A Review of Analyzing Different Agricultural Crop Yields Using Artificial Intelligence

Vijaya Bathini[1], K. Usha Rani[2]
Research Scholar, Department of Computer Science, SPMVV (Women's University), Tirupati, AP, India[1]
Professor, Department of Computer Science, SPMVV (Women's University), Tirupati, AP, India[2]

Abstract—**The advancement of Artificial Intelligence (AI), in particular Deep Learning (DL), has made it possible to interpret gathered data more quickly and effectively in this new digital era. To draw attention to development advancements in deep learning across many industries. Agriculture has been one of the most affected areas in recent advancements of the current globalized world agriculture plays a vital role and makes significant contributions. Over the years, agriculture has faced several difficulties in meeting the growing demands of the global people, which has creased over the last 50 years. Different forecasts have been made regarding this extraordinary population expansion which is expected to grasp almost 9 billion persons worldwide by 2050. More than a century ago, different technologies were brought into agriculture to solve issues related to crop cultivation. Many mechanical technologies are accessible today, and they are evolving at an amazing rate. To support their demands and help them optimize their crop yields based on data and task automation need innovative techniques to aid farmers. This will transform the agricultural industry into a new dimension. Therefore, this study's primary goal was to present a thorough summary of the most current developments based on research interconnected with the digitization of agriculture for crop yields including fruit counting, crop management, water management, weed identification, soil management, seed categorization, disease detection, yield forecasting and harvesting of yields based on Artificial Intelligence Techniques.**

Keywords—Agriculture; artificial intelligence; deep learning; crop yields; management

I. Introduction

Because of the population, the agriculture sector has to meet a wide range of food needs along with social, environmental and economic factors like the lack of workers, water, biodiversity, and land degradation [1]. Since the seasons are hard to predict and the environment is harsh, there are now a number of limits on its growth. For agricultural business growth, it is important to find new methods that will last.

Farmers' understanding of field management has changed by using cutting-edge technologies like robots, drones and sensors on farm equipment. Scientists who study data and farming are getting ideas from these new technologies to make better analytical tools and methods for managing fields and dealing with problems more correctly [2]. Today's technology makes it hard to make sure that everyone has access to a steady supply of high-quality food without putting natural environments at risk. To meet and support farmers' needs help to get the most out of their farming by automating tasks and data.

New developments in uses based on Artificial Intelligence (AI) had a big effect in this area [3]. They have made a big difference in the progress of computer vision, ML(Machine Learning) and DL(Deep Learning) methods for building automated and reliable systems. But Agriculturalists still confront formidable challenges in making affordable, scalable, and ecologically sound solutions to the world's food crisis a reality, despite recent advances. This emphasizes the significance of studies that cover both the theoretical and practical aspects of incorporating technological advances into actual agricultural systems.

As a result, this study main goal is to give an in-depth overview on the latest advances in AI research that has to do with digitizing agriculture for crop yields. To identify existing gaps in the current review of Digitizing agriculture includes fruit counting, crop management, water management, weed identification, soil management, seed categorization, disease detection, yield forecasting, and harvesting of yields.

II. Digitizing Agriculture Crop Yields Using AI Techniques

A. Fruit Counting

A vital component of the world economy is the fruit business. Food security, economic growth, nutritional diversity, processing, shipping and retail are just a few companies that benefit from it, and millions of farmers rely on it for income. Fruits have high vitamin, mineral, fiber and antioxidant content and plays a vital part in healthy diet. As per the FAOSTAT report fruit industry is in the rise worldwide. Producing approximately 909.644 million metric tons of fruits in 2023, the world continued its growing trend in food output, accounting for 19% of total food production. Maintaining accuracy and efficiency in huge fields or orchards becomes increasingly challenging when the volume of agriculture increases, rendering manual counting impracticable defined by Pathan and Rehman [4]. Manual fruit counting can be challenging in outdoor settings due to weather factors including rain and low vision as explained by Hunt and Doraiswamy [5]. The spatial coverage of manual counting is limited since people can't physically inspect every portion of a crop. It also makes coping with different crop architectures more difficult as it makes it harder to address differences in fruit size, shape, or distribution. The consistency and comparability of the data could be compromised due to inconsistent counting techniques caused by the absence of established counting standards.

Fruits calculating or counting flower thickness on images using Computer Vision (CV) algorithms is a commonly used method for autonomous yield estimation. There are two main types of CV-based approaches to estimating agricultural yields:

(1) methods that focus on specific regions or areas, and (2) methods that rely on counting. An automated method for estimating crop production in apple farms was created by Wang et al. [6] using stereo cameras. To lessen the impact of the erratic daylight lighting, they took the photos at night. An in-field cotton recognition system was created by Li et al. [7] using region-based semantic image segmentation. Joint maize tassel and crop segmentation was accomplished by Lu et al. [8] using region based color modelling. Yield estimation approaches based on counting have received surprisingly little attention, in comparison to methods based on regions [9]. Estimating the quantity of apples harvested in fields with natural light was done by Linker et al. [10] using color photographs. There were a lot of false positives because of the problems with direct light and color saturation. A technique for apple fruit segmentation [21] from video utilizing backdrop modelling was developed by Tabb et al. [11].

Counting problems demand one to reason about the total occurrences of an object in a scene, as opposed to the usual picture classification procedure that aims to identify the existence or nonexistence of an object. Multiple real-world applications encounter the counting problem: counting cells in microscopic imaginings, counting wildlife in aerial photos [12], counting fish [13], and crowd monitoring [14] in surveillance systems. Kim et al. [15] presented a system that uses a fixed-shot camera to recognize and follow moving subjects. To improve loss optimization during learning, Lempitsky et al. [16] presented a novel supervised learning structure for pictorial object counting jobs that considers MESA distance. The authors Giuffrida et al. [17] put forward a method for leaf counting that relies on learning in plants that grow in rosette sets. They connected image-based descriptors learned unsupervisedly to leaf counts using a supervised regression model. The present method of estimating production, which involves workers physically counting fruits or flowers, is impractical for vast fields due to its high cost and time requirements. Here, a practical answer is provided via robotic agriculture-based automatic yield estimation.

Nowadays, AI is playing a bigger part in fruit counting as it provides more precise and efficient answers for farming. Automating fruit counting in fields is possible with the usage of AI technologies, especially CV and ML. DL algorithms allows for automated interpretation of captured images or films. Based on visual features like size, shape, texture and color these systems are able to recognize and tally fruits developed by Koirala and Zhang [18]. DL algorithms have been taught to recognize and quantify fruits in images. These algorithms include Convolutional Neural Networks (CNNs) with massive datasets these models gradually get more accurate results by Sa et al. [19]. According to Wang et al. [24] AI is used in combination of LiDAR and 3D imagery to make three-dimensional fruit count estimates. A more precise evaluation of the distribution and volume of fruit can be achieved with this method. The author also explained that the method can be used for vast agricultutal fields. According to Anand et al. and Kumar et al. [20] this combination enables thorough counting and monitoring through effective aerial surveys of vast agricultural fields. Adapting it to different orchard settings and fruit varieties is a breeze. These systems may be adjusted to various situations, which means they can be used with a variety of crops. Methods for counting objects using deep learning have recently become more prominent. Seguíet al. [19] investigated the use of CNN for the job of counting instances of an interest notion. A system for microscopy cell counting was created by Xie et al. [22] using a convolutional regression network. Using deep CNN, Zhang et al. [23] created a framework for cross-scene crowd counting. So far as we are aware, no studies have addressed the topic of deep simulated learning fruit counting. All of the counting algorithms that have included deep learning have focused on object detection and subsequent counting of those instances.

B. Water Management

From legislators to end users, everyone involved in water usage and management is worried about the impending water scarcity. The opinions of many shareholders or a shortage of revised strategies and plans to increase efficacy can make it difficult to execute any freshwater conservation strategy Marston & Cai, [25]. These concerns about effective freshwater management are of particular importance in agriculture, where they may help alleviate sustainability and environmental concerns while also cutting expenses for farmers. According to Salmoral et al. [26], public institutions and lawmakers play a crucial role in this context, specifically under the EU's Common Agricultural Policy (CAP).

Actually, circa the agricultural sector drew around 70% of the world's water. In the Asian and African regions (81%), as well as in Oceania (65%), this is a very pertinent subject. This issue warrants particular attention in southern countries, while it is not as serious in European and American countries (25% and 48%, respectively) Aquastat [27]. Several stakeholders, including farmers, must be involved in the planning and execution of any strategy or plan to improve water efficiency on farms for it to be effective.

According to Koscielniak et al. [28], Nazari et al. [29] the agricultural sector of the European Union relies on proper water management, so it's important to shed light on these factors. Several factors influence the efficiency of water management in irrigation methods. These elements include pertaining to the environmental, social, technical, legal, and political aspects. In view of Castanedo et al. [30], such settings, considerations such as the depth of application and modified drainage systems may be important. Agricultural methods including energy usage and soil management strategies are interdependent on irrigation practices Lee et al. [31]. Surface irrigation agricultural output, and soil yields Kim et al. [32] are three areas where irrigation practices can substantially affect water management efficiency. The morphology and spatial circulation of roots from perpetual crops Deng et al. [33] and economic indices of farms Kumar et al. [34] are also affected.

Regardless, irrigation technology and methods have advanced, allowing farmers more leeway in their decisions and options Roth et al. [35]. Nonetheless, there is always room for improvement in this area van Steenbergen et al. [36]. The selection of water-efficient cultivars in the turf business is another important consideration Githinji et al. [37]. In this context, effective strategies for managing water resources are crucial.

According to Preite et al. [38], 4.0 technologies are being considered as a possible result to enhance the agricultural sector's sustainability. These technologies include blockchain, the Internet of Things (IoT), DL algorithms, ML and other computer applications. The simple, scalable automation that predictive algorithms offer makes them ideal for a 4.0 scenario that spans many different fields Mazzei & Ramjattan [39]. Meshram et al. [41], Liakos et al. [40], and others have grouped the machine learning methods used in agriculture into three distinct phases: before, during, and after harvesting. The first set of applications included topics related to irrigation, with identification of water scarcity, prediction of water demand, and scheduling of irrigation. Conventional irrigation scheduling takes a set period into account while ignoring the fact that environmental and plant variables can vary. In particular, water scarcity identification processes thermal infrared images, weather, and soil data to assess stem water potential, drought stress and plant water gratified.

