Deep Science Publishing
https://doi.org/10.70593/978-81-988918-6-0_10

Chapter 10: Case studies on successful applications of artificial intelligence in global agricultural practices

10.1. Introduction to AI in Agriculture

Agricultural practices have been around for thousands of years, yet our understanding of how to make it more productive, efficient and in sync with nature is still being examined and discovered in new ways. Application of innovations into agriculture aims to satisfy basic needs of mankind. Recent pushes like sustainable agriculture have emphasized the phrase ‘innovative application into agriculture’ to a new high. Our journey of capitalization, to serve 8 billion people of earth, from the age of hunter-gatherers to sky-scrapers has relied heavily upon agricultural implications in all their forms. In that regard, these innovations into agriculture still hold a major share of economic resources and GDP of many nations, especially the developing ones. Conceptually, agriculture has become a multidisciplinary subject, compact covering ground for nano-sciences to space studies, having a large interface with social sciences, engineering and bio-sciences. With the pace of global population growth, the demand for food will be doubled within the next 3 decades and in addition to this, climate change poses a great risk to all farmers. New and innovative technologies would have to be made for our farmers so that they get enough data and inputs to produce food in a precise manner that satisfies the health communities as well as the trade communities. The advanced technologies like Robotics and artificial intelligence will become the main aristocrats behind these new and innovative technologies that will take agriculture out to space (Kamilaris & Prenafeta-Boldú, 2018; Liakos et al., 2018; Li et al., 2020).

Artificial Intelligence in Agriculture is poised to become the next revolution in agriculture which could further advance the agrarian roots cushioned in deep emerging technologies. AI refers to the simulation of human intelligence in machines that are programmed to think, learn and mimic human activities in attempt to tackle complex issues like unpredictability, adaptability, recognition and finally, global optimization. All of these challenges are quite common in most of the complexities faced in modern agriculture, be it pest-resilience in crops, climate-change and warming, security in food trade or resource constraints that drive agricultural laborers into poverty. AI has wide acceptance in agriculture, encompassing plant genomics to pest identification by computer vision and deep learning enhanced drones, non-intrusive analysis coupled with prediction sciences in trimester soil testing, precision farming using robotics and automation, crop monitoring using remote sensing and UAVs, climate monitoring and forecasting to geospatial mapping and machine learning for marketing and insurance (Zhang & Kovacs, 2012; Wolfert et al., 2017).

10.1.1. Significance of Artificial Intelligence in Modern Agriculture

Abstract: Artificial Intelligence comprises a group of technologies which have the capacity to perform functions usually attributed to human intelligence. With its rapid progress, especially in recent years, due to the increase of computational power and the availability of big data, it is being incorporated into a vast number of economic activities all over the globe. The agricultural sector is no exception. There are high expectations for the incorporation of AI into agricultural activities. Particularly important are its anticipated impact on mitigating climate change; increasing productivity, efficiency and safety; ensuring food security; and contributing to rural development and poverty alleviation. Introduction to AI in Agriculture: Artificial Intelligence refers to a set of technologies which have the capacity to perform functions which are usually attributed to human intelligence, such as analysis, planning and decision-making, among others. AI is based on a series of algorithms, models and neural networks, some of their functions focused on deep learning, supervised learning, reinforcement learning, transfer learning, monthly variable and point-variable functions. Taken together, these technologies make it possible to collect and process large quantities of data and learn from it. The agricultural sector is no exception to this trend. There are growing expectations for the incorporation of AI to undertake agricultural activities, as AI is seen to have a substantial impact in areas such as: support for the fight against climate change; increased productivity and efficiency; improvement in food security and rural development; in addressing the problems of poverty and hunger; as well as in ensuring the well-being and safety of producers and workers. This sector is characterized by its dependence on natural resources and its potential influence on climate change. Agriculture contributes about 15% of world greenhouse gas emissions through deforestation, as well as methane and nitrous oxide emissions, while being one of the most vulnerable sectors to the effects of climate change, such as extreme climatic events and increased economic losses.

