be best predicted using multilayer neural networks[141]. The same group of authors showed that the prediction of soybean yield by the VNM model is more accurate at the local level than at the regional or state level. According to Kapach et al.[142], the most important applications of computer vision (CV) in agriculture have been developed for fruit detection. The main goal was to identify individual fruits and leaves, segment them from scenes with branches, and localize them in space, either for yield estimation or for robotic harvesting systems. It is important to note that factors such as soil type, topography, and historical management practices can contribute to yield variability[143]. Yield mapping, when integrated with precision agriculture, can greatly enhance a farmer's ability to optimize resource allocation, improve crop yields, and make more informed decisions for sustainable agricultural practices.

5. Discussion

The use of computer vision is now an integral part of agricultural production. Start-ups are turning to task-specific AI and image-processing solutions to improve yields and achieve the goal of a sustainable food supply by 2050[144]. When it comes to livestock and next-generation farms to manage the greenhouse environment with smart irrigation, start-ups such as cropx aquaspy, hydropoint data systems, alesca life, aero farms, bright farms, connecterra, farmnote, advanced animal diagnostics are using machine learning and computer vision techniques to capture, analyze, model and predict the factors that can improve yields[145]. As mentioned above, the use of computer vision offers many advantages such as accuracy, efficiency, and cost-effectiveness. Animal welfare is a priority in modern agriculture. Specific applications such as monitoring animal health, behavior, and productivity contribute to better animal welfare, especially by detecting signs of distress or disease. Automated systems can analyze video feeds to detect signs of illness, stress, or anomalies in behavior[146]. Optimizing feeding, breeding, and overall resource management on farms helps farmers and leads to better productivity. By monitoring feeding patterns and behavior, computer vision can help optimize feed distribution and reduce feed waste. The advantages of low cost as well as high efficiency of the application of Computer vision technology were represented by other researchers[11,147]. Overall, these benefits contribute to more efficient, sustainable, and humane livestock farming. Machine vision technology has the potential to revolutionize the industry by providing farmers and ranchers with valuable insights and tools to optimize their operations. However, farmers face technical issues, privacy concerns, and the initial cost of setting up such systems. In addition, 24/7 operation of vision systems can be very energy intensive. High energy consumption can drive up operating costs and may not be environmentally friendly. Despite these drawbacks, the benefits of computer vision in livestock production often outweigh the drawbacks, but it is important to carefully plan and address these challenges to ensure the successful implementation of this technology. In crop production, computer vision technology increases precision and efficiency. It enables precise monitoring, data collection, and management of crops, resulting in less wasted resources and higher yields. Monitoring of crop growth with computer vision enables the detection of subtle changes in crops and provides a reliable and accurate basis for timely regulation[85]. It is combined with other precision farming technologies, such as GPS-guided machines and sensor networks, to create comprehensive and data-driven farming systems. The multi-sensor imaging system attached to the drones makes it easier for the farmer to detect fewer infrared-reflecting patches in the farmland, thus reducing the further spread of the disease[144]. The application of computer vision improves crop production practices, reduces environmental impact, and contributes to more efficient, sustainable, and economically viable agriculture. Computer vision is becoming an essential tool for modern farming, helping farmers meet the challenges of a growing global population and changing environmental conditions. As in livestock production in crop production computer vision algorithms may occasionally produce false positives (incorrectly identifying issues) or false negatives (failing to identify issues). This can lead to unnecessary interventions or missed problems in crop management.

6. Conclusion

Technology and artificial intelligence play a key role in transforming agriculture by enabling efficient resource management, crop monitoring, and improving production quality. Companies in agriculture (as well as other industries) are using computer vision and AI applications to drive new innovations and unlock new efficiencies that help them achieve their goals in the face of modern challenges. In the realm of livestock farming, computer vision plays a pivotal role in monitoring animal behavior, health, and welfare. Automated systems equipped with cameras and image analysis software can detect signs of distress or disease in livestock, enabling prompt intervention and preventing disease outbreaks. These technologies have the potential to increase both productivity and animal welfare, contributing to sustainable and responsible livestock farming. In crop production, computer vision aids in phenotyping, weed control, crop grading and sorting, crop irrigation, crop rotation, as well as yield mapping. It provides real-time monitoring of plant health and growth, allowing for precise irrigation and fertilization, which in turn conserves resources and improves crop yield. By increasing food demands, the adoption of computer vision in livestock and crop production promises to not only increase yields but also reduce environmental impact and promote animal welfare. The marriage of cutting-edge technology and traditional farming practices represents a promising future for agriculture, ensuring food security in a rapidly evolving world.

Availability of data and material

Not applicable.

Author contributions

The authors contributed equally to the conceptualization, methods, writing, revision, as well as editing of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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