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Can Precision Agriculture Be the Future of Indian Farming?—A Case Study across the South-24 Parganas District of West Bengal, India †

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Abstract: Agricultural practices such as tilling, sowing, cropping, It's duty but arvesting, and land-use patterns in any agrarian economy depend on climate. Therefore, any adverse climatic conditions can seriously affect the production or yield of crops. Increased temperature enhances the susceptibility of crops to pests and various plant diseases. Weeds are also known to multiply rapidly and decrease the nutritive value of soil, negatively affecting crop production. Our present study is designed to address similar problems faced by the farming community in the South-24 Parganas district of West Bengal, India, and suggest several probable technological solutions. Importantly, West Bengal is included in one of the six agro-climatic zones. Major crops from this study site are rice, wheat, maize, jute, green gram, black gram, pigeon pea, lentils, sugarcane, pulses, rapeseed, mustard, sesame, linseed, and vegetables. Significantly, cultivable land area has decreased in comparison to the overall crop area in this region. Reduced interest in agriculture, irrigation problems, increased profit in the non-agricultural economy, and rapid conversion of agricultural land for commercial purposes (construction of plots, hatcheries for fishing practices), along with uncertainties associated with rainfall patterns and frequent cyclones, are matters of grave concern in this study area. Agricultural scientists, researchers, environmentalists, local bodies, and government organizations are suggesting alternatives to benefit farmers. Thus, precision agriculture or crop management is required to recognize site-specific variables within agricultural lands and formulate strategies for improving decision-making regarding crop sowing, appropriate use of herbicides, weedicides, and precision irrigation, along with innovative harvesting technologies. Thus, the present paper provides a vision for the farming community in our study area to overcome their traditional practices and adopt different techniques of precision agriculture to increase flexibility, performance, accuracy, and cost-effectiveness. Soil temperature, humidity, and moisture monitoring sensors could be beneficial. Precision soil management, precision irrigation, crop disease management, weed management, and harvesting technologies are the different modules considered for discussion in this paper. Machine learning algorithms, such as decision tree, K-nearest neighbor (KNN), Gaussian naïve Bayes (GNB), K-means clustering, artificial neural network (ANN), fuzzy logic system (FLS), and support vector machine (SVM), could prove helpful for progressive farmers. The use of AI-powered weeding machines, drones, and UAVs for rapid weed removal and the localized application of herbicides and pesticides could also improve the accuracy and efficiency of agriculture. Utilizing drones fitted with high-resolution cameras could help gather precision field images, proving to be quite helpful in crop monitoring and crop health assessment. Unmanned driverless tractors and harvesting machines using robotics integrated with data from GPS/GIS sensors or radars could also be considered an effective and time-saving option. Thus, machine learning, along with innovative agricultural technologies, could contribute to improving the livelihoods of the farming fraternity.

Keywords: crop management; drones; machine learning algorithm; precision agriculture; UAVs

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1. Introduction

In the words of Mahatma Gandhi, "Agriculture is the soul of the Indian economy"; therefore, one needs to understand the importance of agriculture for people's livelihoods. Among two-thirds of the Indian population, only one-half of the cropped area is covered by irrigation. With the increase in food demand, there is an urgent need for scientists, agricultural researchers, farmers, and governments to formulate new techniques to increase production. Manual methods involving the use of trained manpower are quite challenging in India due to a lack of awareness and the technological limitations of agricultural workers. Despite being trained agricultural practitioners for generations, Indian farmers are still quite conservative and reluctant to adapt to the changing face of agriculture. Machine learning (ML) algorithms assist in analyzing massive volumes of data with great speed and accuracy. ML thereby involves computational applications for modifying or adapting their action for real-time application. It is classified broadly into two different categories: supervised and unsupervised learning. Significantly, the application of information technology, or more specifically, data mining techniques, in the agricultural domain is targeted to fulfill the goals of precision agriculture (PA). PA is a comprehensive system developed with the aim of optimizing production quality, improving efficiency, and ultimately, conserving energy and protecting the environment. Thereby, PA is designed to obtain increased yields compared to traditional cultivation. The United Nations Environment Programme (UNEP) and the Club of Rome report (1972) have been warning us continuously for decades about serious consequences regarding increased temperatures due to global warming. The IPCC has warned about an increase of 3.7–4.8 °C in global temperature by 2100 [1]. This would probably lead to changes in crop patterns, ultimately affecting agricultural production or yield rates [2]. Increased temperature is also associated with higher evapotranspiration, leading to lower soil moisture. The agriculture sector is directly dependent on climatic conditions, and higher temperature is associated with the multiplication of weeds and the spread of various pests and plant diseases. This adversely affects nutritive value and negatively influences the growth of saplings, ultimately leading to malnutrition and decreasing crop yield [3,4]. The Indian agricultural system is totally dependent on monsoons; therefore, any irregularities associated with rainfall patterns leading to drought or floods would definitely create a serious impact [5].

