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Computer Vision is a Powerful Technology in the Agriculture Industry: A Review

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Abstract - The parallel relationship between increasing the population and food production leads the researchers to figure out new technologies and use them in the agriculture industry, keeping in mind the challenges of efficiency, productivity, sustainability, and reducing the costs. This paper highlights Computer Vision (CV) technology that has been used specifically in the agriculture field during the recent two years. It contains a review of the methods, sensors, and datasets that are used to improve the agriculture sector to meet the needs of people with good quality.

Keywords: Computer Vision, Sensors, Agriculture Industry.

1. INTRODUCTION

The evolution of agriculture can be divided into levels according to the farming period. In 1754, it was agriculture 1.0 (traditional agriculture). During that period the percentage of human labor was high compared with the productivity. Farmers relied on using tools like hoes, sickles, and pitchforks for cultivation. In 1870, a new agriculture period started, which is agriculture 2.0 (mechanization). New tools and methods began to be used, such as tractors, agricultural machinery, fertilizers, and pesticides. The efficiency and productivity of farm labor increased, but the improvement of the agriculture 2.0 period brought with it damage to natural resources and chemical contamination. These problems created challenges that need to be solved. By 1959, agriculture 3.0 (automation) marked some important changes in the agriculture field, like monitoring, global positioning systems, and variable rate applications. At this level, no longer focusing on production and sustainability, but on soil life and resilience. Today is agriculture 4.0 (information technology), which depends on information technology, thrust worthy food supply, ubiquitous sensing, and the Internet of Things (IoT). Using these advanced technologies and data analysis improves efficiency, reduces costs, and increases yields. For the future, it will be agriculture 5.0 (smart agriculture), and it depends on robotic and autonomous, vehicles, artificial intelligence, blockchain, cybersecurity, the Internet of Everything (IoE), fog computing, virtual and augmented reality, and clean energy [1].

Avoiding food famine leads to caring about the agriculture sector. The Food and Agriculture Organization (FAO) of the United Nations (UN) projects mentioned that in 2050 the world's population will further increase by 2 billion. This increase means more attention on food production. Efficiency, productivity, and sustainability—these three factors are the most important issues for researchers to improve technologies for the agriculture industry [2].

In order to determine the suitable methods for watering and fertilizing crops, wireless sensor networks are used. The main functions of it are collecting data such as humidity, temperature, rainfall, and wind speed and also tracking food growth and detecting plant diseases. There are many types of sensors according to their functionality, like temperature sensors, pH sensors, sensors for humidity, soil moisture sensors, rainfall sensors, wind speed trackers, Nitrogen, Phosphorus, and Potassium (NPK), camera sensors, and light dependent resistor sensors [3].

Digital Precision Agriculture (DPA) is a comprehensive approach that depends on advanced technologies such as automation and sensors. DPA is managing and controlling all processes of farming, starting with collecting data and analysing it to controlling the watering and tracking and detecting diseases. Recently, Unmanned Aerial Vehicles (UAVs) have been one of the most widely used drones in DPA. UAVs are used to capture the images, and then these images are used for recognition and classification [4].

Optimizing farming practices, getting higher resource efficiency, and minimizing environmental impact are the aims of precision agriculture [5]. The importance of Machine Learning (ML) in reshaping farming practices appears in the interplay between Information and Communications Technology (ICT) and conventional agriculture. Autonomous vehicles and drones driven by ML bring benefits for precision agriculture. It is ensuring precision in planting, harvesting, and crop monitoring [6]. Technologies such as Deep Learning (DL) and Computer Vision (CV) are applied in the agriculture industry. Some researchers used deep learning based on computer vision aiming to improve the farming production specifically in greenhouses, which are also known as Controlled Environment Agriculture (CEA) [7]. It refers to CEA because it is used in controls and monitors many factors such as temperature, humidity, light, and CO_2.

2. COMPUTER VISION

After working on Artificial Intelligence (AI), many of its subfields appear, like CV, ML, and DL. Whenever there are visual inputs such as images or videos, the CV extracts the useful information and then responds or recommends according to that information. CV is a multidisciplinary field because, besides its own algorithms and methods, it uses ML algorithms such as DL and Convolutional Neural Networks (CNNs) [8] [9].