10.2. Overview of Global Agricultural Challenges

Global agriculture must produce more food, feed, and fiber with fewer resources while sustaining the ecosystem. The four areas of primary concern are increasing food, feed, and fiber production as well as making it more nutritious and accessible to people; promoting high levels of resource use efficiency; conserving and enhancing the natural resource base; and increasing food, feed, and fiber productivity while reducing detrimental environmental externalities. Climate change is causing major disruptions in agriculture; populations are increasingly concentrated in urban areas, and this trend is expected to accelerate in the coming decades. In many countries around the world, efforts to relieve poverty by increasing access to food have resulted in only a temporary reduction in hunger. Furthermore, that reduction may be reversed as environmental conditions deteriorate. People who remain in poverty continue to rely heavily on agricultural resources; resources are being depleted faster than they can be renewed; and the growth and welfare of future generations are threatened. To compound the challenges of poverty alleviation, we must consider the rest of the world: As populations and income levels increase in the emerging economies, the demand for food, feed, and fiber is rising. These countries have the world's fastest-growing need for energy and are massing pressure on freshwater resources. Their agricultural, energy, and trade systems all are highly vulnerable to disruptions in weather patterns. For poorer consumers, all over the world, demand for an improved diet will exert added pressure on global agriculture.

10.2.1. Addressing Food Security and Sustainability Challenges

The outcome of global agrarian practices has a direct impact on food security and the attainment of sustainability goals. The expansion of the global economy over the past decades has raised living standards in many parts of the world, resulting in a sharper increase in income inequality, especially in rural developing areas where most of the poor and food insecure people live. It has been realized that lost progress in poverty reduction and a growing demand for food could lead to renewed pressure to increase agricultural production. With the global population projected to reach 9.7 billion by 2050 and 10.9 billion by 2100, the underlying demand for food will increase at a similar if not faster rate. Global demand for agricultural products is expected to rise by 70% in the next few decades. Across the world, there are 700 million people affected by hunger and poverty.

Intensification through the global expansion of farming systems over the 1960s-1990s initially led to an increase in agricultural productivity and food supply. However, the increasing pressures on agricultural systems, and upon natural resource and ecosystem functions, from pollution, biodiversity loss, and climate change now put at risk sustained increases in agricultural productivity, and increased supply would not be possible without concomitant environmental harm. To reverse this trend, there is a need to develop approaches that achieve productive and sustainable food systems without further jeopardizing the ecosystems that underpin agricultural productivity. The challenges of achieving increased agricultural productivity to support food security while reducing the negative impacts of agriculture on the environment, and thus contributing to achieving the SDGs for food security, poverty, and ecosystem health, have been referred to as a "triple challenge".

In addition to the provision of food for current and future generations, farms and farming systems play many other roles for the multitude of services they provide. The provision of food from farming is one of the main services of agriculture. To deliver on this service, farm output per unit of land must at least match growing demand for food. Agriculture also fulfills a collection of other services, alongside the more familiar food, fiber, and fuel roles that could be called the more hidden services of agriculture. These hidden services are vital for the well-being of communities as well as for some segments of the economy outside agriculture. This diversity of roles exposes agriculture to a multitude of challenges, thus creating the challenge for agricultural systems to deliver successful outcomes across that diverse range of roles.

10.3. AI Technologies Transforming Agriculture

AI is a branch of science that studies intelligent agents. It is a general-purpose technology which has applications in all fields of human endeavor and so is not limited to Agriculture. AI does not have intrinsic unique technological features even though its attributes emerge from the exploitation of more specialized underlying technologies. Nor is its closer cousin, Data Science. Rather, both provide common general scientific principles and shared technological concepts that can be used in a wide variety of different applications. In fact, the algorithms or solutions used by AI and Data Science are common they are often used by both disciplines. For both, it is the specific application of these solutions or algorithms that define the uniqueness of what is being studied or considered. However, in the case of Agriculture, it has specific features related to its biological based and outdoor used by plants and animals in their production and productivity that provide an additional layer of complexity and services.