PA, or, more specifically, crop management, involves identifying site-specific variables within agricultural lands and devising strategies for improving crop sowing, along with the proper application of herbicides, weedicides, precision irrigation, and other innovative harvesting technologies. Technological advancement powered by several ML algorithms could prove beneficial for improving the livelihood of farmers. Therefore, the present study has been designed to explore the different applications of ML algorithms in a farming community in the South 24-Parganas district of West Bengal, India.

2. Methodology

The study area of the South 24-Parganas district of West Bengal, India, extends between 22°12′13″ N–22°46′55″ N latitude and 87°58′45″ E–88°22′10″ E longitudes. Covering an area of 9960 km^2, this district is strategically surrounded by the Bay of Bengal at one end, with the district of Kolkata and North 24-Parganas on the other side [6]. The temperature varies between 16 and 34 °C, and the annual rainfall range is estimated to lie between 150 and 170 cm [7]. Importantly, most of the district is included in the saline coastal region with mostly alluvial, fine, saline soil [8].

The step of implementing machine learning (ML) algorithms for predictive agriculture involves data cleaning and preprocessing. In this case, it should be assumed that the dataset has no missing values. The data should have normal distribution for all their features. The outliners should be removed. When selecting the appropriate ML algorithm for a particular attribute, the dataset is split into a training dataset and a testing dataset.

Thus, different ML algorithms were used for the investigation of various parameters predicting agriculture productivity. K-nearest neighbor (KNN) [9] is a non-complex algorithm that can store all the available data and further classify new cases based on similarity measures. The naïve Bayes classifier (NBC) is a probabilistic classifier model working on the basis of assigning class labels to problem instances, which are represented as features of vector values [10], where the class labels are drawn from a finite set. A decision tree algorithm (DTA) is built using a labeled (training) dataset, and it forms the basis for classifying an unlabeled (testing) dataset for solving problems. The iterative dichotomizer 3 (ID3) algorithm is one of the most effective algorithms used to construct a decision tree [11]. The K-means clustering algorithm is an unsupervised learning algorithm. In this case, a set of dataset items is provided containing certain features along with values of these features. This algorithm operates by categorizing these items into k-groups or clusters based on similarity [12]. Support vector machine (SVM) is the most popular supervised learning algorithm, used for solving both classification as well as regression problems [13,14]. An artificial neural network (ANN) is defined as an information processing model composed of a large number of highly interconnected processing units (neurons) working in unison to solve a specific problem [13,14]. Fuzzy logic systems (FLS) are recognized for generating acceptable but definite output in response to incomplete, ambiguous, distorted, or inaccurate (fuzzy) input [15,16].

Soil moisture sensors, precipitation sensors, and temperature sensors for determining the humidity and temperature profile of the agriculture field could help create a dataset. On the basis of answers to "yes" or "no" questions, the decision tree would be split into parts. Questions regarding the content of sodium, carbon, magnesium, nitrogen, potassium, and phosphate in the soil would be answered, and the soil containing the above nutrients in the best combination would prove beneficial. Accordingly, fertilizer would be selected for increasing productivity. The KNN algorithm would be used to detect the greatest "similarity" in the new case or dataset with the temperature and precipitation of the already available dataset. The goal of the SVM algorithm is to create the best line or decision boundary to segregate "n" dimensional space into classes so that one can easily assign the new dataset regarding the diseased or healthy plant into the correct category. This could benefit farmers and act as a reference manual for the future. The naïve Bayes probabilistic classification algorithm would predict the best soil profile on the basis of probability. This would segregate soil based on its loamy/clayey/saline/alluvial nature for a particular crop. Determination of soil nature would enable farmers to decide on the application of a suitable fertilizer. The use of fuzzy logic systems to devise approximate pest control and disease management tools would benefit farmers. Thus, based on the results obtained from the FL algorithm, proper detection and differential spraying of pesticides would be undertaken for diseased crops. K-means clustering would benefit farmers by segregating the diseased and healthy plants.