According to Zhou et al. [41], the models mostly used in this scenario were gradient-boosted random forests, decision trees and CNN. Using support vector machines, gradient-boosting, artificial neural networks and decision trees algorithms, reference evapotranspiration, soil moisture contented and sap flow possessions were estimated using multispectral and thermal imageries in conjunction with meteorological and soil data. By analyzing sensor data, the authors of Corell et al. [42] present an outline for irrigation that compares three regression models to find optimal irrigation amount for olive farming. The emergent degree days, water provided to plants, and evapotranspiration rate were used in a fuzzy decision support system to evaluate appropriate irrigation quantity for corn, kiwi, and potato crops Giusti & Marsili-Libelli [43]. In order to give watering suggestions for lemon trees, Navarro-Hellín et al. [44] utilized an adaptive neural fuzzy inference system in conjunction with a partial least-square regression to analyze evapotranspiration, soil moisture and humidity. Chandrappa et al. [45] use DL algorithms (Long Short-Term Memory) and ML techniques (Support Vector Regression and Linear Regression) to evaluate soil moisture changes in depth and time. Against this backdrop, a multi-depth link between wind speed and soil moisture was brought to light. By training an artificial neural network to use data from soil sensors and meteorological stations to calculate the optimal irrigation period, a 20% reduction in water use was accomplished by Gu et al. [46]. Kavya et al. [47] have investigated the use of AI for short-term water demand prediction. In particular, using both univariate and multivariate time series assessed the prediction ability of deep learning and machine learning. While the multivariate scenario also took weather into account, the univariate series was applied just to the flow meter data. A probabilistic framework was created by Srivastava et al. [48] to ascertain irrigation methods using three distinct parameters: leaf area index, soil moisture, and evapotranspiration. These indicators show water deficiency in the soil, water stress in crops, and the water demand, in that order. Here they utilized a Recurrent Artificial Neural Network (long short-term memory) to make predictions, and employed a random forest regression to find good predictors for each parameter. The last step was compared the expected and actual numbers to tweak the resulting weights.

Aly et al. [49] used a super learning ensemble to predict the evapotranspiration with limited meteorological data. They achieved good accuracy by utilizing additional tree regression, k-nearest neighbour, support vector regression, and AdaBoost regression. Yong et al. [50] also noted the latter difficulty as the primary obstacle to evapotranspiration rate prediction and proposed a hybrid neuro-fuzzy inference method to overcome it. Adnan et al. [51] examined practicality of hybrid support vector regression models from this angle. These models integrate ML methods with optimization meta-heuristic algorithms, such as Particle Whale Optimization, Swarm Optimization, Differential Evolution, and Covariance Matrix Adaptation Evolution Approach. By integrating ML and feature engineering, Považanová et al. [52] enhanced prediction accuracy for reference evapotranspiration estimation, shedding light on the efficacy and generalizability of the suggested models. Using a variety of machine learning algorithms including k-nearest neighbors, support vector machine, decision tree, and multilinear regression the authors of Youssef et al. [53] demonstrated how to estimate reference evapotranspiration with an accuracy close to 99%.

C. Crop Management

One of the most significant parts of agriculture has always been crop production management. In order to feed both cattle and humans, crop production is crucial. Throughout human agrarian history, one of the key objectives is to upsurge the economic efficacy of farming. To ensure consistently high-quality output, agricultural production sites should undergo routine inspections and implement all required crop production strategies. Because farmers invest time and energy into each visit, the crop's price tag reflects that. As a result of farmers' obsession with crop monitoring and evaluation, smart agriculture has emerged as a critical tool. Although digitalization will have a greater effect on wide-area communication networks that include rapid data transmission, it permeates most areas of engineering [54]. Cultivating field crops, producing vegetables, and fruit are all part of crop production, which is a subset of agriculture [55]. "Smart farming" refers to a new paradigm that maximizes agricultural output with the help of cutting-edge information technology [56] with advancements in AI, automation, and connectivity, farmers can effectively monitor different procedures and provide targeted treatments for cultivation using robots that are superhumanly efficient.

These tasks only require a set of guidelines based on mathematics or logic because to derive valuable correlations from data, machine learning makes use of learning rules like supervised learning, unsupervised learning, hybrid learning and reinforced learning [57].

These features allow deep learning networks to potentially uncover hidden structures in data that is neither labeled nor structured. A major improvement over previous methods, deep learning networks are able to extract features with little to no human intervention. The proliferation of high-speed wireless transmission networks led to dramatic increase in consumer demand for such services [58]. When comparing Deep Anomaly to region-based convolution neural networks (RCNN), the former is superior for human detection at 45–90 meters [59]. This method can detect anomalies and generate uniform field characteristics. In this article, learned about the DL classification of land cover and crop kinds using remote sensing data [60]. Traditional fully linked MLPs and random forests were compared to CNN. We talk about how to use visual sensor data to train self-learning CNN to identify diverse types of plants [61].Offers automatic weed detection in UAV photos of line crops using deep learning with unsupervised data labeling [62]. Use of convolutional neural networks (CNNs) on unsupervised training datasets will provide fully autonomous weed detection. Incorporating a deep residual neural network onto a mobile capturing equipment allowed for the introduction of a crop disease classification system. Thorough testing enhanced the precision of the balancing process. 0.78 to 0.8 [63] is the range.

To diagnose mildew disease on millet crop photos, a deep neural network with transfer learning is employed [64]. The f1-score was 91.75%, recall was 94.50%, precision was 90.0%, and accuracy was 95% in the experiments. A deep convolutional neural network was employed to estimate agricultural yields using NDVI and RGB data acquired by UAVs [65]. In terms of CNN performance, RGB images beat NDVI images. In terms of critical characteristics, low-altitude remote sensing-based images and CNN architecture for rice grain production were considered [66]. During the ripening stage, Deep CNN performed significantly improved and was stable. Researchers have looked at a deep learning-based multi-temporal crop classification system [67]. DL models LTSM and Conv1D were compared to XGBoost, SVM, and RF parameters. The development of a new crop vision collection that makes use of deep learning classification and accurate agricultural recognition has also been accomplished [68]. On agricultural datasets, his proposed algorithm achieved a 99.81% accuracy rate, surpassing VGG, DenseNet, ResNet, SqueeztNet, and Inception. Recognizing and differentiating crops in soil is made possible by deep learning technology [69]. Information is derived from a digital surface model with a high level of resolution. For the purpose of crop pest classification, automatic feature extraction is used in conjunction with transfer learning approaches involving convolutional neural networks [70]. The most accurate datasets are Xie1, NBAUR, and Xie2, with respective accuracies of 94.47%, 96.75%, and 95.9%.

D. Soil Management

For the vast majority of creatures, the soil is the food web, providing them with the mineral resources they need to survive. When soils are well-managed, plants do not suffer from mineral element deficiencies or toxicities, and the right minerals make it into the food chain. Crop yield, ecological stability, and human well-being are all impacted by poor soil management in some way.

According to Dickson et al. [72] and Bhaskar et al. [71] soil categorization opens up numerous sectors including soil improvement, crop management, land consolidation and more. Physiological factors assessed from real-time field models are the most important criteria for soil identification. Root development, plant emergence rate, water penetration, and crop production are all affected by physical variables such as temperature and moisture, which affect the formation of particles and pores. Chemical features including pH, organic carbon, and the nitrogen, phosphorus, potassium (NPK) parameters dictate the accessibility of nutrients, the existence of other species, and the motility of pollutants. The various components that make up soil include clay, sand, peat, silt, and loam. Soil particles in the target zone consist mostly of sand, clay, and silt, with very little peat and loam.

It is considerably more challenging to keep these soils suitable for farming. Soils like laterite, which are mostly composed of rock deposits from hot climates, are abundant in iron and aluminum. Soils with large concentrations of iron oxides, such as laterite, have a reddish hue [72]. Almost all laterites have a rusty-red hue because to the significant iron oxide content. Soil surface formation is guaranteed by periodic rainfall and sunny seasons. The crops are adequately nourished by this soil type. The southern Indian subcontinent is a significant producer of the rice variety Oryzasativa. Rice is a staple crop and a source of income for many farmers in the area surrounding the exploration location. Milling, visual, culinary, and nutritional qualities are all part of what makes rice grain quality. It is widely recognized that the root's balanced qualities are closely related to grain quality in rice. Root morphological and physiological features impact rice vegetative growth and grain satisfying, which in turn affects grain quality. The features that were researched and described and are applicable to the exploration site, which consists primarily of clay and laterite soil.

A methodology for digital soil mapping was created by Behrens et al. [73] using Artificial Neural Networks (ANNs). This methodology is able to predict soil units in a test area in Rhineland, Germany, Palatinate. Grinand et al. [74] developed a classification tree-based method for predicting soil distribution at an unexplored location by using a soil-landscape pattern obtained from a soil map. Soil datasets and exploration site data should be collected as part of the proper method for soil classification at the exploration site. After that, the datasets should be pre-processed. Finally, models should be trained using Deep Neural Network and Machine Learning techniques, and the soil should be classified into four distinct groups. They rely on accurate soil detection to help with nutrient supply to the field, which in turn increases crop production. It's also crucial for their livelihood to determine what kind of weeds will grow from the soil so that they can eradicate them.

E. Weed Identification

One of the most important things that can influence crop yield is weed control. Khan et al. [75] found that weeds can reduce crop output and production quality by competing with crops for water, fertilizer, light, growing space and other nutrients. Insects and diseases that harm crops could also call this place home. A study found that weed suppression resulted in a 13.2% annual loss of crop production enough to feed one billion people for a year Yuan et al. [76]. A key component of crop management and ensuring food security is weed control. Manual weeding, chemical weeding, biological weeding, mechanical weeding, etc. are all common weed management strategies Stepanovic et al. [78], Marx et al. [77], Morin [80], Kunz et al. [79], Andert [81].

