Weed Detection in Wheat Crops

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Wheat (*Triticum aestivum* L.) is a commonly cultivated cereal worldwide that covers about 237 million hectares annually, producing 765 million tons of yield. Weeds cause economic losses in wheat crops that can range from 40 to 50%, and must be controlled throughout the crop's growing season to achieve an appropriate crop yield. Weeds constitute unwanted plants that fight with crops for nutrients, resources, and sunlight. They can have a number of detrimental effects, including reducing agricultural yields and unmanageable weed populations.

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1. Introduction

Wheat (*Triticum aestivum* L.) is a commonly cultivated cereal worldwide that covers about 237 million hectares annually, producing 765 million tons of yield [1]. Pakistan is expecting huge population growth over the coming decades. It is expected that the population will reach 225 million in 2025. To meet the demand of a large population, we need to produce more food. Wheat is the most widely consumed food grain; its output outnumbers rice, maize, and potatoes [2]. Wheat accounts for 1.6% of the overall GDP, and generates 8.9% of added agricultural value [3].

Its ideal growing temperature is around 25 °C, with minimum and maximum temperatures of 3 to 4 °C and 30 to 32 °C, respectively [4]. Wheat is tolerant of a wide variety of moisture levels, and can be grown in most climates, with annual precipitation ranging from 250 to 170 nm [5]. Spring and winter wheat crops are the most commonly classified, and these terms relate to the season in which the crop is grown. After cloudy winter temperatures (0° to 5°C), winter wheat heads will appear. Spring wheat is sown in the spring and matures over the summer, despite the fact that it may be cultivated in the autumn in places such as Pakistan that have mild winters [6].

Weeds cause economic losses in wheat crops that can range from 40 to 50%, and must be controlled throughout the crop's growing season to achieve an appropriate crop yield. Weeds constitute unwanted plants that fight with crops for nutrients, resources, and sunlight. They can have a number of detrimental effects, including reducing agricultural yields and unmanageable weed populations [7]. Weeds infect crops and provide food for insect pests. Weeds are referred to as pests in agriculture because they harm produce. Weed infestation is the most damaging but least visible variable adversely impacting wheat crop production. Weeds are the most unappealing, destructive, and problematic vegetation worldwide. These off-type plants have grown out of their natural habitat, and their value has yet to be identified. Weeds also serve as a pool for the food and protection of various pests and diseases during the off-season. Weed density has been investigated with regard to yield losses depending on different densities of Melilo indica in both rainfall and irrigated conditions.

Implementing healthy farming requires modern technologies and methods, such as processing images, videos, machine vision, and artificial intelligence. These enable the maximum application of pesticides in machine vision applications in agriculture [8], accurate assessment of crop nitrogen levels, determination of crop growth, calculation of the solar radiation received by the crop, and the identification of plant diseases and grasses. The most important part of designing machine vision systems is segregation, because of the risk of extracting and sorting identified objects from the process.

Nowadays, the development of computer vision and automated expert systems has made it possible to distinguish between crops and weeds in an easy and fast way. Multiple groundwater detection techniques for selective herb application and site-related grass management have been studied as environmentally friendly techniques to reduce the consumption of chemical pesticides and their environmental impact on fields. For this purpose, some researchers used remote sensing technology to distinguish weeds, crops, and soil-based measurements reflected at different wavelengths. In contrast, others distinguish plants based on color, texture, and shape characteristics. An image-processing system to detect weeds based on classification was developed by [9].

Real-time target identification relies on a number of variables, such as the amount and quality of pictures, the architecture of deep convolutional neural networks (DCNN), the hardware, and the memory storage, including GPUs [10]. Quantifying the phenotypic changes resulting from genetic or environmental differences using convolutional neural networks (CNNs) produced an 86.6% detection accuracy in recognizing wheat spikes. Using DL models, a 95.9 and 99.7% accuracy in identifying wheat spikes and spikelets, respectively, was achieved. Samseemoung et al. [11] reported that DCNNs support agricultural applications. They classified weeds with an accuracy of more than 95% using DCNN models. Partel et al. [12] described an extraordinary organization accuracy of 99% when using CNNs to distinguish between weeds and sugar beets.