The key word of CV is "see" making the machine model the human ability of seeing and understanding the rounded environment. Building artificial systems by simulating the visual system of the human brain, which enables the machine to sense information from images or videos, is the aim of CV, which is also commonly referred to as machine vision [10].

CV is applied in many fields like healthcare, where [11] mentioned that many commercial companies specialized in patient monitoring. This monitoring includes detection and measurement, especially in the development and testing phases. The CV can be used in radiology and histology. The use of CV is not limited to the hospital setting but also extends to outpatient and community settings. In [10] showed the application of intelligent robotic that is based on CV technology, like robots that are used in garbage classification, detection, and sorting. Advertising researchers also get benefits from using CV models to analyse images in order to measure the consumer attention that is effective at marketing strategies [12]. CV is also considered a powerful technology in the agriculture field, which will be discussed in more detail in this paper in the methods section.

The main tasks of CV are image classification, object detection, image segmentation, and object tracking. The way CV works is divided into several stages. The first stage is gathering the visual data (images or videos) and then starting to pre-processing the collected data. The third stage is extracting features, after that interpreting the extracted features and finally the output. Figure 1 shows how CV works.

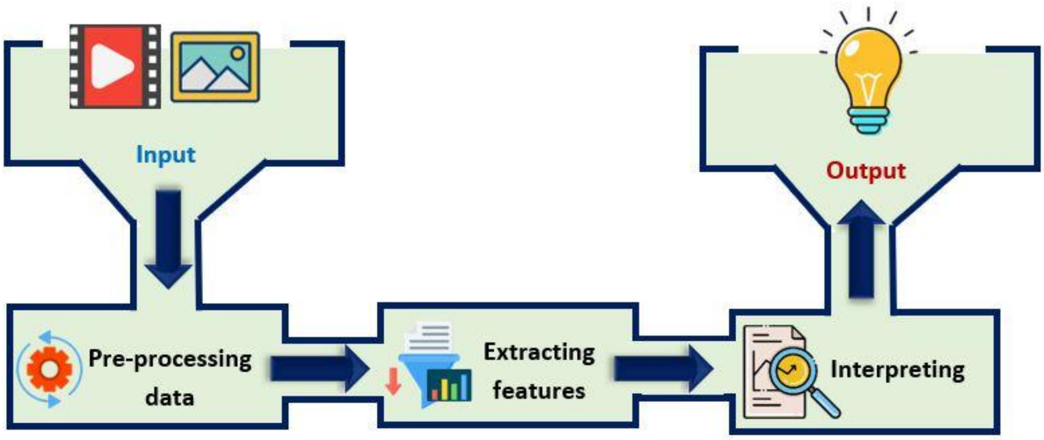

Fig -1: How Computer Vision Works

The output type is various according to the aimed task that CV is used for, such as labels, bounding boxes, coordinates, and numerical values. This output can be an input for new processes, which creates more complex intelligent systems, like giving a robot a command to do a specific task.

3. SENSORS

Without data, how can CV work? So, how are these datasets (inputs) collected? Here come the benefits of sensors. Every type of sensor is responsible for measuring specific factors or capturing specific kinds of images and videos. Nowadays the sensors' companies continue developing sensors and manufacturing various types of sensors with different specifications. Here are some of these sensors.

3.1 RGB Cameras

RGB cameras that use Bayer pattern sensors can be based on Charge-Coupled Device (CCD) and Complementary Metal Oxide Semiconductor (CMOS) based sensor technologies. Bryce Bayer is the inventor of Bayer pattern sensors. Its feature is to capture light in Red-Green-Blue colour [13]. RGB has three separate bands, which provide a discrete portion of the spectral range. Figure 2 presents the Bayer pattern and the wavelength spectrum.