Machine Learning is the most widely used approach to AI as it is concerned with the classification and quantification of Inputs of an intelligent system. Its main two sub divisions are Supervised Learning and Unsupervised Machine Learning. The former requires that the Input and Output vectors are known by the AI system being designed. Time series on crop production are examples of such data. The objective is to create a relationship between Inputs and Outputs. The later does not require such supervised information and attempts to group Inputs into clusters with rich internal relationships. In the case of Agriculture, it primarily provides unique or customized options that can be used to train a Supervised Machine Learning system. These options could involve field size, location of agricultural activity, crop and crop type at particular times of the year, and whether farming is conventional or organic among other variables considered important for specific activities like estimating crop yields and assessing crop responses to agronomic treatments.

10.3.1. Machine Learning in Crop Management

Machine learning tools available in the cloud have seen rapid adoption in agricultural production in recent years. Deep learning models can now detect leaf problems, weather forecasting, weed management, pest control, and irrigation scheduling management. Additional use-cases in plant pathology and phenotyping services for farmers and plant breeders/suppliers have also appeared. They are using AI for exact diagnosis (with some human intervention) around the world, including Asia and South America. Others provide plant disease predictive services, which could reduce the need for spraying fungicides. Some companies are combining machine learning, hyperspectral imaging, and weather data for disease prediction. Others are using multispectral imaging instead, in order to develop prediction models. Drones using multispectral imaging are also assessing plant nutrient deficiencies with an alternative proprietary image processing methodology.

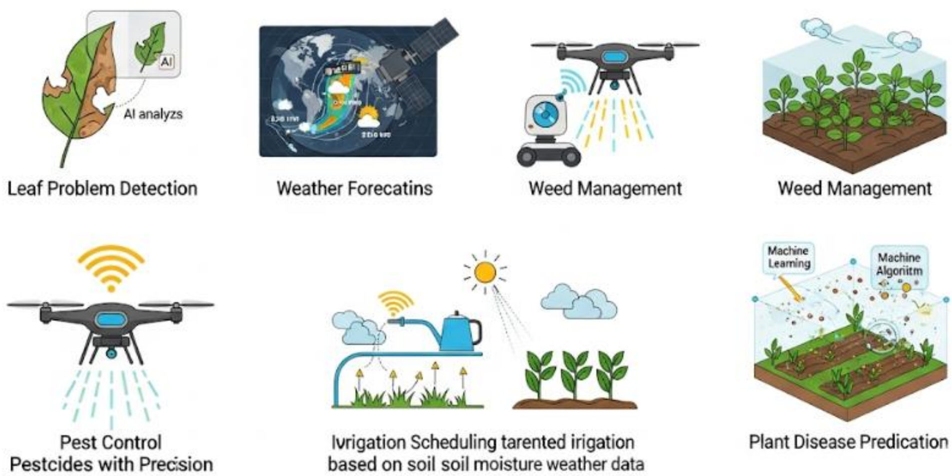

Fig 10 . 1 : Smart Agriculture with Machine Learning

In the area of weed management, data on weed density can now be collected by growers at low cost on hand-held devices, patched directly into machine learning prediction algorithms for weed density by species. This greatly increases the accuracy of predictive weed density maps based on limited historical data available from extension and weed scientists – tree map type algorithms for large datasets, and random forest regression of small datasets, and can be used to assess treatment options for grower field trials. For farmers with planting equipment equipped with weather stations and GPS modules, the SOC for their fields can also be directly fed from their planting input data into a service, which then provides mushroom prediction maps from random forest modeling of the weather-soil-plant input data.