From linear regression to CNNs, the dataset using which a machine learning model can be presented is constrained. The literature contains many grasses and plant life image datasets. The Annual Life CLEF Plant Identification Challenge 2015 Dataset 25 features 113,205 pictures with 41,794 explanations of 41,794 trees. This vast dataset is unique compared with most other work sites that offer particular datasets of scientific interest. All of these approaches provide high-ranking accuracy for target datasets. However, most datasets capture plant life to the best of their ability under perfect lab conditions. Although perfect lab conditions allow strong theoretical classification results, determining a classification model on a grass control robot requires an image dataset that captures plants in realistic environmental conditions [13].

Agriculture productivity is predicted to increase significantly with robotic grass control. The main benefits of an autonomous weed control system are lower labor costs and the potential to use fewer herbs, while using weeds more effectively. Improving the efficacy of weed control will have a huge economic impact. Farmers are thought to lose US 2.5 billion each year due to adversely impacted agricultural productivity, and to spend USD 1.5 billion on grass management efforts in Australia alone. Agricultural robot technology offers the opportunity to eliminate these losses and boost output [14].

In comparison to variable rate application (VRA), uniform application of agrochemicals (UA) causes over-application of harmful chemicals, greater agricultural input costs, and environmental deterioration (VA). The design, implementation, and testing of a smart variable ratio sprinkler (SVRS) for VA pesticide application uses deep learning (DL). The SVRS is used to quickly identify healthy potato plants and those affected by early blight, lambs' quarter's weed, and other pests. Approximately 24,000 images of farmlands in Prince Edward Island and New Brunswick were shot in a range of bright, overcast, and partly cloudy situations to present and train the YOLOV3 and mini YOLOV3 models. The tiny YOLOV3 was chosen for SVRS improvements because of its increased performance. The two spraying methods (UA and VA) and three weather conditions (cloudy, partly cloudy, and sunny) functioned as the two independent factors in a factorial laboratory experiment, with spray volume consumption acting as the response variable [15].

The development of optical techniques and artificial intelligence to distinguish crop plants and weeds is a critical step toward the automation of nonchemical herbal control systems in agriculture and decreasing chemical use through spot spraying. Large-scale bold spraying of chemical herbicides is not only a waste of herbal medicines and labor, but also a cause of environmental pollution and food quality problems. Traditional methods are concerned with the need for high light and sample quality. Therefore, proper identification of weeds and precise sprays are important strategies for promoting sustainable agricultural development. To avoid the effect of different light on the pictures, the color model and then the gray picture component are suggested. The method of vertical projection and the method of linear scanning have been developed to identify the main line of crop rows quickly. To reduce the complexity of the math, the Classical view efficiency rate (WIR) has been modified, and a better method of horizontal scanning has been adopted to make calculations within the cells. Finally, the revised broad inflation rate (MWIR) is typically used to capture real-time decisions through the minimum error ratio of the basin decision under distribution [16].

2. Weed Detection in Wheat Crops

In [13], a useful technology for efficient farming-related implementations is outlined: UAV (unmanned aerial vehicles). Aerial surveillance of UAV farms in agriculture allows for crucial decision-making on the monitoring of crops. Developments have further improved the accuracy and reliability of aerial imagery-based research in deep learning models. Remote crop assessment applications such as plant categorization and aggregation, crop counting, yield estimate and comparison, weed identification, disease detection, crop mapping, and nutrient deficiencies, among others, may accommodate various types of sensors (spectral cameras, RGB) on UAVs. UAVs are abundantly used to practice farming activities, and are cited by several researchers. An analysis of research studies adapting deep learning to UAV imagery for deficient farming is provided in this report. Depending on the requirement, these studies were categorized into five main classes, which include identification of vegetation, classification and segmentation, crop estimation and yield expectations, crop mapping, crop disease and detection of weeds, and detection of inadequate intake. A comprehensive analysis of each area of research is presented.