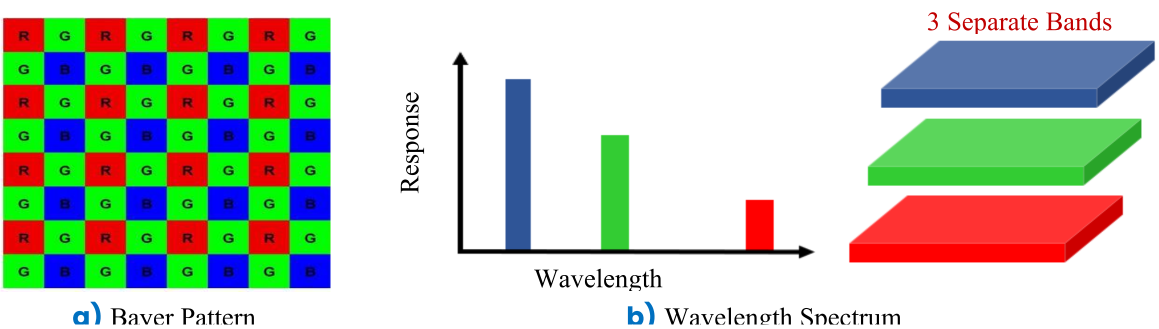

Fig -2: RGB Imaging

Some examples of research that used RGB cameras are intelligent ship marine object detection (ISMOD) [14], monitoring of the rice leaf area index (LAI) [15], and using RGB cameras to generate thermal images in advanced driver assistance systems (ADAS) [16].

3.2 Multispectral and Hyperspectral Sensors

Multispectral and hyperspectral imaging depend on the electromagnetic spectrum. Hyperspectral imaging (HSI) can capture over 100 contiguous bands, which provides a high-resolution spectrum "spectral signature" for each pixel. A continuous (smooth) spectrum will be generated by drawing the relation between the response and wavelength in the case of HSI. Multispectral imaging (MSI) can capture few bands compared with HIS, and it provides several spectral bands. Figure 3 referred to MSI and HIS.

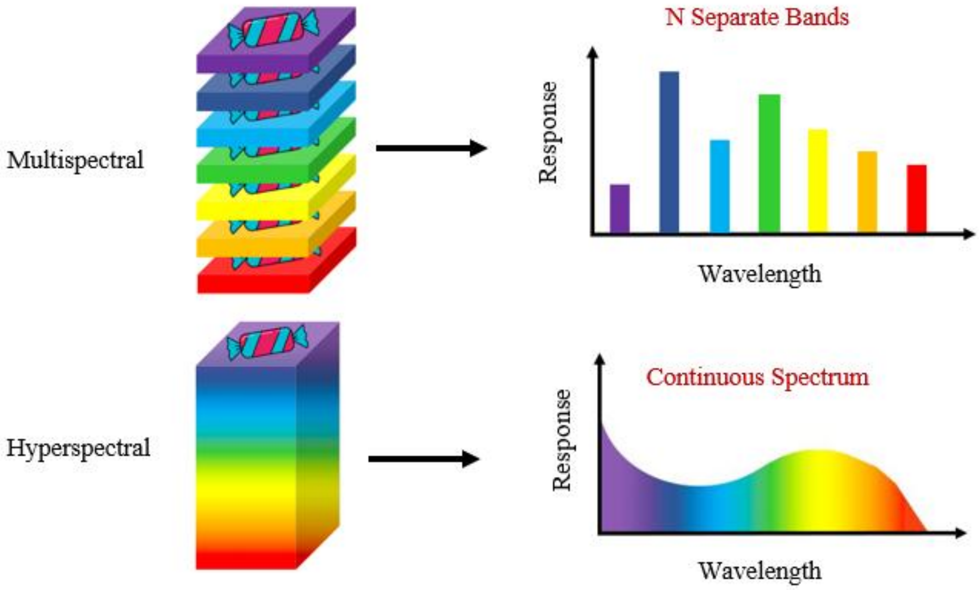

Fig -3: Multispectral and Hyperspectral Imaging

A high classification-accuracy mangrove species mapping is being done for mangrove forest imagery in Guangxi, China, by using two types of high-resolution images: multispectral and hyperspectral [17]. The paper [18] focused on using multispectral and hyperspectral sensors to classify blight disease in wild blueberry. The experiment that was used in this research proved that these sensors are effective in managing the disease without destroying the wild blueberry fields. The deterioration of asbestos-cement roofs is considered a real environmental and health risk because of the release of asbestos fibres into the atmosphere. In [19] this issue is highlighted in the urban area and concentrated on analysing two classification methods for the identification of asbestos-cement roofs: supervised and unsupervised methods. The data that were used to achieve this are multispectral and hyperspectral remote sensing data. The above research are some examples of the use of multispectral and hyperspectral sensors in different sectors.