10.3.2. Computer Vision for Pest Detection

The adoption of machine learning and Artificial Intelligence (AI) research methods has soared in the cotton industry over the last decade as major stakeholders, growers, and the public desire increases in crop yield. Cotton is a hard crop to grow that is vulnerable to damaging pests, and the traditional method of scouting cotton fields for pests is both tedious and not always timely. AI-powered vision systems that accurately and rapidly identify the presence of pests in fields make it possible to spray only those areas that have pest infestations. Automated pest detection leads to reduced pesticide costs and decreased environmental impact as reducing the amount of pesticide used conserves biological agents that help combat pests naturally. Pest detection combined with timely pesticide spraying at the right locations not only prevents damage to the cotton but also preempts the development of resistance to common pesticides. Other reported benefits include greater savings in costs incurred by a farm: a 25% reduction in pesticide expenditures, a decrease in pesticide applications where beneficial insects such as ladybugs and wasps are affected, and increased yields. These benefits have seen the worldwide commercial adoption of several vision systems since 2017, including a drop system for caterpillars, a system for in-season and post-harvest pest detection, and the first autonomous machine. The broad user base and ensuing results have led to investments in insecticide spraying mission automation. Other players have also developed pest-specific sensors to offer highly localized treatment by growers.

10.3.3. Drones and Aerial Imaging

Drones and the associated technology allow the agricultural sector to examine and process fields comparatively quickly and thoroughly, at a much lower cost than more traditional surveillance methods. Spraying pesticides and herbicides with drones, for example, reduces the amount of labor needed in comparison to performing that same task with a manned vehicle. Some drones are large enough to carry as much as 200 kg of water, pesticides, or other substances, and can travel as fast as 25 km per hour. In addition, drones can also be used to efficiently transport other small agricultural products, including the seedlings used for transplanting rice. Drones are well suited for rice transplanting in part because of the limited field areas where BMPs can be applied. The precise low altitude spraying allows for BMP pesticide application only on the current cultivated rice.

The costs of drone-supported agricultural activities are also significantly lower than satellite-supported methods. One example estimates the detection cost from satellite-based images and drone images of brown planthopper, a pest of rice, to be about USD 352.56 km2 and USD 15—25 km2, respectively. Note, however, that in the comparison of costs, one study on drone support applications assumed the drone would run eight flights per day for 90 days during a year. Traditional methods, such as scouting from the ground, are also more expensive than the drone-supported detection method. In the same study, the scouting method reported a cost of USD 99 for just two fields during a 20-day period, of which the majority (over 80%) was from scouting.

10.3.4. Robotics in Harvesting

Automation is a growing trend in agriculture that aims to take some of the burdens of labor from humans. Reports indicate that finding sufficient farm labor is becoming increasingly difficult, resulting in many farms not harvesting all of their mature crop. The advanced robotics technologies of today can be designed and programmed to assist with tasks that traditionally require a lot of human labor. There are many farm chores that could use help from robotic systems, including planting, spraying, and harvesting. Robotics has opened up the possibility of automating the harvesting of field crops such as potatoes, sugar beets, strawberries, apples, and wine grapes. Products developed have been proven useful in the harvesting of dull but laborious crops.

In academia, there are efforts to develop general robotic systems that could be programmed to work in many of the different controlled environments found in an agricultural setting. Take, for instance, two different robotic systems designed to harvest production strawberries, a tedious manual chore that requires many human workers and whose available labor supply is at risk. Work combined two years of effort, exercise, and design using a commercial robotic vehicle to implement a state-of-the-art strawberry-harvesting system. This helped create one of the first successful strawberry-harvesting robots. It is hoped that these advanced robotic technologies can be used in the agriculture sector to mitigate the depleting labor pool, keeping both costs to consumers at a reasonable price while helping farmers' bottom line. These products should be commercially available in the coming years.