3. Discussion

Globally, the geometric rise in population has a direct influence on agriculture, stressing the importance of newer and innovative technological advancements for sustaining and improving agricultural practices. The induction of AI, including big data analytics, robotics, IoT, sensors and cameras, drone technologies, and widespread internet coverage on geographically dispersed fields are becoming indispensable in Indian farming. Traditional farming entails many uncertainties, along with problems due to weeds and pests, soil degradation, and climate change.

Precision agriculture (PA) refers to merging all technologies for augmenting agricultural productivity with input use efficiency [17,18]. Thus, PA can simply be defined as a data-cum-technology-driven farming practice used to detect, analyze, and formulate effective measures to manage variations in field parameters. Indian agriculture is predominantly managed by small and marginal farmers; further technological advancements associated with the integration of a farmer's knowledge with precision agricultural practices and simulation modeling could prove beneficial for poor-performing patches in the farming sector [19].

Management-oriented modeling (MOM) uses a set of alternative management techniques including using a simulator to evaluate each alternative and an evaluator to determine which alternative satisfies the user-weighed multiple criteria. MOM also employs "hill-climbing", a strategic search method that works on the principle of "best–first" as a tactical search method to determine the shortest path from start nodes to reach the goals [20].

Precision crop management (PCM) is a popular agricultural system devised to target crops and inputs in accordance with field requirements in order to increase profitability [21]. Cropping alternatives are selected based on the timing, intensity, and predictability of drought conditions [22]. A well-planned crop prediction methodology is targeted to protect the suitable crops by sensing several parameters (soil type, pH, nitrogen, phosphate, potassium, organic carbon, calcium, magnesium, sulfur, manganese, copper, and iron) along with temperature, rainfall, and humidity [23]. A similar result in the present study using a decision tree algorithm would help to predict the presence of sodium, carbon, iron, sulfur, nitrogen and its oxides, potassium, phosphates, and magnesium in the soil profile across agricultural fields.

Support system (SRC-DSS) follows three steps: knowledge gain, planning a conceptualized design followed by system implementation [24]. Additionally, soil texture (sand, clay, and silt content) can be predicted based on pre-existing coarse-resolution soil maps combined with hydrological parameters derived from a digital elevation model (DEM) working using ANN [25]. ANN is also reported to provide above 90% success in predicting crop nutritional problems [26]. Remote sensing devices associated with a higher-order neural network can be used to investigate and characterize the dynamics of soil moisture control [27]. Robots are innovative computer-controlled speed-sowing machines equipped with a pair of video cameras along with global positioning sensors. Thus, robotics have reported an 80% success rate in harvesting [28].

The principle of precision irrigation management (PIM) employs the most popular irrigation tools, i.e., Arduino and Raspberry Pi. Further, Zigbee has been employed successfully to communicate the measured parameters, i.e., soil temperature, humidity, radiation, and air temperature. This also includes a web server along with IoT-controlled water pumps [29]. Thus, water management involving water quality and irrigation is an essential component in crop management systems. Machine learning has also benefitted different areas of irrigation, i.e., crop yield prediction, crop disease identification, crop weed detection, and livestock welfare [29]. The most popular tools of ML algorithms applied for the benefit of the irrigation sector include linear logistic regression (LR), classification and regression tree (CART), K-nearest neighbor (KNN), Gaussian naïve Bayes (GNB), and support vector machine (SVM). Farmers' knowledge and potential were tapped to utilize an FL-based model system to identify suitable crops based on land suitability maps [16]. Researchers have recommended using the ANN method to estimate the soil moisture content in paddy [30].

According to the temperature sensor used at the study site, the recorded temperature value varied from a low of 5 °C to a high of 48 °C. However, the values remained between 20 and 30 °C for most of the year. The precipitation sensor recorded rainfall between 100 cm during drier conditions and a maximum of 300 cm during monsoons at the study site.