The best method for controlling weeds in the field is to do it by hand. The high cost and labor intensity, however, make it impractical for cultivation on a broad scale. Because it doesn't harm non-target organisms much, biological weeding is eco-friendly and safe, but it takes a lengthy time to restore ecosystem afterward. The majority of weeds are eliminated with chemical weed killers, which is the most popular method of weed control. However, other problems, including chemical residues, weed resistance, and environmental contamination, have resulted from the excessive use of herbicides. The study found that in different farmland systems, 513 biotypes of 267 weed species have become resistant to 21 different herbicides Heap, [82]. Therefore, it will be crucial to use technologies like detailed spraying or mechanical weed management on individual weeds in order to prevent the over-application of herbicide.

Automatic mechanical weeding is becoming more popular as a result of the organic farming movement Cordill and Grift [83]. It prevented needless tillage, which saved gasoline, and allowed for weed management without chemical input. Nevertheless, intelligent mechanical weeding has faced significant challenges because to the low accuracy of weed detection and the resulting unforeseen harm to the plant-soil system Gašparović et al. [85], Swain et al. [84]. So, it's critical to make weed detection more precise in the fields.

So using AI models like SVM, decision tree, a random forest algorithm, and KNN classifiers are some of traditional AI methods that have been utilized in weed identification research. It is expected that these algorithms will employ intricate manual craftsmanship to extract weed image color, texture, form spectrum, and other attributes. As a result, the weed image extraction was lacking or features were obscured, it would be impossible to differentiate between weed species that are otherwise comparable. Image processing technology was utilized by traditional weed detection algorithms to extract characteristics of weeds, crops, and backgrounds from images. A model that uses wavelet texture information to differentiate sugar beets from weeds was presented by Bakhshipour et al. [86]. A total of fourteen of the fifty-two texture features were chosen using principal component analysis. Despite numerous occlusions and overlapping leaves, it proved wavelet texture features might accurately differentiate among crops and weeds. Only crops and weeds with clearly distinct pixel values in the RGB matrix or other parameter matrices derived from it could be identified by the color feature-based models. In most cases, the color feature was utilized in conjunction with other features; for instance, Kazmi et al. [87] suggested a technique that combined surface color with edge form to detect leaves and integrate vegetation indices. With a precision of 99.07%, the vegetation index was combined with regional characteristics. It was challenging to differentiate between weed species using traditional image processing approaches, even if same methods could differentiate between crops and weeds.

To improve weed detection, deep learning networks can generate abstract high-level properties instead of the low-level attributes used by traditional machine vision networks, such as color, shape, and texture. The present target identification models have, as is well-known, benefited from deep learning's increased accuracy and generalizability. A few examples of popular target detection networks are the YOLO model, Faster R-CNN, and Single Shot Detector Redmon et al. [88], Ren et al. [89], Quan et al. [90]. Using a total of 10,413 pictures, Dyrmann et al. [91] employed CNN to distinguish 22 distinct plant species. The weed species with the most picture resources had the highest classification accuracy, according to the results. Therefore, there needs to be enough datasets for deep learning-based weed identification.

The author Hinton et al. [92] proposal highlighted the deep and highly-connected topology of DL networks, which led to the idea of deep learning being introduced. The dataset is trained by Deep learning has been demonstrating strong accuracy and resilience in image identification as of late. To be more specific, ImageNet a massive multi-variety dataset with 3.2 million images demonstrated the significance of large-scale datasets in enhancing the identification accurateness of the models trained with DL methods by Russakovsky et al. [93]. Unfortunately, dataset for training deep learning weed identification models have very tiny scales in both the number of images and the type of weeds.

F. Seed Categorization

Farmers and food processors alike are understandably worried about seed segregation in mixed cropping. Farmers and agro-industries also have the difficult challenge of classifying and packing seeds according to their quality. Additionally, the conventional methods of seed separation after thrashing like sieving, hand-picking, etc. are laborious and time-consuming. Therefore, seed segregation must be automated.

For that AI methods play an important role in yield prediction [94], improvement of image contrast [95], illness categorization[96], etc. inspired each of the study [97] in order to broaden the scope in seed categorization according to variety, size, they are of high quality. Using SVM, the authors of [98] were able to categorization of normal and broken maize kernels [99]. The SVM classifier achieved a 95.6% success rate for healthy and an 80.6% success rate for the process of identifying damaged or defective seeds, an error rate of about 19% was noted. Researchers [100], [101], and [102] continued this line of inquiry by classifying four different types of maize seeds using models based on SVM, K-means and DCNN. They used the DCNN and claimed a perfect training accuracy rate based strategy. However, when measuring the model's efficacy on the testing dataset, a significant amount of incorrect classifications was found in relation to a single corn category.

In addition, the researchers [103] automated the process of inspecting maize kernels by utilizing ML and DL models' capabilities. For kernel separation, they utilized k-means clustering. In order to distinguish between kernels that were flawed and those that were not, they used a number of models, including ResNet, VGGNet, and AlexNet. Outperforming VGGNet and AlexNet, the ResNet model achieved an accurateness of 98.2%. The writers in [104] also distinguished between healthy and malformed corn seeds using SVM, AlexNet, VGG-19, and GoogleNet. The GoogleNet model had the highest accuracy rate of 95% out of all of these models. In order to classify and test seeds, the following works [105] employ ML and DL algorithms effectively. In order to distinguish between haploid and diploid seeds, detect seed coating, distinguish between common maize seed and silage seed for animal feed, and identify defective from non-defective seeds, they utilized Convolutional Neural Network (CNN) classifiers. Sunflower seed identification was accomplished by the authors [106] using DL models. By utilizing optimization procedures, they successfully circumvent the issue of overfitting. It was asserted by the authors that the optimized GoogleNet model attained a 95% accuracy rate. Unlike a large lot, however, the model calls for human involvement to arrange the seeds.

When training the model, the authors also took into account just one perspective on seeds. Consequently, by training the model on numerous perspectives of seeds, there is a chance to enhance its robustness and reliability. In order to incredulous the obstacles stated in the previous study, the authors in [107] took into account the entire soybean seed surface. They achieved a 98.87% success rate by using a circumrotating method for full surface detection. When applied to the dataset that included defective seeds, the MobileNet model enhanced the classification accuracy. In addition, the technique for identifying soybean seeds was suggested by the authors in [108]. To demonstrate the effect of transfer learning, they used pre-trained CNN models such as AlexNet, Xception, ResNet18, Inception-v3, DenseNet201, and NASNetLarge. With a reported accuracy of 97.2%, the authors asserted that NASNetLarge was the most accurate model. Using morphological and textural characteristics of seeds, the authors of [109] extended the use of ML models for weed detection by applying the naïve Bayes algorithm [110]. The model's accuracy on the grayscale and monochrome photos was 98%, according to the research. Colored images, however, show a marked decline in accuracy.

G. Yield Forecasting

Predicting how much food will be harvested from a specific plot of land is known as Crop Yield Prediction (CYP). Businesses, governments, and farmers all rely on it to help them make educated decisions on agricultural output. The varied temperature, topography, temporal dependencies inherent inyields and farming techniques across India make accurate crop yield forecast a difficult undertaking. Nonetheless, one can anticipate crop production based on a number of criteria, such as: Outside conditions: When it comes to determining harvest success, the weather is a major player. When it comes to plant growth, factors like rainfall, temperature and humidity are important. Crop yield is also prejudiced by the soil's type and fertility. To account for these aspects and anticipate crop yield, one might utilize crop yield prediction models. These models can use machine learning, statistical methods, or a mix of the two.

Consequently, better approaches for assessing and modelling agricultural data are required to enhance crop yield forecast and management.Using ML algorithms and proximate sensing, Farhat Abbas et al. [111] established a CYP system. In order to conduct training, four datasets that are available to the public were gathered: PE-2017, PE-2018, NB-2017, and NB-2018. In order to forecast agricultural output, the gathered data were fed into machine learning models such k-nearest neighbor (KNN), support vector regression (SVR), linear regression (LR), and elastic net (EN). With a smaller Root Mean Square Error (RMSE) than competing techniques, the SVR outperformed them on all four datasets. Martin Kuradusenge et al. [112], introduced many ML models in order to improve the system's performance, the Irish potato and maize datasets were first collected and pre-processing activities, such as removing null values and determining association, were executed. Afterwards, three ML models SVM, Random Forest (RF) and Polynomial Regression (PR) were used to classify the pre-processed data for CYP. When it came to forecasting potato and maize crop yields, the RF model outperformed the SVM and PR models, with RMSEs of 510.8 and 129.9, respectively, on the datasets that were examined.

Recurrent neural networks and temporal convolutional networks are examples of the hybrid DL techniques that Liyun Gong et al. [113] suggested for CYP. The data was gathered from many actual tomato-growing greenhouses. Before feeding the standardized data to the RNN for processing, gathered data was pre-processed using data normalization. Lastly, TCN was instructed to process tomato CYP using the RNN's output. For the datasets that were collected, the technique outperformed the similar methods with reduced RMSE. For CYP with agrarian characteristics, Dhivya Elavarasan and P. M. Durai Raj Vincent [114] introduced a hybrid method known as reinforced RF. At first, the system retrieved crop data from the agricultural dataset and input it into the reinforced RF hybrid DL model. The relevance of the input data was determined by the reinforced RF using the reinforcement learning approach in every internal node. After that, the RF classified crop yield using the most important variables found by the reinforcement model. Outperforming state-of-the-art ML models for CYP including SVM, LR, and KNN, the hybrid technique produced superior results.

To optimize CYP, Aghila Rajagopal et al. [115] created a deep-learning approach. After the data was pre-processed, principal component analysis was used to extract the important features from the pre-processed dataset. After that, an updated chicken swarm technique was used to further optimize the characteristics that were chosen in order to boost the classifier's performance. Lastly, a discrete DBN-VGGNet classifier was used for classification. Outperforming the prior state-of-the-art models, the system attained a 97% accuracy rate with a 0.01% MSE. For large-scale CYP, Dilli Paudel et al. [116] proposed a set of machine-learning models. Data on agricultural yields, including results from crop growth simulations, weather measurements, and yield statistics, were first gathered by the system from a variety of sources. Preparation for categorization procedures involved cleaning the acquired data. The classifier was then fed samples of input data that had undergone feature design. As for CYP, it made use of ML classifiers such as SVM, Ridge regression, KNN, and gradient-boosted decision trees.