10.4. Case Study: Precision Farming in the United States

Traditionally in the US, more than 80% of government subsidized funds for crop production farmers received was spent on irrigation support. However, over the last four decades, irrigation technologies have become prevalent among producers. As a response to this growing adoption of precision irrigation technologies as well as serious challenges in the form of increased demand for, and competition over, available freshwater supply, the Federal Crop Insurance Reform Act of 1996 set out to promote supplement insurance programs. These programs shifted their basic eligibility products from whole-farm insurance to area yield index insurance based upon the county-above average yield, less-than-average yield, and average yield as small percentages of average county corn yields. Before the 1996 Act, about 20% of the farmers in major corn-producing states had purchased area programs because both historic area yields and the expected yield of the area program were lower compared to the traditional crop insurance programs that a small percentage of producers purchased. However, since the Act was passed, increasing farmer curiosity about precision technologies has stimulated demand for area yield index insurance and its research. Currently, satellite remote sensing-based estimate of percent planted area and forecasting of yield distribution patterns are some of the most promising areas of research in precision agriculture, for both the private and public sectors.

Use of AI for Soil Health Monitoring. Precision agriculture has become a major focus area for various agricultural research departments and universities in developed as well as developing countries. Its potential use is being actively studied for soil monitoring, pest management, precision irrigation difference in crop health and productivity, nitrogen use efficiency, using robots, unmanned aerial vehicles, satellite remote sensing, sensors, big data, blockchain data structures, etc. AI is also being used extensively in soil health monitoring by many private firms.

10.4.1. Use of AI for Soil Health Monitoring

The movement towards sustainable aromatic rice production aims to conserve the environment while ensuring the profitability of farmers. Soil acts as an ecosystem, providing plants with vital nutrients, but modern agricultural and industrial practices have led to the depletion of micronutrients in soil and reduced micronutrient bioavailability. Farmers largely depend on chemical fertilizers to enhance soil fertility, but this has various negative consequences, including greenhouse gas emissions, depletion of soil microbial populations, and soil acidification. As a result, continuous monitoring of soil health is very important to avoid soil degradation. Conventional soil monitoring requires soil sampling from hundreds of locations, followed by laboratory testing, which is expensive and time-consuming, and cannot be performed with high-frequency temporal resolution. Thus, smart farming technology, with remote-sensing-based soil monitoring solutions combined with machine learning algorithms, to predict soil micronutrient availability can help farmers make better decisions and improve aromatic rice production.

Traditionally, soil and residue samples are taken and sent for chemical analysis in laboratories. This approach may take weeks, even months, before the results are available. Particularly in areas subjected to different agricultural treatments, monitoring residue decomposition and soil nutrient release at short time intervals is critical for successful crop production. However, predicting the instantaneous soil nitrogen and micronutrient content is difficult. Remote sensing techniques can provide a rapid assessment of soil nutrients and can be utilized in precision agriculture for site-specific nutrient management, crop health monitoring, and optimal harvest time prediction. Various reflectance-based approaches have been utilised for soil properties estimation, which includes soil organic matter and nitrogen, phosphorous and potassium nutrients utilization.

10.4.2. Yield Prediction Models

AI yield prediction models monitor changes in crop and soil conditions and input pixel images to machine learning algorithms. Results of visually estimating yield have been mixed because overhead view images of crops become available only a few weeks before the harvest; hence, determining whether the algorithms can predict crop yield accurately weeks earlier is difficult. The overhead visual imagery models are thus more applicable for researchers wanting to identify crop visual trends that can be used as key performance parameters for prime yield than for producers seeking a reliable prediction of yield variance across fields and over space and time.

Past estimates of variance in accurate agricultural yield prediction as well as the current ability to estimate variance even a day before harvest indicate that if satellite oversample frequency data can be visualized accurately for corn and soybeans on an hourly basis, the complex Potato Early Dying Disease Physiology can be tracked sufficiently to provide at least a week or two of lead time about predictions of low yields, short shelf life potato insect crisis or not harvest potatoes in proper season or not, and date of harvest. These month 1-3 early predictions are primarily due to knowledge of crop physiology. The optical window data can also be supported by radar data, if required, and such models are also applicable to primarily canopy making crops in countries other than the U.S., provided data or expertise can be acquired about specific market driven crop physiology.