Significantly, a reduction in productivity per unit area and a decrease in natural resources associated with growing threats from global warming and climate change lead to reduced farm income. In such cases, precision crop management is required to recognize site-specific variables within agricultural lands and to design management strategies for improving decision-making capabilities. Importantly, progressive farmers are quite aware of the variation in crop yield as per previous experiences [31]. Instead of manually selecting a field for crop plantation purposes, farmers have the option of utilizing GPS/GIS data. Soil preparation techniques using specific sensors for monitoring temperature, humidity, or volatile matter could be employed. Instead of leveling land using bullocks and tractors, high-quality laser-guided precision land levelers could be a much better option. Automatic tools such as precision drills, seed drills, air seeders, and broadcast seeders can be quite effective compared to manual seeding and planting [31]. Automated and controlled fertigation systems powered by IoT are being successfully employed for irrigation purposes [32]. ML technologies can be employed for the creation of chatbots [33] for communication with farmers, providing them with relevant suggestions about modern agricultural technologies. Unmanned aerial vehicles (UAVs) are capable of monitoring, taking pictures of, and collecting data about a particular location. By maneuvering over a large area, UAVs create new avenues for increasing crop yield through spraying, counting crops, detecting any abnormalities, etc. ML technologies also assist in detecting movement and predicting the activities of UAVs. Driverless, unmanned tractors and machine-driven harvesting technologies can be possible through the use of robots. Instead of conventional harvesting techniques, robotic arms can be highly efficient and time-saving [31]. Robotic arms assist in harvesting by interpreting the ripening state of the crops. Data from GPS/GIS, radars, and sensors could be successfully sorted out using ML to locate any obstacle and decide on the application of farm input [34]. Automated irrigation, along with conventional weather forecasting, can be useful for water resource management. Such ML-based technologies could prove beneficial for maintaining the level of water and nutrients in soil [31].

AI can be effectively utilized for crop disease management [21]. With AI, a farmer can efficiently control crop diseases by successfully adopting an integrated disease management and control system encompassing physical, chemical, and biological measures [35]. Rule promotion using fuzzy logic (FL) along with webGIS is required to predict intelligent interferences for crop disease management. A text-to-speech converter (TTS) is capable of creating a text-to-talking user interface. Additionally, web-based FL, along with a web-based intelligent disease diagnostic system (WIDDS), predicts and responds swiftly to any type of crop disease with sufficient accuracy. However, being a web-based system, limited internet connectivity can compromise its effectiveness [36]. Although ANN and GIS provide 95% accuracy in crop disease management, limited accessibility to the internet among rural folks may be challenging at times [37]. However, web-based expert systems provide excellent performance in some instances [15]. Some researchers have proposed a FL-based intelligent technique to predict crop disease based on leaf wetness duration [38]. Further work has proposed a FL-based method and integrated it with image processing to predict the percentage of leaf damage [39]. Additionally, in disease management, ANN was coupled with image processing to detect disease in seedlings [40].

An intensive AI-based weed management system has been designed to minimize the harmful effect of weeds on crops [21]. Unmanned aerial vehicles (UAVs) have been employed successfully in several instances to monitor weeds [41]. The crop row algorithm classifies, distinguishes, and segregates weed and crop pixels. Online weed detection using digital image analysis employing drones (UAVs), computer-based decision, and global positioning system (GPS) -controlled patch spraying [42] are also quite effective. Optimization using invasive weed optimization (IWO) along with ANN is cost-effective and increases performance [43]. Employing mechanical weed control using robotics and sensor machine learning (sensor ML) is known to be time-saving and also removes resistant weeds [44]. Although it requires big data and high usage expertise, the Saloma expert system, designed for evaluation, prediction, and weed management, has a high adaption rate and impressive prediction levels [45].

Ultimately, predicting and estimating crop yields are serious issues for designing market estimates and, subsequently, preparing crop cost estimations. Researchers utilized ANN and employed a backpropagation learning algorithm to predict crop yield from soil parameters [46]. Thus, [47] successfully harnessed the possibilities of crop yield by estimating profitability while reducing environmental impact by decreasing the use of fertilizers. Detection of different crop diseases, i.e., blight, rot, mildew, wilt, leaf spot, Scotch scab disease of potato, and mold, using the FL algorithm, could prove beneficial for the farming community in the study area. Subsequent application of pesticides (methyl parathion, imidaeloprid, phorate) in proper composition in the study area could prove immensely beneficial.