In [17], the use of fungicides and herbicides in agriculture can be substantially reduced or even eliminated using precision weeding. The specific selection of weeds, low-cost plant identification, and high speed are necessary to achieve high precision. Using combined red, green, and near-infrared reflectance, the current system is combined with a size differentiation system to classify weeds and crops in lettuce fields. LED arrays are presented at 525, 650, and 850 nm, and pictures are captured in a single shot using a modern RGB camera. A kinematic stereo system is used to compensate for parallax errors in pictures, and the precise position data of plants are presented. The scheme was tested within three lettuce fields ranging from 0.5 to 10 km/h at various growth stages in field trials around fields. The results of in-field trials showed values of 69% and 56%, respectively, in crop and weed identification. Post-trial processing led to average crop and weed processing values of 88% and 81%, respectively.

The demand for wheat is also growing as the world's population grows [18]. It is essential to monitor weeds in wheat crops and the barren/wasteland areas in order to decrease the production of weeds so that wheat productivity can be enhanced. The important variable evaluated was the detection of weeds. An unmanned aerial vehicle (UAV) is utilized in various stages of gathering wheat crop data to capture high-quality RGB pictures. The recommended backdrop subtraction approach speeds up the processing of weeds, wheat, and barren land inside the wheat crop region. The results show that background subtraction is a good method for detecting weeds, barren land, and wheat.

In [14], pictures were taken, and the study describes a machine vision system for weed detection in the field of vegetable crops, while avoiding illumination and sharpness difficulties throughout the acquisition phase. This design will serve as a foundation for a mobile weed removal robot with a camera obscura (Latin for "dark room") in light-controlled areas.

The authors of [19] stated that weed control in modern agriculture usually consists of pouring herbicides all around the agricultural field. Substantial waste and herbicide rates for farmers and environmental degradation are involved in this activity. Allocating the appropriate herbicide dosages in the correct location and at the right time is one approach for reducing costs and environmental consequences (precision agriculture). Unmanned aerial vehicles (UAV) are becoming an attractive acquisition approach for weed optimization and control due to their capacity to capture pictures of the whole agricultural field area with extremely fine spectral resolution and at a reasonable cost. Despite the substantial advancements in UAV acquisition systems, automated weed detection remains difficult because of weeds' strong similarity to crops. The latest deep learning technique has shown promising results in various complex classification problems. This method, however, requires a certain amount of time in a training phase; it is highly time-consuming to create large agricultural datasets with expert pixel-level annotations.

The work [20] seeks to thoroughly map the latest technology of weed mapping in crop fields from aerial agricultural pictures. Four digital repositories were checked: Science Direct, Springer. IEEEXplore, ArXiv, and Link.

The paper [21] provides a detailed research survey on the implementation of artificial intelligence approaches in agriculture farming. There are many problems in the world of agriculture, including infestation of diseases and pests, insufficient soil management, in adequate irrigation and drainage, and much more. All these lead to substantial crop loss, including environmental challenges resulting from the severe and unnecessary usage of chemicals. There have been some academic reports carried out to solve these problems. The artificial intelligence field, with its robust learning abilities intelligence, has become a primary technique for tackling challenges related to agriculture. In order to assist agricultural specialists, technologies for effective applications are being built throughout the world. This research survey assesses 100 major contributions, in which artificial intelligence strategies were used to tackle the issues associated with agriculture farming.

The paper [9] discusses that one of the most significant ways to assess apple growth phases and calculate output in orchards is the real-time detection of apples. Apples alter their size, color, cluster density, and other growth features as they mature. Conventional detection methods can only identify apple plants at a specific stage of development, and they cannot be modified to various phases of development using the same model.