10.5. Case Study: AI in Rice Production in India

Agriculture is a sector in need of immediate transformation in order to build a more sustainable and secure future. As various sectors have started adopting advanced technologies to drive efficiencies and innovation, agriculture too must look to technology as a key factor. Adoption of agriculture-specific technology will allow governments to track crop yield in real-time, help farmers assess damages during natural disasters, and undertake research in more resilient crop production. AI and other technologies present in the Fourth Industrial Revolution are set to transform the agricultural paradigm. With the advancement of data collection sensors, machine learning techniques, geo-spatial technology, and affordable digital devices, AI is now able to tackle challenges in different aspects of agriculture.

An intelligent rice crop management system was developed using machine learning techniques, satellite images for data sourcing, a mobile application for data inputs, and a decision support system for practical application. Data collection was executed through primary surveys and a secondary synthesis. Three use cases have been developed considering three machine-learning problems: irrigation scheduling, predicting diseases of rice and varietal identification through image-based deep learning classifiers. Use cases were developed through five machine learning methods. The objective of optimal yield with minimum resources used and to minimize losses is strived through use cases. Besides the use cases, the contributions of advanced technologies to Agribots and an artificial human-like brain for smart services are also discussed for futuristic perspective.

10.5.1. AI-Driven Irrigation Management

Irrigation management is a very essential agricultural practice for crop production. It is labor-intensive, time-consuming, and difficult to manage. A small mistake with the irrigation management, either deficient or excess water, leads to crop yield loss. Water is considered one of the essential factors in successful rice cultivation. Inappropriate irrigation can lead to excessive growth of foliage, delaying flowering, maturity periods, increase labor and production costs, and reduce yield and quality, especially when growth is delayed and maturity occurs during late summer or rainy seasons. In India, nearly 60–70% of rice is produced under irrigation conditions. Hence, it becomes important to predict irrigation scheduling to manage the crop yield. Accurate irrigation management is possible with the use of effective models.

In the current era of modern agriculture technology, Artificial Intelligence (AI)-based systems are being used to improve productivity and sustainability. The deep learning models are very effective for time series forecasting. The long short-term memory (LSTM) model is used to predict the irrigation scheduling as part of the crops' precision irrigation in the future scenarios using past estimates. The present investigation is planned to use the LSTM model for predicting day-wise irrigation scheduling for transplanting and direct seeded maize and rice crops. The data for prediction is taken from the available data sources. The output from the model is validated with the available observed data. The LSTM approach is novel compared with the existing models as it is an AI-based system.

10.5.2. Disease Prediction Systems

Rice productivity however suffers due to diseases, pest infestations, and the climatic changes causing quick onset of unpredictable epidemic conditions. Losses in yield can be significant and, in some cases, have increased to severe levels. Predictions of the occurrence of a disease long before the actual incidence will allow for preventive measures to be taken with timely availability of resources. The main advantage of prediction is that farmers can avoid crop loss by using pest management with small resources. The use of Expert System for prediction and decision support, Neural Network, and Bayesian model for disease prediction, and the use of simulation models and hybrid models for pest epidemic prediction have been discussed.

The Neural Network technology has been found to be very effective for pest and disease prediction as it is capable of making better prediction, detection, and diagnosis without being explicitly programmed. Computer-based Expert Systems have been designed for early identification of pests/disease and latest information on their control measures. Fuzzy Logic systems combined with Neural networks are being developed to accommodate uncertainties and non-linear relationships of factors affecting insect pests and disease prediction. Fuzzy and Bayesian Networks are used to represent the cybernetic pest prediction. Fuzzy Sets depict the uncertainties in a time series and Bayesian Networks model the causal relationship between parameters to build probabilistic inferences. The Association and Markov Model has been made for plant disease prediction.