Exploring different opportunities associated with the application of robotics in the agriculture sector is worth mentioning [48]. Utilization of the benefits associated with IoT by the farming community is also noteworthy. By overcoming any constraints associated with the availability of the internet, a farmer can provide timely data regarding crop sowing, flowering, ripening, and harvesting. Using soil or moisture sensors, temperature sensors, pH sensors, CO_2 sensors, and wind speed detection sensors associated with UAVs or drones could prove effective for monitoring soil, topographic, and climatic parameters required for the proper management of crops. This could lead to improvements in crop productivity, leading to advancements in the food sector. Automatic robots could also help harvest crops at a higher volume and faster rate than human laborers. Green seeker sensors assess the demands of plants and determine the amount of fertilizer to be applied and the pesticides required. The modern countryside is also developing sensor-based small electric motors that are remotely controlled. These small agricultural robots successfully differentiate between crops and weeds using AI by performing camera imaging and high-precision spraying. Precision spraying helps to overcome the harmful effects of blanket spraying of pesticides, weedicides, or insecticides. A detailed 3D map of the farmland, its terrain, irrigation, and soil viability is developed by a drone. Additionally, soil N2 level monitoring can be conducted by a drone. Aerial spraying of pods with seeds and plant nutrients directly into the soil can also be performed by a drone [49].

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References

1. *Climate Change 2007: Synthesis Report, Contribution of Working Group I, II and III to the Fourth Assessment Report of the Intergovermental Panel on Climate Change*; IPCC Report; IPCC: Geneva, Switzerland, 2007.
2. Rosegrant, M.W.; Perez, N.; Pradesha, A.; Thomas, T.S. *The Economy Wide Impacts of Climate Change on Philippine Agriculture, Research Program on Climate Change and Food Security*; International Food Policy Research Institute: Washington, DC, USA, 2015.
3. Kim, C.-G. Strategies for Implementing Green Growth in Agricultural Sector. In Proceedings of the Green Korea 2009 Conference, Seoul, Republic of Korea, 9 September 2009.
4. Chatterjee, A. Climate Change and Indian Agriculture. 2021. Available online: https://www.devalt.org/newsletter/nov03/of_5.htm (accessed on 10 September 2023).
5. Climate Change and Agriculture in India, 2016. Climate Change and Its Impact on Agriculture-MANAGE. Available online: https://www.manage.gov.in (accessed on 10 September 2023).
6. District Census Handbook, South Twenty Four Parganas, Village and Town Directory, Directorate of Census Operations, West Bengal. 2011. Available online: https://censusindia.gov.in/nada/index.php/catalog/1362 (accessed on 10 September 2023).
7. Dhole, M.; Topno, S. Change in climatic elements impact on agriculture: A case study on 24 PGS(S). *Int. J. Health Sci.* **2022**, *6*, 5685–5705. [CrossRef]
8. *West Bengal State Action Plan on Climate Change (2017–2020)*; Government of West Bengal: Howrah, India, 2020.
9. Bazmara, M.; Jafari, S. K-Nearest Neighbor Algorithm for finding soccer talent. *J. Basic Appl. Sci. Res.* **2013**, *3*, 981–986.
10. Sibyan, H.; Svajlenka, J.; Hermawan, H.; Faqih, N.; Arrizqi, A.N. Thermal comfort prediction accuracy with machine learning between Regression Analysis and Naïve Bayes Classifier. *Sustainability* **2022**, *14*, 15663. [CrossRef]
11. Bishnoi, S.; Hooda, B.K. Decision Tree Algorithms and their Applicability in Agriculture for Classification. *J. Exp. Agric. Int.* **2022**, *44*, 20–27. [CrossRef]