3.3 Thermal Cameras

The thermal camera is unlike the cameras that rely on light to capture the image. It focuses on frequencies that are not visible to the human eye. Referring to the fact that bodies with temperatures greater than absolute zero emit infrared radiation, the thermal cameras work on this principle. It captures this infrared radiation (nonvisible to humans) and then starts to convert it into a visible image. This image is called a thermogram, while the thermal camera is also known as a thermographic camera or an infrared camera [20].

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The first part of the thermal camera is the lens. In order to be transparent to infrared radiation, these lenses are manufactured from specific material such as germanium. The second part is the thermal sensor that has a focal plane array (FPA), which is the core of the camera. The sensor divides into a huge number of microbolometer pixels. The electrical resistance changes when the infrared radiation hits the pixels. The camera has the ability to measure this change for every individual pixel. A thermogram, which is a detailed matrix of temperature data, is generated by the camera's processor that reads the resistance values from the sensor. The created image is also called "False Colour". Different temperatures have different colours; for example, warmer areas are displayed as reds, oranges, and yellows, and cooler areas as blues and purples. Figure 3 presents the thermal camera's work.

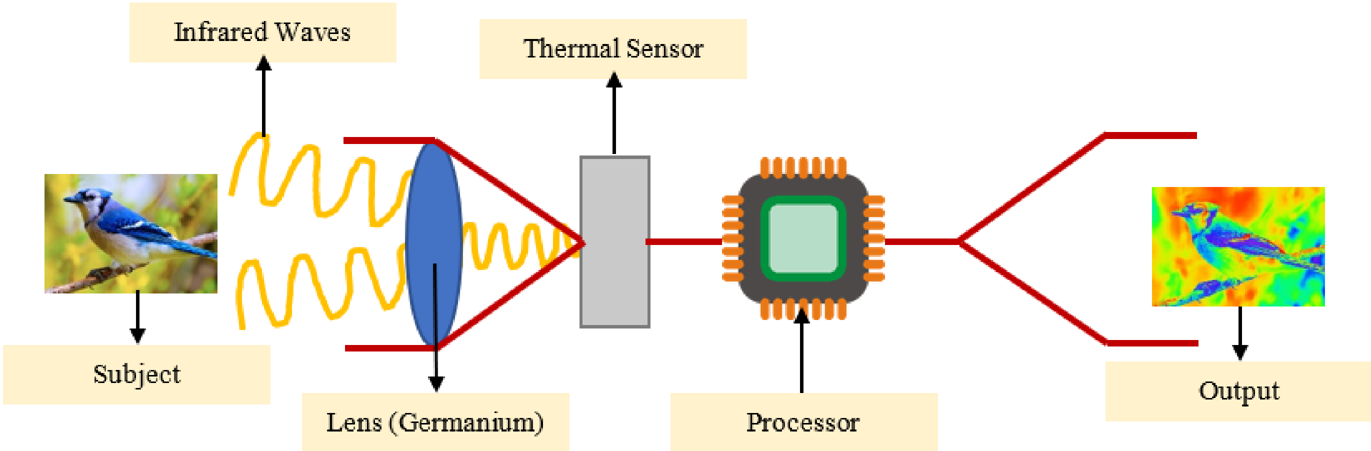

Fig -4: Thermal Camera

Various papers used thermal cameras to achieve development in their research. These research like: [21] thermal cameras are used for object detection (people, bikes, strollers, and count people) in pedestrian areas. In [22], a comprehensive study is made for six commonly adopted postures. The dataset is generated by capturing the sleep postures using RGB and thermal cameras for two conditions, which are with and without blankets. A clinical study [23] used an infrared thermal camera for monitoring 28 rats after they underwent reverse McFarlane flap surgery. Also, capture thermal images for flaps of 22 patients, and it is realized that there are differences in temperature between normal skin and the perforator.