Keeping these points in consideration, group of researchers utilized Artificial Intelligence Techniques for the prediction of blast disease, sheath blight disease, and black rice bug pest of rice crop. In this study, Disease-Pest-Climate-Soil-Crop-Nutrient-Water Quality-Remote Sensing Based Expert System have been developed for all the three diseases which are the state-of-the-art prediction models for blast disease, sheath blight disease, and black rice bug pest.

10.6. Case Study: AI Applications in Livestock Management

AI is transforming the field of livestock management and increasing its potential for improved economic and environmental outcomes. Although it is projected that plant-based food will comprise 70% of our diet in 2050, demands for meat, dairy, and animal-derived fibers are expected to rise. Future generations will rely heavily on the efficiency of livestock output per animal. A company has designed and developed an intelligent sensor collar that utilizes sensors to detect animals' movements using advanced AI algorithms. The collar is designed for easy use and aims to monitor animal behaviors 24/7. Changes in motion data are captured and reported. Anomaly detection is performed on accelerometer and gyroscope data to identify changes in routine grazing or resting behavior. The sensor collar helps farmers detect with a reliability of about 95% that cattle are sick, thus guiding treatment choices and reducing misdiagnosis and economic losses.

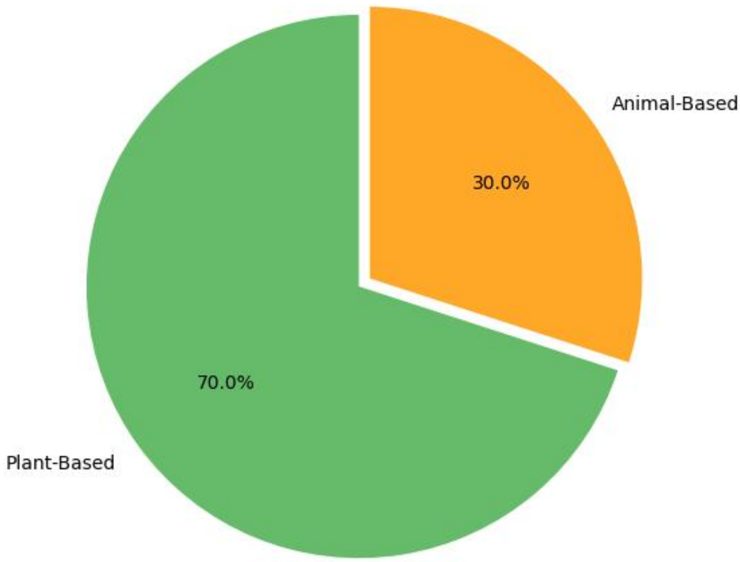

Fig 10 . 2 : Projected Diet Composition by 2050

In Indiana, researchers are using AI to allow cows to "eat smart." Designed to collect information on the nutritional value of what dairy cows eat, a system is capable of creating "detailed nutrient maps" of a herd's diet allowing farmers to optimize the herd's feed. Samples taken throughout the year are analyzed for vitamins, minerals, and other nutrients, which are then paired with data collected through the device. The researchers partnered with a dairy farm to finalize the device and look into methods to further optimize cow nutrition. So far, the system is able to identify nutrient variation, specifically for protein, phosphorus, potassium, and sodium. In addition, the information revealed nutrient variations throughout the year for potassium and phosphorus levels, allowing the researchers to take a closer look into lactose variations and what it means for feeding dairy herds year-round.

10.6.1. Health Monitoring with Wearable Tech

With 1.5 billion cattle worldwide, it's crucial to understand how to manage them sustainably, as they contribute an important quantity of methane to the greenhouse effect. The agricultural technology sector has been innovating in response to skyrocketing demand for meat alternatives and pressure for lower environmental impact. A zero-emissions airplane prototype has been developed which promises to operate at lower cost than traditional jets, and considering that flying contributes a big chunk of greenhouse gas emissions, they may well become the future standard.