H. Disease Detection

Plant diseases are a worldwide threat to food security and can also have serious personal consequences. The economy and the security of our food supply depend critically on healthy crops. A crop's health can only be gauged by its growth and leaf condition.

Therefore, by analyzing symptoms seen in leaf images can learn about many plant illnesses. Every year, farmers can lose a substantial amount of money due to several plant diseases that impact vegetables like potatoes, tomatoes, and peppers. Early blight and late blight are the two varieties of blight. Though a particular bacterium causes late blight, a fungus causes early blight. By promptly detecting and efficiently treating these diseases, farmers can save both time and money. In the next twenty-five years, the human population is projected to surpass 9 billion. A 70% upsurge in food production is necessary to keep up with the continuously increasing demand for food. Many nations, particularly those with a strong agricultural economy, face the devastating threat of crop disease.

By extracting data from real time image processing with ML and DL become prominent tool for plant disease identification because it will effectively diagnose plant illness by exploring with computer vision, machine learning approaches have shown promise by extracting data from real-time image processing. There has been extensive use of classic ML methods for plant disease detection, including feature extraction and classification. Color, texture, and form are some of the visual attributes that may be extracted using these methods to train a classifier to distinguish between healthy and sick plants. Diseases like leaf blotch, powdery mildew and rust as well as symptoms of diseases caused by abiotic stresses like drought and nutrient deficiency, have been extensively detected using these methods Anjna et al. [118], Mohanty et al. [117], Genaev et al. [119]. However, these methods do not accurately identify subtle symptoms of diseases or detect diseases in their early stages. They also have trouble management complicated and high-resolution images.

By using DL technology like CNNs and DBNs to detect pests and irregularities in plants. The use of these technologies to detect and identify lesions from digital pictures has been yielding encouraging results by Kaur and Sharma [120], Siddiqua et al. [121], Wang [122]. Deep learning models have the ability to automatically learn image attributes, allowing them to detect subtle disease symptoms that could otherwise go undetected by typical image processing approaches. However, not all applications can accommodate Deep Learning models due to their high processing requirements and large amounts of labelled training data. In order to locate and identify certain areas of interest in images, like disease symptoms or plant leaves, CV methods like object detection and semantic segmentation can be employed Kurmi and Gangwar [123]. By combining these techniques with ML or DL algorithms, images can be automatically transformed into patterns or features that can be used for disease identification and categorization. To train their models, CV algorithms require massive amounts of labelled picture data, which means they might not be able to handle previously discovered diseases.

Image, sensor, and meteorological data, among other massive datasets, have been subjected to ML and DL-based analysis in order to uncover patterns and generate forecasts. Cedric et al. [125], Yoosefzadeh-Najafabadi et al. [124] and Domingues et al. [126] are just a few examples of ML algorithms that are actuality used to forecast crop yields, detect plant diseases and pests and optimize plant growth. Sladojevic et al. [127], Alzubaidi et al. [128], and Dhaka et al. [129] all found that DL models, including CNNs and DBNs, outperformed standard image processing approaches when it came to plant lesion diagnosis using image analysis and classification. Compared to more conventional ways, ML and DL-based methodologies provide many benefits in the fields of agriculture and botany. These techniques can evaluate massive amounts of data, automate activities, and improve accuracy and efficiency.

I. *Harvesting of Yields*

Rising food demand due to population growth is the biggest threat to food security. In order to increase supply, farmers will need to enhance yields while utilizing the same amount of land. Technology can help farmers increase production through agricultural output prediction. For better crop selection and management during the growing season, decision-makers can employ CYP a decision-support tool powered by ML and DL. During the growing season, it may choose which crops to harvest and how to tend to them.

With the use of agricultural yield estimation, farmers may increase output when weather is good and reduce output loss when weather is bad. Positive predictions of agricultural output are affected by a great deal of variables, including farmer practices, decisions, pesticides, fertilizers, weather, and market pricing. Climate, area wise production, rainfall, and historical yield statistics can all be used to make educated guesses about future crop yields. AI methods has been making strides in many sectors, including farming, as of late.

In order to predict the harvest used the dataset that includes the entire cultivated area, the length of the canals, the average highest temperature and irrigation water sources like wells and tanks. The researcher created computational model outperformed alternatives built with Regression Tree, Lasso, Deep Neural Network and Shallow Neural Network techniques. The RMSE for dataset validation using forecasted weather data is 12% of the average yield and 50% of the standard deviation [130]. Using the following parameters: minimum/maximum/average temperatures, rainfall, area, production and yield, the accuracy was 97.5% from 1998 to 2002 for the Kharif season [131]. Crop production estimates during the Kharif season in Andhra Pradesh's Vishakhapatnam district were the primary focus of the study. Because rainfall has such a large impact on the yield of Kharif crops, researchers first employed modular artificial neural networks to predict when it would rain, and then they used SVR to estimate the yield of crops based on both area and rainfall. These two methods were used to increase the harvest productivity.

The research aimed to accomplish four things: first, study how well the ANN model predicted corn and soybean yields when weather was bad; second, compare the evolved ANN model to other multivariate linear regression models; and last, test how well the model estimated yields at the regional, state, and local levels. Researchers in India's Maharashtra state employed artificial neural networks to compare rice harvests in different urban areas. They used the Indian government's accessible records to compile data for Maharashtra's 27 districts.

This study estimates higher crop yields utilizing ML methods like KNN, SVR, RF and ANN. The research's data set consists of 745 examples; 70% of those cases were randomly assigned to train the model, while 30% were used for testing and performance evaluation. Random Forest is found to obtain the highest level of accuracy in the final analysis of maya gopal P.S [132]. The study proposes a novel model for soybean yield prediction using Long-Short Term Memory (LSTM) satellite data collected in southern Brazil [133]. The main objective of the study is to evaluate LSTM neural networks, random forest, and multivariate OLS linear regression for their effectiveness [134]. The first stage in using rainfall, land surface temperature, and vegetation indices as self-determining variables to forecast soybean data is to find out how soon the model can reliably expect the yield. All algorithms are outperformed by Long Short Term Memory for all forecasts except DOY 16. According to [135], when it comes to DOY 16, multivariate OLS linear regression is the best algorithm. This study discusses the outcomes of applying a Sequential Minimal Optimization Classifier. Data from 27 districts in Maharashtra, India, and the WEKA tool were used to conduct the experiment. Other strategies perform better than Sequential minimum optimization, according to the results of the experiment on the same dataset. While Multilayer Perceptron and BayesNet showed the greatest accuracy and enhanced quality, sequential minimum optimization showed the worst accurateness and poor quality [136]. One method that has been suggested for estimating crop productivity is the use of Parallel Layer Regression (PLR) and Deep Belief Networks (DBNs). Pulses, ragi, rice, and cassava are five of Karnataka's most important crops that are being studied using a DBN technique. Each entry in the applicable database is forecasted by the proposed methodology to produce one of the five crops. Finally, the experimental results show that the method has great promise for real-time data and human interaction validated accurate prediction of agricultural efficiency in terms of specificity, sensitivity and accuracy [137].

By utilizing a KNN algorithm, a CYP System (CYPS) is put into place. Yield projections, on the other hand, need to take into account a number of variables that can affect the quantity and quality of a farmer's harvest. In order to forecast yield production, authors employ precise fields such as year, crop, area, region, and season. These factors, along with crop type and production area, have a significant impact on yield production. Accurate understanding of crop yield history is necessary for decisions linked to agricultural risk management [138]. Rao et al. [139] used two separate metrics, entropy and GINI, to compare Random Forest, Decision Tree Classifier, and KNN. RF has produced the most precise outcomes, according to the findings. Based on feature vectors, VGG_19 achieved a good performance of 91.35% and VGG_16 achieved a good performance of 91.17% [140]. Because of its great efficiency, hydroponics has been suggested by Vanipriya et al. [141] as a solution to the problem of low agricultural production in India. Furthermore, it provides a more environmentally friendly option for soil cultivation. The economy and agricultural output are two factors that determine food production [142].

III. Limitations and Future Study

Based on the study, the findings of agriculture based on image processing has a lot of potential to automate and improve farming tasks with different agriculture farming. For future comprehensive insights there is a need to enhanced farming by combining image, IoT, data fusion techniques, transfer learning and domain adaption and computing techniques. The techniques like DeepLab [143] can be used to classify plants, detect pests, and analyze soil because it is a semantic segmentation model for classifying every pixel. The other method is efficient net [144] which is used to detect disease, fruit counting and yield prediction effectively because it is designed to optimize the model and computation. While our study mainly highlighted the CNN model mostly because it can understand the decision making process in farmers to balance perspective for further refinement. While this review has different datasets for different farming which highlights class imbalance, performance scenario for model evaluation, and comparability. In farming, sustainability is considered as a main factor for long term viability of the environment through energy consumption, and electronic waste associated with cost environment.

However, it isn't perfect for all jobs because of some problems. Here's a look at how these limits affect different farming tasks:

A. Fruit Counting

1) Occlusions and crossing over: Fruits that are hidden by leaves or that intersect with other fruits can make it hard to count or identify them.

2) Changes in lighting: Sunlight or artificial lighting can cast shadows and create effects that make it harder to see fruits and vegetables.

3) Challenges unique to each species: Because fruits come in many shapes, sizes, and colors, they require very specific formulas.

4) Environments that change: Moving wind or changes in the shape of the tree can make it harder to locate the fruit.

B. Water Management

1) Problems with surface reflection: High reflection from bodies of water or irrigation systems can make it hard to determine how much water is in an area or how it is distributed.

2) Limitations of resolution: Images from satellites or drones might not have enough detail for micro-irrigation and other small-scale water management tasks.

3) Estimating the soil moisture: Indirect methods, like NIR imaging, might not provide an accurate reading of soil moisture because dryness on the top can mask the conditions below.