3.4 3D Sensors

3D sensors (depth sensors) present the captured image in three dimensions (width, height, and depth). It has a depth map that provides distance information for each pixel. The working concept of 3D sensors changes depending on the technology that is used. Stereo vision [24] is one of these technologies, and the principle of it is to use two or more cameras to capture the object from different angles.

Structured light [25], [26] is another technology that consists of a projector and a camera. The projector sends a known pattern of light onto the object surface. The camera is located in another position to capture the reflected (distortion) pattern from another angle. Using equations, the depth value of each pixel is calculated, and this accrues after analysing the reflected pattern and comparing it with the projected pattern.

3D sensors have another technology that depends on measuring the traveling time for light called time-of-flight (ToF). It is based on light detection and ranging (LiDAR) systems. The steps of work are as follows: emitting a modulated infrared light onto the object and measuring the time for the light after it returns from the object for each pixel individually. Using the phase difference between transmitted and received light and the distance of the object to get the distance information and creating a depth map [27].

3D sensors are applied in many directions, like in the livestock industry to measure the livestock's live body dimension in an accurate way [28]. In the construction field to evaluate the safety conditions of the building's structure from any deformation and displacement [29]. Providing accurate 3D contours of cracks on large structures such as bridges [30].

4. METHODOLOGIES

This section will highlight the recent research for computer vision in the agriculture sector, the methods that were used, the datasets, and the achieved results.

Weeds are affecting the crop production. Therefore, the importance of developing precision agriculture and providing intelligent systems for detecting weeds and crops is increased. In [31], researchers focused on three kinds of plants: individual radish plants, radish rows, and weeds. The convolutional neural network models that were used in this experiment are YOLOv5, YOLOR, and YOLOv7. The first stage of this research is creating the dataset. Five locations in the South Bohemia region were chosen to take the images of radishes from, and they were taken from both outdoor plots and greenhouses. The mobile phones that were used have the same camera resolution (12 Mpx). The height that the photos are taken from is 0.5 m. The images were for all growth stages of the plant (from a small individual plant to a row of plants). YOLOv5-l, YOLOv5-x, YOLOR-D6, YOLOR-E6, YOLOv7-D6, and YOLOv7-E6 are the CNN models that were used in training (100 epochs, 1280x1280 input image data, and SGD (Stochastic Gradient Descent) optimizer). The results after comparing showed that among all the tested models, YOLOv5-x presented the highest accuracy and robustness for detection of individual radish plants, radish rows, and weeds, while when speed is the highest priority factor, YOLOv7 is better to use in those cases.

Tomato leaves can be infected by various diseases. Detecting and classifying these diseases is a complex task. The paper [32] presented a novel model with lightweight architecture to detect and classify tomato diseases. The research was working on five kinds of diseases (early blight, late blight, Septoria leaf spot, yellow leaf curl, and mosaic virus). The dataset that was used to examine the model is taken from the Plant Village dataset, which consists of many types of plants, but the researchers focused on one type of plant (tomato). The size of the images is 256*256*3 pixels. The fruit fly optimization algorithm (FOA) and simulated annealing (SA) techniques are used together to create a hybrid model that is used during the processes of the faster R-CNN work to solve the hyper parameters issue.

The FOA was inspired by the foraging performance of fruit fly. This technique is responsible for updating the features, which leads to easier implementation and getting a good optimal solution. The idea of the combinatorial optimization technique “SA” comes from the hardening process of metallurgy. SA can evaluate the objective function by using a probabilistic criterion and based on the current and neighbouring solutions. The hybrid model FOA-SA is used to solve the problem of hyper parameters in Faster R-CNN by fine tuning the parameters of the Faster R-CNN approach. The FS -FRNet method has a simple network architecture, and it can study image information, obviously, like texture, spots, lines, etc. The results were provided in excellent performance, and the overfitting was avoided.