The paper [22] deals with weeds known as yield reducers, which can be more economically damaging than fungi, insects, and other crop pests in many cases. Crop productivity and financial losses due to weeds (off-type plants) are key components of agricultural research that contribute to the development of effective weed control techniques. Researchers utilized data from 1581 agricultural research studies on weed control in important field crops, carried out by the ALL India Coordinated Research Project in diverse locations of Indian states between 2003 and 2021, to estimate productivity and economic losses due to weeds. The study discovered that in the case of soybeans (50–76%) and groundnuts (45–71%), there was higher variation in prospective outcome decline among the various locations than in the case of direct seeded rice (15–66%) and maize (18–65%). There was higher variation in potential yield losses among different locations in the case of direct seeded rice (15–55%) and maize (15–55%). Three factors highly influenced (p.0001) the variation in real yield losses due to weeds in farmers field, location, crop type, and soil type. There were also significant variations between various locales, crops, and soil types. Rice had the highest economic losses (USD 4420 million), followed by wheat (USD 3376 million), and soybeans (USD 1559 million). Groundnut (35.8%), soyabean (31.4%) green gram (30.8%), pearl millet (27.7%), maize (25.3%), sorghum (25.1%), sesame (23.7%), mustard (21.4%), direct seeded rice (21.4%), wheat (18.6%), and transplanted rice (21.4%) were among the ten major crops in India in which weeds caused a total economic loss of about USD 11 million (13.8%).

In [23], one of the most essential components of agricultural yield is identified as weed control; determining the number and position of weeds has been a difficulty for specialists for decades.

Authors of [8] conducted a field study, they found that outcome losses caused by six normally occurring and most plentiful weeds in wheat fields, namely *Phalaris minor* Retz., *Rumex dentatus* L., *Coronopus didymus* (L.) Sm., *Medicago denticulata* Willd., *Chenopodium album* L., and *Poa annua* L., were investigated. These weeds were cultivated in a 1:1 weed-crop ratio with two commercially farmed wheat types, Inqalab 91 and Punjab 96. *P. annua* caused the highest yield losses of 76 percent in Inqalab 91, followed by *C. Didymus* at 75 percent, while other weeds caused yield losses of 60–70 percent. *R. dentatus* produced the greatest yield decrease of 55 percent in Punjab 96, followed by *P. minor* (28 percent), *M. denticulate*, *C. album* (23 percent), *C. Didymus* (10 percent), and *P. annua* (10 percent) (0 percent). In comparison to Inqalab 91, Punjab 96 proven to be more resistant to weeds.

In [15], the new technology of deep learning convolutional neural networks (CNNs) was shown to help farmers boost their efficiency by using remote sensing and automated field condition inference. This study investigated how CNNs were used to identify two weeds in pictures of wild blueberry fields: hair fescue and sheep sorrel. To control patches of these weeds, commercial herbicide sprayers apply agrochemicals uniformly. Three objects were identified, and three images were classified. Using pictures from 58 wild blueberry fields, CNNs were taught to recognize hair fescue and sheep sorrel. The CNNs were trained on pictures with a resolution of 1280 x 720 and tested at four different internal resolutions. The CNNs were retrained with progressively reduced training datasets ranging from 3780-472 images to explore the influence of dataset size on accuracy. The best object detection CNN was YOLOv3 small; it detected at least one target weed per image at 1280 × 736 resolution, and had F-1 scores of 0.97 for hair fescue and 0.90 for sheep sorrel. The reference of the darknet for the image classification CNN was the most accurate, with F1-scores of 0.96 and 0.95 for pictures containing hair fescue and sheep sorrel, respectively, at 1280 × 736. At the lowest resolution, 864 × 480, MobileNetV2 produced comparable findings, with F1-scores of 0.95 for both weeds. Except for the darknet reference, the quantity of the training dataset has no influence on accuracy. This technique may be used in smart sprayer to manage individual spray treatments for specific targets, which would reduce herbicide use. The CNN will be put to the test on a smart sprayer, and an app will be developed to provide producers with field-specific data. For wild clue berry growers, using a CNN to improve agricultural efficiency will result in significant cost savings.

In the paper [20], in military navigation, environmental monitoring, and civic applications, accurate and quick identification in remote sensing pictures is critical. Due to the difficulty of recognizing tiny items in remote sensing pictures, object detection technology faces greater demands and obstacles. One-stage object detectors and the two-stage object detectors based on convolutional neural networks have made considerable progress in the field of image classification and detection in recent years. The one-stage object detector outperforms the two-stage object detector in terms of detection speed, while the two-stage target detector outperforms the other in terms of detection accuracy.

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