C. Crops Management

1) Changes in growth stages: The appearance of crops changes significantly over time, so adaptive programs are needed to monitor them continuously.

2) Problems with the environment: When taking images outdoors, weather conditions like rain or fog can make it difficult to see crops.

3) Difference between weeds and crops: It's challenging to differentiate between crops and weeds that are grown closely together because they appear similar.

D. Soil Management

1) Data at the surface level: Image-based methods usually only show what's on the surface and don't reveal things like nutrient levels or soil compaction.

2) Dependence on indirect indicators: The color and texture of soil that are inferred from images might not always be a reliable indicator of its fertility or organic content.

3) Environmental factors: Changes in light, moisture, or plant debris can complicate the assessment of soil condition.

E. Weed Identification

1) How they are like crops: Weeds that look like crops in terms of leaf structure or color can be difficult to tell apart.

2) Lots of plants: It's hard to tell the difference between weeds and crops in areas with a lot of crops.

3) Changes with the seasons: Weed growth trends change with the seasons, requiring models to be retrained frequently.

F. Seed Categorization

1) Changes in size and shape: Seeds from the same species can naturally vary in size, shape, and texture, complicating classification.

2) Waste and impurities: Misclassification can occur when images contain trash or damaged seeds.

3) Problems with lighting and contrast: Uneven lighting can obscure crucial features of a seed necessary for identification.

G. Yield Forecasting

1) Complex networks of dependencies: Yield depends on many factors that are difficult to discern from images alone, such as weather, soil health, and pest presence.

2) Lack of data: Model accuracy suffers from the absence of historical image data for certain crops or regions.

3) Problems with spatial resolution: Low-resolution images might not capture important crop features essential for accurate predictions.

H. Disease Detection

1) Signs of an early stage: In the early stages of a disease, subtle changes in the texture or color of leaves might be too faint for standard image processing to detect.

2) Nutrient deficiencies and other problems: Some diseases exhibit symptoms that are very similar to those caused by nutrient deficiencies, which can lead to incorrect diagnoses.

3) Noise in the environment: Dust, water droplets, and other impurities on plant surfaces can make accurate disease identification challenging.

I. Harvesting

1) Conditions of the dynamic field: Changing field conditions, such as uneven terrain or variable lighting, complicate the task for robots to harvest crops using image processing.

2) Produce that is Covered or hidden: Fruits and vegetables that are fully or partially hidden are difficult to locate and harvest accurately.

3) Risk of damage: During automated picking, damage can occur if items are not properly positioned or identified.

J. General Cons Across Applications

1) Dependence on data quality: Models perform less reliably when images are of poor quality, resolutions are not uniform, and diverse datasets are lacking.

2) Problems with scalability: Real-time processing for large-scale systems (like entire farms) requires substantial computational resources.

3) Issues with adaptability: Image processing algorithms need to be retrained for new crops, regions, or weather conditions.

4) Hardware limitations: Small-scale farmers may not be able to afford as many drones, cameras, and other imaging tools, increasing costs and reducing accessibility.

K. Pros that Apply to All Situations

1) Real-Time monitoring: Imaging and sensors provide up-to-the-minute information, allowing immediate responses to changes in the field.

2) Scalability: Data analysis tools can handle large datasets, making them suitable for both small farms and large-scale operations.

3) Cost savings: Optimizing resource use reduces expenses on water, chemicals, and labor.

4) Sustainability: Promotes environmentally friendly practices by minimizing the use of excessive energy, water, and chemicals.

5) Precision agriculture: Delivers precise, relevant information that increases output and reduces waste.

6) Risk reduction: Predictive models identify potential risks such as drought, pests, or diseases.

7) Enhanced Decision-Making: Provides valuable insights based on historical trends, current conditions, and predictive algorithms.

8) Accessibility: Data analysis tools are accessible to farmers worldwide, even in remote locations, via mobile apps and cloud-based platforms.

L. Potential Author Bias

- Potential bias in evaluation and model selection
- Limitations related to Dataset: like data quality, imbalance, insufficient data
- Overfitting and generalization of model for different contexts.
- Uncertainty in discussion of model prediction.

IV. Conclusion

This study details the newest developments in AI research aimed at digitizing farming to increase food yields. Modern agriculture has been changed by AI technologies that help with things like counting fruits and vegetables, managing water and soil, keeping an eye on crops, identifying weeds, sorting seeds into groups, predicting yields, finding diseases and gathering crops automatically. The results show that AI has the potential to make farming more accurate, efficient and environmentally friendly. These new technologies help farmers make the best use of their resources, do less work by hand and make decisions based on data, which leads to better productivity and greater resilience against environmental problems for 9 billion people living on the planet. By the end of 2050, using new tools in farming is no longer a choice but a must because it put a lot of stress on farming systems that try to meet rising food needs in a way that doesn't harm the environment. So it is most important to keep researching and developing the integration of AI with agriculture for helping farmers to deal with problems that makes agriculture resilient and build a healthy future.

REFERENCES

[1] T. Saranya et al., "Engineering applications of artificial intelligence survey paper: A comparative study of deep learning and internet of things for precision agriculture," *Eng. Appl. Artif. Intell.*, 2023.

[2] M. Altalak et al., "Smart agriculture applications using deep learning technologies: A survey," *Appl. Sci.*, 2022.

[3] P. Bharman et al., "Deep learning in agriculture: A review," *Asian J. Res. Comput. Sci.*, 2022.

[4] Pathan SK, Rehman MA, "A review on development of sensor node for precision agriculture," *Proced Eng*, vol. 64, pp. 96–104, 2013.

[5] Hunt ER, Doraiswamy PC, "Assessing sensor performance and potential of an ultrasonic anemometer–temperature–humidity sensor network," *Comput Electron Agric*, vol. 70, no. 1, pp. 15–26, 2010.

[6] Wang, Q.; Nuske, S.; Bergerman, M.; Singh, S., "Automated crop yield estimation for apple orchards," *Experimental Robotics*, Springer: Berlin, Germany, pp. 745–758, 2013.

[7] Li, Y.; Cao, Z.; Lu, H.; Xiao, Y.; Zhu, Y.; Cremers, A.B., "In-field cotton detection via region-based semantic image segmentation," *Comput. Electron. Agric.*, 127, 475–486, 2016.

[8] Lu, H.; Cao, Z.; Xiao, Y.; Li, Y.; Zhu, Y., "Region-based colour modelling for joint crop and maize tassel segmentation," *Biosyst. Eng.*, 147, 139–150, 2016.

[9] Schillaci, G.; Pennisi, A.; Franco, F.; Longo, D., "Detecting tomato crops in greenhouses using a vision-based method," *Proceedings of the International Conference Ragusa SHWA2012*, Ragusa Ibla, Italy, 3–6 September 2012; pp. 252–258.

[10] Linker, R.; Cohen, O.; Naor, A., "Determination of the number of green apples in rgb images recorded in orchards," *Comput. Electron. Agric.*, 81, 45–57, 2012.

[11] Tabb, A.L.; Peterson, D.L.; Park, J., "Segmentation of apple fruit from video via background modeling," *Proceedings of the 2006 ASABE Annual Meeting*, Oregon, Portland, 2006.

[12] Laliberte, A.S.; Ripple, W.J., "Automated wildlife counts from remotely sensed imagery," *Wildl. Soc. Bull.*, 31, 362–371, 2003.

[13] Del Río, J.; Aguzzi, J.; Costa, C.; Menesatti, P.; Sbragaglia, V.; Nogueras, M.; Sarda, F.; Manuèl, A., "A new colorimetrically-calibrated automated video-imaging protocol for day-night fish counting at the obsea coastal cabled observatory," *Sensors*, 13, 14740–14753, 2013.

[14] Ryan, D.; Denman, S.; Fookes, C.; Sridharan, S., "Crowd counting using multiple local features," *Proceedings of the Digital Image Computing: Techniques and Applications*, Melbourne, Australia; pp. 81–88, 2009.

[15] Kim, J.-W.; Choi, K.-S.; Choi, B.-D.; Ko, S.-J., "Real-time vision-based people counting system for the security door," *Proceedings of the International Technical Conference on Circuits/Systems Computers and Communications*, Phuket Arcadia, Thailand, pp. 1416–1419, 2002.

[16] Lempitsky, V.; Zisserman, A., "Learning to count objects in images," *Proceedings of the Advances in Neural Information Processing Systems*, Vancouver, BC, Canada, pp. 1324–1332, 2010.

[17] Giuffrida, M.V.; Minervini, M.; Tsaftaris, S.A., "Learning to count leaves in rosette plants," *Proceedings of the British Machine Vision Conference (BMVC)*, Swansea, UK, 2015.

[18] Koirala A, Zhang Q, "Applications of computer vision for assessing quality of fruits: A review," *Comput Electron Agric*, 153:123–134, 2018.

[19] Sa I, Ge Z, Dayoub F, Upcroft B, Perez T, McCool C, "Deepfruits: A fruit detection system using deep neural networks," *Sensors*, 16(8):1222, 2016.

[20] Anand R, Sahni RK, Kumar SP, Thorat DS, Kumar AK, "Advancement in agricultural practices with use of drones in the context of precision farming," *Glob J Eng Sci*, 11(2):1–7, 2023.

[21] Bargoti, S.; Underwood, J., "Image segmentation for fruit detection and yield estimation in apple orchards," *arXiv*, 2016, arXiv:1610.08120.

[22] Xie, W.; Noble, J.A.; Zisserman, A., "Microscopy cell counting with fully convolutional regression networks," *Proceedings of the MICCAI 1st Workshop on Deep Learning in Medical Image Analysis*, Munich, Germany, 5–9 October 2015.

[23] Zhang, C.; Li, H.; Wang, X.; Yang, X., "Cross-scene crowd counting via deep convolutional neural networks," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Boston, MA, USA, 7–12 June 2015; pp. 833–841.

[24] Wang, L.; Liu, S.; Lu, W.; Gu, B.; Zhu, R.; Zhu, H., "Laser detection method for cotton orientation in robotic cotton picking," *Trans. Chin. Soc. Agric. Eng*, 30, 42–48, 2014.