Hue and saturation factors are critical components to evaluate the health of the oil palm leaves. In [33], a suitable cost-effective system for small-scale farmers was discussed. The main idea is to use MATLAB to convert the RGB images to HSV (Hue, Saturation, Value). Since the plant's physiological condition can be known from the leaf colour, HSV colour space has benefits over RGB colour space. Hue presents the dominant colour wavelength, saturation is for colour purity, and value is for brightness. The experiment was started by image acquisition and then pre-processing them. After that the evaluation and extraction of the colour feature processes are made. After the image conversion from RGB to HSV, the colour component values were analysed.

The average value of the hue and saturation components is calculated, where hue is the type of basic leaf colour and saturation is how bright or faded the leaf colour is. The leaves can be healthy if the leaf has high saturation and the hue is in the green range, which means around 60°–120° in HSV space. The leaf is considered unhealthy when it has low saturation and the hue value shifted toward yellow. This approach provided a quick, efficient, and economic assessment of oil palm plant health condition.

The plant diseases are not the only problems that face the farmers. Insects also cause pests. In [34], the researchers used different models of YOLOv8, which are n, s, m, and l. Each model can be characterized by parameters, number of layers, and GFLOPs (Giga Floating Point Operations Per Second). The experiment focused on the presence of pests, not detecting specific instances of insects. The IP102 dataset is used, and it contains 102 classes. The first stage was analysing the data. The second stage is data augmentation, and the samples of this stage are the original image, random HSV adjustments, image translation, horizontal flip, image scaling, and mosaic augmentation. The results of the trained models showed better performance for model m with an mAP50 value of 0.967 and model l with an mAP50-95 value of 0.632.

Table -1: Summary of Recent Research on Computer Vision in The Agriculture Field

Research	Method	Dataset	Outcomes
[31] 2025 Detecting weeds and crops	YOLOv5 (YOLOv5-l, YOLOv5-x) YOLOR (YOLOR-D6, YOLOR-E6) YOLOv7 (YOLOv7-D6, YOLOv7-E6)	Individual radish plants, radish rows, and weeds	**Results:** - Highest accuracy and robustness for detection: YOLOv5-x - Highest speed: YOLOv7 **Challenges:** - Detecting weeds with low representation in datasets
[32] 2025 A novel for identification and classification of tomato plant leaf diseases	Hybridized FOA-SA based faster R-CNN (FS -FRNet Method)	Plant village dataset (Tomato directories)	**Results:** - Light weighted architecture and improves the accuracy of detection **Future Work:** - Diagnose diseases in other plants - Develop a mobile tool powered by the FS-FR Net algorithm
[33] 2025 Assessing the health of oil palm plants	HSV-based digital image processing method	Oil palm leaves	**Results:** - The healthy leaves have higher average values for hue and saturation comparing with the unhealthy leaves which is an important

through color analysis of leaves			parameter for leaf condition classification in the automated processes. - Providing an effective, efficient, and economical solution.
[34] 2024 Insect detection to find pests	YOLOv8 (YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l)	IP102 (dataset of insects)	**Results:** - Best performance: YOLOv8m and YOLOv8l **Future work:** - Creating a dataset to improve the detection - Create a real-time pest-detection system

Table 1 presents a summary of recent research on computer vision in the agriculture field, showing the methods that were used, the datasets, results, future work, and challenges. The purposes are various, such as classification and detection.

5. CONCLUSIONS

The need for increasing the production of food with good quality and not an expensive price encourages researchers to develop new methods, techniques, and devices that help farmers and investors in the agricultural sector in general. The aim of this review is highlighting the role of computer vision technology in the agriculture industry. It provided information on the stages that agriculture developed through. Also, it introduced the computer vision principle of work. In short summary, showing different kinds of sensors, which are used to capture images for the datasets that are used in the training or decision-making, with some examples from research that depended on these sensors during their work. Finally, it discussed some of the latest research in this field, which includes detecting weeds and crops, identification and classification of tomato plant leaf diseases, assessing the health of oil palm plants through colour analysis of leaves, and insect detection to find pests. Summarize the used datasets, methods, and outcomes.

The development of technology in the agricultural field, which provides sustainability of production with increased quality and reduced costs, is very mandatory but puts researchers in front of other challenges, such as not creating more environmental pollution and non-refundable sources and trying to exploit renewable energy. On the other hand, looking for innovative solutions for recycling while keeping safety in mind.

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