12. Hassan, I.H.; Abdullahi, M.; Ahmad, B.I.; Ali, Y.S. K-means clustering algorithm based classification of soil fertility in north-west Nigeria. *FUDMA J. Sci.* **2020**, *4*, 780–787. [CrossRef]
13. Russell, S.; Norvig, P. *Artificial Intelligence: A Modern Approach*, 3rd ed.; Pearson: London, UK, 2009; p. 1152.
14. Patrício, D.I.; Rieder, R. Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. *Comput. Electron. Agric.* **2018**, *153*, 69–81. [CrossRef]
15. Virparia, P. A web based Fuzzy Expert System for insect Pest Management in Groundnut crop Prajna. *J. Pure Appl. Sci.* **2007**, *15*, 36–41.
16. Sicat, R.S.; Carranza, E.J.M.; Nidumolu, U.B. Fuzzy modelling of farmers' knowledge for land suitability classification. *Agric. Syst.* **2005**, *83*, 49–75. [CrossRef]
17. Hakkim VM, A.; Joseph, E.A.; Gokul, A.J.A.; Mufeedha, K. Precision Farming: The future of Indian Agriculture. *J. Appl. Biol. Biotechnol.* **2016**, *4*, 68–72. [CrossRef]
18. Shafi, U.; Mumtaz, R.; García-Nieto, J.; Hassan, S.A.; Zaidi, S.A.R.; Iqbal, N. Precision Agriculture Techniques and Practices: From Considerations to Applications. *Sensors* **2019**, *19*, 3796. [CrossRef]
19. Oliver, Y.M.; Robertson, M.J.; Wong, M.T.F. Integrating farmer knowledge, precision agriculture tools, and crop simulation modelling to evaluate management options for poor performing patches in cropping fields. *Eur. J. Agron.* **2010**, *32*, 40–50. [CrossRef]
20. Li, M.; Yost, R. Management-oriented modelling: Optimizing nitrogen management with artificial intelligence. *Agric. Syst.* **2000**, *65*, 1–27. [CrossRef]
21. Eli-Chukwu, N.C. Applications of Artificial Intelligence in Agriculture: A Review. *Eng. Technol. Appl. Sci. Res.* **2019**, *9*, 4377–4383. [CrossRef]
22. Debaeke, P.; Aboudrare, A. Adaptation of crop management to water-limited environments. *Eur. J. Agron.* **2004**, *21*, 433–446. [CrossRef]
23. Dahikar, S.S.; Rode, S.V. Agricultural crop yield prediction using artificial neural network approach. *Int. J. Innov. Res. Electr. Electron. Instrum. Control. Eng.* **2014**, *2*, 683–686.
24. Lopez, E.M.; Garcia, M.; Schuhmacher, M.; Domingo, J.L. A fuzzy expert system for soil characterization. *Environ. Int.* **2008**, *34*, 950–958. [CrossRef]
25. Zhao, Z.; Chow, T.L.; Rees, H.W.; Yang, Q.; Xing, Z.; Meng, F.R. Predict soil texture distributions using an artificial neural networks. *Comput. Electron. Agric.* **2009**, *65*, 36–48. [CrossRef]
26. Song, H.; He, Y. Crop Nutrition Diagnosis Expert System Based on Artificial Neural Networks. In Proceedings of the 3rd International Conference on Information Technology and Applications 2005, Sydney, Australia, 4–7 July 2005.
27. Elshorbagy, A.; Parasuraman, K. On the relevance of using artificial neural networks for estimating soil moisture content. *J. Hydrol.* **2008**, *362*, 1–18. [CrossRef]
28. van Henten, E.J.; Hemming, J.; van Tuijl BA, J.; Kornet, J.G.; Meuleman, J.; Bontsema, J.; van Os, E.A. An Autonomous Robot for Harvesting Cucumbers in Greenhouses Autonomous Robots. *Auton. Robot.* **2002**, *13*, 241–258. [CrossRef]
29. Singh, D.K.; Sobti, R.; Malik, P.K.; Shrestha, S.; Singh, P.K.; Ghafoor, K.Z. IoT-driven model for weather and soil conditions based on precision irrigation using machine learning. *Secur. Commun. Netw.* **2022**, *2022*, 7283975. [CrossRef]
30. Arif, C.; Mizoguchi, M.; Setiawan, B.I. Estimation of soil moisture in paddy field using Artificial Neural Networks. *arXiv* **2013**, arXiv:1303.1868. [CrossRef]
31. Bhattacharyay, D.; Maitra, S.; Pine, S.; Shankar, T.; Peera Sk, P.G. Future of Precision Agriculture in India. In *Protected Cultivation and Smart Agriculture*; Maitra, S., Gaikwad, D.J., Shankar, T., Eds.; New Delhi Publishers: New Delhi, India, 2020; pp. 289–299.
32. Maitra, S.; Shankar, T.; Sairam, M.; Pine, S. Evaluation of Gerbera (*Gebera jamesonii* L.) cultivars for growth, yield and flower quality under protected cultivation. *Indian J. Nat. Sci.* **2020**, *10*, 20271–20276.
33. Mostaco, G.M.; Ramires, C.S.I.L.; Campos, L.; Cugnasca, C.E. Agronomobot: A smart answering chatbot applied to agricultural sensor networks. In Proceedings of the 14th International Conference on Precision Agriculture, Montreal, QC, Canada, 24–27 June 2018; 14p.
34. Chunhua, Z.; John, K. The application of small unmanned aerial systems for precision agriculture: A review. *Precis. Agric.* **2012**, *13*, 11119.
35. BEA. Value Added by Industry as a Percentage of Gross Domestic Product 2018. Available online: https://apps.bea.gov/iTable/iTable.cfm? (accessed on 10 September 2023).
36. Kolhe, S.; Kamal, R.; Saini, H.S.; Gupta, G.K. A web-based intelligent disease-diagnosis system using a new fuzzy-logic based approach for drawing the interferences in crops. *Comput. Electron. Agric.* **2011**, *76*, 16–27. [CrossRef]
37. Liu, G.; Yang, X.; Ge, Y.; Miao, Y. An artificial neural network-based expert system for fruit tree disease and insect pest diagnosis. In Proceedings of the International Conference on Networking, Sensing and Control, Lauderdale, FL, USA, 23–25 April 2006.
38. Tilva, V.; Patel, J.; Bhatt, C. Weather based plant diseases forecasting using fuzzy logic. In Proceedings of the 2013 Nirma University International Conference on Engineering (NUiCONE), Ahmedabad, India, 28–30 November 2013; IEEE: Piscataway, NJ, USA, 2013.
39. Sannakki, S.S.; Rajpurohit, V.S.; Nargund, V.B.; Kumar, A.; Yallur, P.S. Leaf disease grading by machine vision and fuzzy logic. *Int. J. Comp. Technol. Appl.* **2011**, *2*, 1709–1716.