[25] Marston, L. & Cai, X., "An overview of water reallocation and the barriers to its implementation," *Wiley Interdisciplinary Reviews-Water*, 3, 658–677, 2016.

[26] Salmoral, G., Willaarts, B. A., Garrido, A. & Guse, B., "Fostering integrated land and water management approaches: evaluating the water footprint of a Mediterranean basin under different agricultural land use scenarios," *Land Use Policy*, 61, 24–39, 2017.

[27] Aquastat (2019). Water use [WWW Document]. Available at: http://www.fao.org/aquastat/en/overview/methodology/water-use (accessed 12 December 2019).

[28] Koscielniak, J., Janowiak, F. & Kurczych, Z., "Increase in photosynthesis of maize hybrids (Zea mays L.) at suboptimal temperature (15 degrees C) by selection of parental lines on the basis of chlorophyll alpha fluorescence measurements," *Photosynthetica*, 43, 125–134, 2005.

[29] Nazari, B., Liaghat, A., Akbari, M. R. & Keshavarz, M., "Irrigation water management in Iran: implications for water use efficiency improvement," *Agricultural Water Management*, 208, 7–18, 2018. https://doi.org/10.1016/j.agwat.2018.06.003.

[30] Castanedo, V., Saucedo, H. & Fuentes, C., "Comparison between a hydrodynamic full model and a hydrologic model in border irrigation," *Agrociencia*, 47, 209–223, 2013.

[31] Lee, T., Kim, S. & Shin, Y., "Development of landsat-based downscaling algorithm for SMAP soil moisture footprints," *Journal of the Korean Society of Agricultural Engineers*, 60, 49–54, 2018.

[32] Kim, D.-J., Han, K.-H., Zhang, Y.-S., Cho, H.-R., Hwang, S.-A., Ok, J.-H., Choi, K.-S.& Choi, J.-S., "Evaluation of evapotranspiration in different paddy soils using weighable lysimeter before flooding stage," *Korean Journal of Soil Science & Fertilizer*, 51, 510–521, 2018.

[33] Deng, S., Yin, Q., Zhang, S., Shi, K., Jia, Z. & Ma, L., "Drip irrigation affects the morphology and distribution of olive roots," *Hortscience*, 52, 1298–1306, 2017.

[34] Kumar, R., "Ecohydrologic modeling of crop evapotranspiration in wheat (Triticum-aestivum) at sub-temperate and subhumidregion of India," *International Journal of Agricultural and Biological Engineering*, 6, 19–26, 2013.

[35] Roth, G., Harris, G., Gillies, M., Montgomery, J. & Wigginton, D., "Water-use efficiency and productivity trends in Australian irrigated cotton: a review," *Crop & Pasture Science*, 64, 1033–1048, 2013.

[36] van Steenbergen, F., Basharat, M. & Lashari, B. K., "Key challenges and opportunities for conjunctive management of surface and groundwater in mega-irrigation systems: lower Indus. Pakistan," *Resources-Basel*, 4, 831–856, 2015.

[37] Githinji, L. J. M., Dane, J. H. & Walker, R. H., "Water-use patterns of tall fescue and hybrid bluegrass cultivars subjected to ET-based irrigation scheduling," *Irrigation Science*, 27, 377–391, 2009.

[38] Preite, L., Solari, F., & Vignali, G., "Technologies to Optimize the Water Consumption in Agriculture: A Systematic Review," *Sustainability (Switzerland)*, 15, 7, 2023b, MDPI. doi: 10.3390/su15075975.

[39] Mazzei, D., & Ramjattan, R., "Machine Learning for Industry 4.0: A Systematic Review Using Deep Learning-Based Topic Modelling," *Sensors*, 22, 22, 2022, MDPI. doi: 10.3390/s22228641.

[40] Liakos, K., Busato, P., Moshou, D., Pearson, S., Bochtis, D., "Machine Learning in Agriculture: A Review," *Sensors*, 18 (8), 2674, 2018. https://doi.org/10.3390/s18082674.

[41] Zhou, Z., Majeed, Y., Diverres Naranjo, G., Gambacorta, E.M.T., "Assessment for crop water stress with infrared thermal imagery in precision agriculture: A review and future prospects for deep learning applications," *Comput. Electron. Agric.*, 182, 106019, 2021. https://doi.org/10.1016/J.COMPAG.2021.106019.

[42] Corell, M., P´erez-L´opez, D., Martín-Palomo, M.J., Centeno, A., Gir´on, I., Galindo, A., Moreno, M.M., Moreno, C., Memmi, H., Torrecillas, A., Moreno, F., Moriana, A., "Comparison of the water potential baseline in different locations. Usefulness for irrigation scheduling of olive orchards," *Agric Water Manag*, 177, 308–316, 2016.

[43] Giusti, E., Marsili-Libelli, S., "A Fuzzy Decision Support System for irrigation and water conservation in agriculture," *Environ. Model. Softw.*, 63, 73–86, 2015. https://doi.org/10.1016/J.ENVSOFT.2014.09.020.

[44] Navarro-Hellín, H., Martínez-del-Rincon, J., Domingo-Miguel, R., Soto-Valles, F., Torres- S´anchez, R., "A decision support system for managing irrigation in agriculture," *Comput. Electron. Agric.*, 124, 121–131, 2016. https://doi.org/10.1016/J. COMPAG.2016.04.003.

[45] Chandrappa, V.Y., Ray, B., Ashwatha, N., Shrestha, P., "Spatiotemporal modeling to predict soil moisture for sustainable smart irrigation," *Internet of Things*, 21, 100671, 2022.

[46] Gu, Z., Zhu, T., Jiao, X., Xu, J., Qi, Z., "Neural network soil moisture model for irrigation scheduling," *Comput. Electron. Agric.*, 180, 105801, 2021.

[47] Kavya, M., Mathew, A., Shekar, P.R., P, S., "Short term water demand forecast modelling using artificial intelligence for smart water management," *Sustain. Cities Soc.*, 95, 104610, 2023. https://doi.org/10.1016/J.SCS.2023.104610.

[48] Srivastava, S., Kumar, N., Malakar, A., Sruti, Choudhury, D., Chittaranjan Ray, & Roy, T., "A Machine Learning-Based Probabilistic Approach for Irrigation Scheduling," *Water Resource Management*, doi: 10.1007/s11269-024-03746-7, 2024.

[49] Aly, M. S., Saad, Darwish, M., & Aly, A. A., "High performance machine learning approach for reference evapotranspiration estimation," *Stochastic Environmental Research and Risk Management*, doi: 10.1007/s00477-023-02594-y, 2024.

[50] Yong, S.L.S., Ng, J.L., Huang, Y.F., Ang, C.K., Ahmad Kamal, N., Mirzaei, M., Najah Ahmed, A., "Enhanced Daily Reference Evapotranspiration Estimation Using Optimized Hybrid Support Vector Regression Models," *Water Resour. Manag.*, 2024.

[51] Adnan, R.M., Mostafa, R.R., Reza, A., Islam, M.T., Kisi, O., Kuriqi, A., Heddam, S., "Estimating reference evapotranspiration using hybrid adaptive fuzzy inferencing coupled with heuristic algorithms," *Comput. Electron. Agric.*, 191, 106541, 2021.

[52] Pova˘zanov´a, B., ˘Cistý, M., Bajtek, Z., "Using feature engineering and machine learning in FAO reference evapotranspiration estimation," *J. Hydrol. Hydromech*, 71, 425–438, 2023. https://doi.org/10.2478/johh-2023-0032.

[53] Youssef, M.A., Peters, R.T., El-Shirbeny, M., Abd-ElGawad, A.M., Rashad, Y.M., Hafez, M., Arafa, Y., "Enhancing irrigation water management based on ETo prediction using machine learning to mitigate climate change," *Cogent Food and Agriculture*, 10 (1), 2348697, 2024. https://doi.org/10.1080/23311932.2024.2348697.

[54] S. Dhanasekar, T. Jothy Stella, Mani Jayakumar, "Study of Polymer Matrix Composites for Electronics Applications," *Journal of Nanomaterials*, vol. 2022, Article ID 8605099, 7 pages, 2022. https://doi.org/10.1155/2022/8605099.

[55] Dhanasekar S, Malin Bruntha P, Martin Sagayam K, "An Improved Area Efficient 16-QAM Transceiver Design using Vedic Multiplier for Wireless Applications," *International Journal of Recent Technology and Engineering*, vol.8, no. 3, pp.4419-4425, doi: 10.35940/ijrte.C5535.098319, 2019.

[56] Dhanasekar, S. Bruntha, P.M. Neebha, T.M, Arunkumar, N, Senathipathi, N, Priya, C, "An Area Effective OFDM Transceiver System with Multi-Radix FFT/IFFT Algorithm for Wireless Applications," *In Proceedings of the 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)*, Coimbatore, India, 19–20 March 2021, pp. 551–556.

[57] Zeynep Unal, "Smart Farming Becomes Even Smarter with Deep Learning-A Bibliographical Analysis," *IEEE Access*, 8, 2020, doi:10.1109/ACCESS.2020.3000175.

[58] Oksana Mamai, Velta Parsova, Natalya Lipatova, Julia Gazizyanova, and Igor Mamai, "The system of effective management of crop production in modern conditions," *BIO Web of Conferences 17*, 00027, doi:https://doi.org/10.1051/bioconf/20201700027, 2020.

[59] Dhanasekar S, Ramesh J, "VLSI Implementation of Variable Bit Rate OFDM Transceiver System with Multi-Radix FFT/IFFT Processor for wireless applications," *Journal of Electrical Engineering*, vol. 18, 2018- Edition: 1 – Article 18.1.22. ISSN:1582-4594, 2018.

[60] Dhanasekar S, Ramesh J, "FPGA Implementation of Variable Bit Rate 16 QAM Transceiver System," *International Journal of Applied Engineering Research*, vol.10, pp.26479-26507, 2015.

[61] Dhanasekar S, Suriavel Rao R S and Victor Du John H, "A Fast and Compact multiplier for Digital Signal Processors in sensor driven smart vehicles," *International Journal of Mechanical Engineering and Technology*, vol. 9, no.10, pp. 157–167, 2018.

[62] P. Christiansen, L. N. Nielsen, K. A. Steen, R. N. Jørgensen, and H. Karstoft, "DeepAnomaly: Combining background subtraction and deep learning for detecting obstacles and anomalies in an agricultural field," *Sensors*, vol. 16, no. 11, pp. 2-21, 2016.

[63] N. Kussul, M. Lavreniuk, S. Skakun, and A. Shelestov, "Deep learning classification of land cover and crop types using remote sensing data," *IEEE Geosci. Remote Sens. Lett.*, vol. 14, no. 5, pp. 778 - 782, 2017.

[64] F. J. Knoll, V. Czymmek, S. Poczihoski, T. Holtorf, and S. Hussmann, "Improving efficiency of organic farming by using a deep learning classification approach," *Comput. Electron. Agricult.*, vol. 153, pp. 347-356, 2018.

[65] M. Bah, A. Haane, and R. Canals, "Deep learning with unsupervised data labeling for weed detection in line crops in UAV images," *Remote Sens.*, vol. 10, no. 11, p. 1690, 2018.

[66] A. Picon, A. Alvarez-Gila, M. Seitz, A. Ortiz-Barredo, J. Echazarra, and A. Johannes, "Deep convolutional neural networks for mobile capture device-based crop disease classication in the wild," *Comput. Electron. Agricult.*, vol. 161, pp. 280290, 2019.

[67] S. Coulibaly, B. Kamsu-Foguem, D. Kamissoko, and D. Traore, "Deep Neural networks with transfer learning in millet crop images," *Comput. Ind.*, vol. 108, pp. 115 - 120, 2019.

[68] P. Nevavuori, N. Narra, and T. Lipping, "Crop yield prediction with deep convolutional neural networks," *Comput. Electron. Agricult.*, vol. 163, Art. no. 104859, 2019.

[69] Q. Yang, L. Shi, J. Han, Y. Zha, and P. Zhu, "Deep convolutional neural networks for Rice grain yield estimation at the ripening stage using UAV based remotely sensed images," *Field Crops Res.*, vol. 235, pp. 142 -153, 2019.

[70] L. Zhong, L. Hu, and H. Zhou, "Deep learning based multi-temporal crop classification," *Remote Sens. Environ.*, vol. 221, pp. 430-443, 2019.

[71] Bhaskar B.P. et al., "Soil informatics for agricultural land suitability assessment in Seoni district, Madhya Pradesh, India," *Indian J. Agric. Res.49(4), 315-320, 2015.10.5958/0976-058X.2015.00057.8*.

[72] DicksonA.A. et al., "Fertility capability classification based land evaluation in relation to socio-economic conditions of small holder farmers in bayelsa state of Nigeria," *Indian J. Agric. Res.36(1), 10-16,2002.*.

[73] BehrensT. et al., "Digital soil mapping using artificial neural networks," *J. Plant Nutr. Soil Sci.2005. https://doi.org/10.1002/jpln.200421414*.

[74] GrinandC. et al., "Extrapolating regional soil landscapes from an existing soil map: sampling intensity, validation procedures, and integration of spatial context," *Geoderma*.

[75] Khan, S., Tufail, M., Khan, M. T., Khan, Z. A., and Anwar, S., "Deep learning based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer," *Precis. Agric.*, 22, 1711–1727, doi: 10.1007/s11119-021-09808-9, 2021.

[76] Yuan, H., Zhao, N., and Chen, M., "Research progress and prospect of field weed recognition based on image processing," *J. Agric. Machinery*, 51, 323–334, 2020.

[77] Marx, C., Barcikowski, S., Hustedt, M., Haferkamp, H., and Rath, T., "Design and application of a weed damage model for laser-based weed control," *Biosyst. Eng.*, 113, 148–157, doi: 10.1016/j.biosystemseng.2012.07.002, 2012.

[78] Stepanovic, S., Datta, A., Neilson, B., Bruening, C., Shapiro, C., Gogos, G., et al., "The effectiveness of flame weeding and cultivation on weed control, yield and yield components of organic soybean as influenced by manure application," *Renew. Agric. Food Syst.*, 31, 288–299, doi: 10.1017/S1742170515000216, 2016.

[79] Kunz, C., Weber, J. F., Peteinatos, G. G., Sökefeld, M., and Gerhards, R., "Camera steered mechanical weed control in sugar beet, maize and soybean," *Precis. Agric.*, 19, 708–720, doi: 10.1007/s11119-017-9551-4, 2018.

[80] Morin, L., "Progress in biological control of weeds with plant pathogens," *Annu. Rev. Phytopathol.*, 58, 201–223, doi: 10.1146/annurev-phyto-010820-012823, 2020.

[81] Andert, S., "The method and timing of weed control affect the productivity of intercropped maize (Zea mays l.) and bean (Phaseolus vulgaris l.)," *Agriculture*, 11, 380, 2021.

[82] Heap, I., "The international herbicide-resistant weed database," Available at: www.weedscience.org, 2022.

[83] Cordill, C., and Grift, T. E., "Design and testing of an intra-row mechanical weeding machine for corn," *Biosyst. Eng.*, 110, 247–252, 2011.

[84] Swain, K. C., Nørremark, M., Jørgensen, R. N., Midtiby, H. S., and Green, O., "Weed identification using an automated active shape matching (AASM) technique," *Biosyst. Eng.*, 110, 450–457, doi: 10.1016/j.biosystemseng.2011.09.011, 2011.

[85] Gasparovic, M., Zrinjski, M., Barkovic, D., and Radocaj, D., "An automatic method for weed mapping in oat fields based on UAV imagery," *Comput. Electron. Agric.*, 173, 105385, doi: 10.1016/j.compag.2020.105385, 2020.

[86] Bakhshipour, A., and Zareiforoush, H., "Development of a fuzzy model for differentiating peanut plant from broadleaf weeds using image features," *Plant Methods*, 16, 153, doi: 10.1186/s13007-020-00695-1, 2020.

[87] Kazmi, W., Garcia-Ruiz, F., Nielsen, J., Rasmussen, J., and Andersen, H. J., "Exploiting affine invariant regions and leaf edge shapes for weed detection," *Comput. Electron. Agric.*, 118, 290–299, doi: 10.1016/j.compag.2015.08.023, 2015.

[88] Redmon, J., Divvala, S., Girshick, R., and Farhadi, A., "You only look once: Unified, real-time object detection," in *2016 IEEE conference on computer vision and pattern recognition (CVPR)*, Las Vegas, NV, USA: IEEE, 779–788, 2016.

[89] Ren, S., He, K., Girshick, R., and Sun, J., "Faster r-CNN: Towards real-time object detection with region proposal networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, 39, 1137–1149, doi: 10.1109/TPAMI.2016.2577031, 2017.

[90] Quan, L., Jiang, W., Li, H., Li, H., Wang, Q., and Chen, L., "Intelligent intra-row robotic weeding system combining deep learning technology with a targeted weeding mode," *Biosyst. Eng.*, 216, 13–31, doi: 10.1016/j.biosystemseng.2022.01.019, 2022.

[91] Dyrmann, M., Karstoft, H., and Midtiby, H. S., "Plant species classification using deep convolutional neural network," *Biosyst. Eng.*, 151, 72–80, doi: 10.1016/j.biosystemseng.2016.08.024, 2016.

[92] Peteinatos, G. G., Reichel, P., Karouta, J., Andujar, D., and Gerhards, R., "Weed identification in maize, sunflower, and potatoes with the aid of convolutional neural networks," *Remote Sens.*, 12, 4185, doi: 10.3390/rs12244185, 2020.

[93] Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., et al., "ImageNet Large scale visual recognition challenge," *Int. J. Comput. Vis.*, 115, 211– 252, 2015.

[94] Deepak Sinwar, Vijaypal Singh Dhaka, Manoj Kumar Sharma, and Geeta Rani. 2020. AI-Based Yield Prediction and Smart Irrigation. *2*, (2020), 155–180.

[95] Monika Agarwal, Geeta Rani, and Vijaypal Singh Dhaka. 2020. Optimizedcontrast enhancement for tumor detection. *Int. J. Imaging Syst. Technol.* 30, 3 (2020), 687–703. DOI:https://doi.org/10.1002/ima.22408.

[96] Nidhi Kundu, Geeta Rani, and Vijaypal Singh Dhaka. 2020. Machine Learning and IoT based Disease Predictor and Alert Generator System. *Proc. 4th Int. Conf. Comput. Methodol. Commun. ICCMC 2020 Iccmc* (2020), 764–769.

[97] Tianwei Ren, Zhe Liu, Lin Zhang, Diyou Liu, Xiaojie Xi, Yanghui Kang, Seeds Classification and Quality Testing Using Deep Learning and YOLO v5,*DSMLAI'21, August 9-12, 2021*

[98] Kantip Kiratiratanapruk and Wasin Sinthupinyo. 2011. Color and texture for corn seed classification by machine vision. *2011 Int. Symp. Intell. Signal Process. Commun. Syst. "The Decad. Intell. Green Signal Process. Commun. ISPACS 2011* (2011), 7–11.

[99] Tony Vaiciulis. SVM. Retrieved from https://www-cdf.fnal.gov/physics/statistics/recommendations/svm/svm.html

[100] Jun Zhang, Limin Dai, and Fang Cheng. 2021. Corn seed variety classification based on hyperspectral reflectance imaging and deep convolutional neural network. *J. Food Meas. Charact.* 15, 1 (2021), 484–494.

[101] Te Ma, Satoru Tsuchikawa, and Tetsuya Inagaki. 2020. Rapid and non-destructive seed viability prediction using near-infrared hyperspectral imaging coupled with a deep learning approach. *Comput. Electron. Agric.* 177, April (2020).

[102] Pengcheng Nie, Jinnuo Zhang, Xuping Feng, Chenliang Yu, and Yong He. 2019. Classification of hybrid seeds using near-infrared hyperspectral imaging technology combined with deep learning. *Sensors Actuators, B Chem.* 296, May (2019), 126630.