40. Huang, K.Y. Application of artificial neural network for detecting Phalaenopsis seedling diseases using color and texture features. *Comput. Electron. Agric.* **2007**, *57*, 3–11. [CrossRef]
41. Ortiz, M.P.; Gutierrez, P.A.; Pena, J.M.; Sanchez, J.T.; Granados, F.L.; Martinez, C.H. Machine Learning Paradigms for Weed Mapping via unmanned Aerial Vehicles. In Proceedings of the 2016 IEEE Symposium Series on Computational Intelligence (SSCI), Athens, Greece, 6–9 December 2016.
42. Gerhards, R.; Christensen, S. Real-time weed detection, decision-making and patch-spraying in maize, sugerbeet, winter wheat and winter barley. *Weed Res.* **2003**, *43*, 385–392. [CrossRef]
43. Moallem, P.; Razmjooy, N. A multi-layer perception neural network trained by invasive weed optimization or potato color image segmentation. *Trends Appl. Sci. Res.* **2012**, *7*, 445–455. [CrossRef]
44. Swanton, C.J.; Harker, K.N.; Anderson, R.L. Crop losses due to weeds in Canada. *Weed Technol.* **1993**, *7*, 537–542. [CrossRef]
45. Stigliani, L.; Resina, C. Seloma: Expert system for weed management in herbicide-intensive crops. *Weed Technol.* **1993**, *7*, 550–559. [CrossRef]
46. Liu, G.; Yang, X.; Li, M. An artificial neural network model for crop yield responding to soil parameters. In *Advances in Neural Networks–ISNN 2005: Second International Symposium on Neural Networks, Chongqing, China, 30 May–1 June 2005*; Springer: Berlin/Heidelberg, Germany, 2005.
47. Liu, S.Y. Artificial Intelligence (AI) in Agriculture. *IT Prof. IEEE Comput. Soc.* **2020**, *22*, 14–15. [CrossRef]
48. Talaviya, T.; Shah, D.; Patel, N.; Yagnik, H.; Shah, M. Implementation of artificial intelligence for optimisation of irrigation and application of pesticides and herbicides. *Artif. Intell. Agric.* **2020**, *4*, 58–73. [CrossRef]
49. Dharmaraj, V.; Vijayanand, C. Artificial Intelligence (AI) in Agriculture. *Int. J. Curr. Microbiol. Appl. Sci.* **2018**, *7*, 2122–2128. [CrossRef]