[103] Chao Ni, Dongyi Wang, Robert Vinson, Maxwell Holmes, and Yang Tao. (2019) Automatic inspection machine for maize kernels based on deep convolutional neural networks. *Biosyst. Eng.* 178, 131–144.

[104] Sheng Huang, Xiaofei Fan, Lei Sun, Yanlu Shen, and Xuesong Suo. (2019). Research on Classification Method of Maize Seed Defect Based on Machine Vision. *J. Sensors* 2019, 1 DOI:https://doi.org/10.1155/2019/2716975

[105] Lei Pang, Sen Men, Lei Yan, and Jiang Xiao. 2020. Rapid Vitality Estimation and Prediction of Corn Seeds Based on Spectra and Images Using Deep Learning and Hyperspectral Imaging Techniques. *IEEE Access* 8, (2020), 123026–123036.

[106] Ferhat Kurtulmuş. 2020. Identification of sunflower seeds with deep convolutional neural networks. *J. Food Meas. Charact.* 0123456789 (2020).

[107] Guoyang Zhao, Longzhe Quan, Hailong Li, Huaiqu Feng, Songwei Li, Shuhan Zhang, and Ruiqi Liu. 2021. Real-time recognition system of soybean seed full-surface defects based on deep learning. *Comput. Electron. Agric.* 187, May (2021), 106230. DOI:https://doi.org/10.1016/j.compag.2021.106230.

[108] Shaolong Zhu, Jinyu Zhang, Maoni Chao, Xinjuan Xu, Puwen Song, Jinlong Zhang, and Zhongwen Huang. 2020. A rapid and highly efficient method for the identification of soybean seed varieties: Hyperspectral images combined with transfer learning. *Molecules* 25, 1 (2020).

[109] Pablo M. Granitto, Pablo F. Verdes, and H. Alejandro Ceccatto. (2005). "Large-scale investigation of weed seed identification by machine vision", *Comput. Electron. Agric.* 47, 1 (2005), 15–24.

[110] Tom M. Mitchell. 2019. Machine Learning. DOI:https://doi.org/10.1109/ICDAR.2019.00014

[111] F. Abbas, H. Afzaal, A.A. Farooque, S. Tang (2020) "Crop yield prediction through proximal sensing and machine learning algorithms", *Agronomy*, 10 (7) (2020), p. 1046

[112] M. Kuradusenge, E. Hitimana, D. Hanyurwimfura, P. Rukundo, K. Mtonga, A. Mukasine, C. Uwitonze, J Ngabonziza, A. Uwamahoro (2023) "Crop yield prediction using machine learning models: case of Irish Potato and Maize", *Agriculture*, 13 (1) (2023), p. 225

[113] K. Gavahi, P. Abbaszadeh, H. Moradkhani (2021) DeepYield: a combined convolutional neural network with long short-term memory for crop yield forecasting *Expert Syst. Appl.*, 184 (2021), Article 115511.

[114] D. Elavarasan, P.D.R. Vincent (2021) “A reinforced random forest model for enhanced crop yield prediction by integrating agrarian parameters”, *J. Ambient Intell. Humaniz. Comput.*, 12 (2021), pp. 10009-10022

[115] A. Rajagopal, S. Jha, M. Khari, S. Ahmad, B. Alouffi, A. Alharbi (2021) “A novel approach in prediction of crop production using recurrent cuckoo search optimization neural networks”, *Appl. Sci.*, 11 (21) (2021), p. 9816

[116] Palaniappan, M. & Annamalai, M. (2019). Advances in signal and image processing in biomedical applications. 10.5772/intechopen.88759.

[117] Mohanty, S. P., Hughes, D. P., Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Front. Plant Sci.* 7 (September).

[118] Anjna, Sood, M., Singh, P. K. (2020). Hybrid system for detection and classification of plant disease using qualitative texture features analysis. *Proc. Comput. Sci.* 167 (2019), 1056–1065. doi: 10.1016/j.procs.2020.03.404

[119] Genaev, M. A., Skolotneva, E. S., Gultyaeva, E. I., Orlova, E. A., Bechtold, N. P., Afonnikov, D. A. (2021). Image-based wheat fungi diseases identification by deep learning. *Plants* 10 (8), 1–21. doi: 10.3390/plants10081500

[120] Kaur, L., Sharma, S. G. (2021). Identification of plant diseases and distinct approaches for their management. *Bull. Natl. Res. Centre* 45 (1), 1–10. doi: 10.1186/s42269-021-00627-6.

[121] Siddiqua, A., Kabir, M. A., Ferdous, T., Ali, I. B., and Weston, L. A. (2022).Evaluating plant disease detection mobile applications: Quality and limitations.*Agronomy* 12 (8), 1869. doi: 10.3390/agronomy12081869

[122] Wang, B. (2022). Identification of crop diseases and insect pests based on deeplearning. *Sci. Program.* 2022, 1–10. doi: 10.1155/2022/9179998

[123] Kurmi, Y., and Gangwar, S. (2022). A leaf image localization based algorithm fordifferent crops disease classification. *Inf. Process. Agric.* 9 (3), 456–474. doi: 10.1016/j.inpa.2021.03.001

[124] Yoosefzadeh-Najafabadi, M., Earl, H. J., Tulpan, D., Sulik, J., and Eskandari, M (2021). Application of machine learning algorithms in plant breeding: Predicting yieldfrom hyperspectral reflectance in soybean. *Front. Plant Sci.* 11 (January). doi: 10.3389/fpls.2020.624273

[125] Cedric, L. S., Adoni, W. Y. H., Aworka, R., Zoueu, J. T., Mutombo, F. K., Krichen, M.,et al. (2022). Crops yield prediction based on machine learning models: Case of WestAfrican countries. *Smart Agric. Technol.* 2 (March), 100049. doi: 10.1016/j.atech.2022.100049

[126] Domingues, T., Brandão, T., and Ferreira, J. C. (2022). Machine learning fordetection and prediction of crop diseases and pests: A comprehensive survey.*Agriculture* 12 (9), 1350. doi: 10.3390/agriculture12091350;

[127] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., and Stefanovic, D. (2016).Deep neural networks based recognition of plant diseases by leaf image classification.*Comput. Intell. Neurosci.* 2016, 1–12. doi: 10.1155/2016/3289801

[128] Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O.,et al. (2021). Review of deep learning: concepts, CNN architectures, challenges,applications, future directions. *J. Big Data* 8, 1–74. doi: 10.1186/s40537-021-00444-8

[129] Dhaka, V. S., Meena, S. V., Rani, G., Sinwar, D., Ijaz, M. F., and Wozniak, M. (2021).A survey of deep convolutional neural networks applied for prediction of plant leafdiseases. *Sensors* 21 (14), 4749. doi: 10.3390/s21144749

[130] Saeed Khaki and Lizhi Wang. (2019) Crop yield predictionusing deep neural networks. *Frontiers in plant science*,10:621.

[131] Ekaansh Khosla, Ramesh Dharavath, and RashmiPriya. (2020) Crop yield prediction using aggregated rainfall basedmodular artificial neural networks and supportvector regression. *Environment, Development andSustainability*, 22:5687–5708.

[132] Maya Gopal PS (2019) Performance evaluation of best featuresubsets for crop yield prediction using machine learningalgorithms. *Applied Artificial Intelligence*, 33(7):621–642.

[133] The Food and Agriculture Organization (FAO).FAOSTAT. https://www.fao.org/faostat/en/#rankings/countries%20_by_com%20modity_exports, 2023.[Online; accessed Jan. 20, 2023].

[134] Francisco Raimundo, Andre Gloria, and PedroSebastiao. (2021) Prediction of weather forecast for smartagriculture supported by machine learning. In*2021 IEEE World AI IoT Congress (AIIoT)*, pages0160–0164. IEEE.

[135] A Suruliandi, G Mariammal, and SP Raja. (2021) Cropprediction based on soil and environmentalcharacteristics using feature selection techniques.*Mathematical and Computer Modelling of DynamicalSystems*, 27(1):117–140.

[136] Pushpa Mohan and Kiran Kumari Patil. (2017) Cropproduction rate estimation using parallel layerregression with deep belief network. In *2017International Conference on Electrical, Electronics,Communication, Computer, and OptimizationTechniques (ICEECCOT)*, pages 168–173. IEEE.

[137] Ms Kavita and Pratistha Mathur. (2020) Crop yieldestimation in india using machine learning. In *2020IEEE 5th International Conference on ComputingCommunication and Automation (ICCCA)*, pages 220–224. IEEE.

[138] Saiteja Kunchakuri, S Pallerla, Sathya Kande, andNageswara Rao Sirisala. (2021) An efficient crop yieldprediction system using machine learning algorithm. In*4th Smart Cities Symposium (SCS 2021)*, volume 2021,pages 120–125. IET.

[139] Madhuri Shripathi Rao, Arushi Singh, NV SubbaReddy, and Dinesh U Acharya. (2022) Crop prediction usingmachine learning. In *Journal of Physics: ConferenceSeries*, volume 2161, page 012033. IOP Publishing.

[140] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and JianSun. (2016) Deep residual learning for image recognition. In*Proceedings of the IEEE conference on computer visionand pattern recognition*, pages 770–778.

[141] CH Vanipriya, Subhash Malladi, Gaurav Gupta, et al. (2021)Artificial intelligence enabled plant emotion xpresser inthe development hydroponics system. *Materials Today:Proceedings*, 45:5034–5040.

[142] Abhishek Tomar, Gaurav Gupta, Waleed Salehi,CH Vanipriya, Nagesh Kumar, and BrijbhushanSharma. (2022) A review on leaf-based plant disease detectionsystems using machine learning. *Recent Innovations in Computing: Proceedings of ICRIC 2021, Volume 1*,pages 297–303.

[143] [143]Song, Z., Zou, S., Zhou, W.et al.Clinically applicable histopathological diagnosis system for gastric cancer detection using deep learning.Nat Commun 11, 4294 2020. https://doi.org/10.1038/s41467-020-18147-8.

[144] [144]Kabir, H., Wu, J., Dahal, S.et al.Automated estimation of cementitious sorptivity via computer vision. Nat Commun 15, 9935 2024. https://doi.org/10.1038/s41467-024-53993-w