The global market for precision livestock farming is growing rapidly, with established industry players and new ventures alike innovating in Internet-of-Things solutions that allow for livestock management at scale. Veterinarians' exams are costly due to labor costs and travel. Many harmful conditions can be detected by monitoring activity levels, sleep, or eating habits. Wearable tech capable of constant data collection reduces costs, permits high-frequency measurements, and alleviates reliance on human experts or farmers. A major downside to using wearables is their maintenance; farmers must keep track of collars and tags, replace them if broken, and ensure their adequacy to the animal. Animals may ingest collars or tags which may create health problems. Studies on the impact of wearables on behavioral change have been inconclusive; therefore, potential collateral effects must be carefully weighed.

Cattle are increasingly managed at scale, which makes individual attention infeasible. Cattle can be affected by bottleneck conditions, such as pneumonia or other pathogens that can spread through breath. Horse groups are again managed by well-identified individuals but large masses are also becoming common, with horse events welcoming thousands of horses from all over the world. Detecting and treating illnesses as soon as possible is crucial to ensuring low mortality and optimal productivity levels in animal groups. In such context, a data-collection system for detecting specific respiratory conditions at scale has the potential to be the key to managing such large quantities of animals and its solution is offered by a precise livestock industry.

10.6.2. Feed Optimization Algorithms

Feed optimization is a significant component of animal management that can be improved using wireless technologies. As livestock populations grow to meet demand, the quantity of nutrients required to ensure health will increase as well. This in turn exacerbates the existing tensions generated by limited ground space—and the land needed to produce the feed crops for livestock—and large methane emissions, which contribute to climate change. Feed accounting typically involves the long-term use of feed tables; however, these can be inaccurate for predicting nutrient requirements and intakes. Decision support systems can help make feeding decisions on-farm. There are many different types of nutrient optimization models, either simple or complex, deterministic or stochastic, mathematical programming, linear or nonlinear, spatial or temporal or simply based on expert knowledge. Researchers developed an interactive computerized decision support tool to help beef producers formulate rations for suckling beef calves. The system solves a linear programming model to minimize the cost of the ration while meeting animal nutrient requirements.

Rational feeding that reduces feed costs and methane production must also be accurate and simple to use. The software attempts to balance variability in animal weight and introduce a simple feed budgeting guideline to minimize the effects of unexpected variations in animal weight. The system can also consider diet that accounts for nutrient values from other than cereal grains; and additionally corrects nutrient concentrations of diets when rice straw is added, because the nutrient concentration from the estimated protein, fiber and fat shows highly negative correlation with rice straw addition level. The result shows that quality check should be incorporated into the feeding model. Using high-quality criteria of rice straw, additional roughage should not be incorporated in the high-quality production stage, but be calculated and allowed in other producing periods.

10.7. Conclusion

As we come to a close on this body of work detailing successful applications of artificial intelligence in global agricultural practices, we can draw several conclusions on the importance of these efforts. AI technologies are providing much-needed solutions for challenges that agriculture is facing. These challenges can vary and encompass such issues such as global food security, environmental sustainability, rising costs, global health crises, and reductions in the agricultural labor force. AI technologies can certainly provide unique and innovative solutions that can help alleviate many of the challenges. From the accurate management of farming equipment to the efficient application of pesticides and fertilizers, the providing of advisory services for farmers, skip-level management of crop and soil conditions, and providing insight details on the entire agricultural practice and production process, AI has proven to enhance various agricultural practices.

These case studies serve as a resource to other agricultural producers, service providers, and industry stakeholders in learning from others' lessons learned and key success factors in their AI implementation process, and will ideally allow them to create or expand upon their own agricultural digital transformations to achieve similar successful results. As the global agriculture landscape continues its transition into incorporating advanced technologies to support agricultural operations, we believe that an increased allocation of investment capital towards AI innovation in the agricultural space will aid in this transition, and the case studies included will ideally serve as an initial resource into this practice. Further, as the case study contents in this body of work merely detail a high-level overview of each respective project, we would also encourage collaboration among similar stakeholders involved in these innovative projects who may be willing to share details for the sake of collectively moving the industry and its challenges forward.

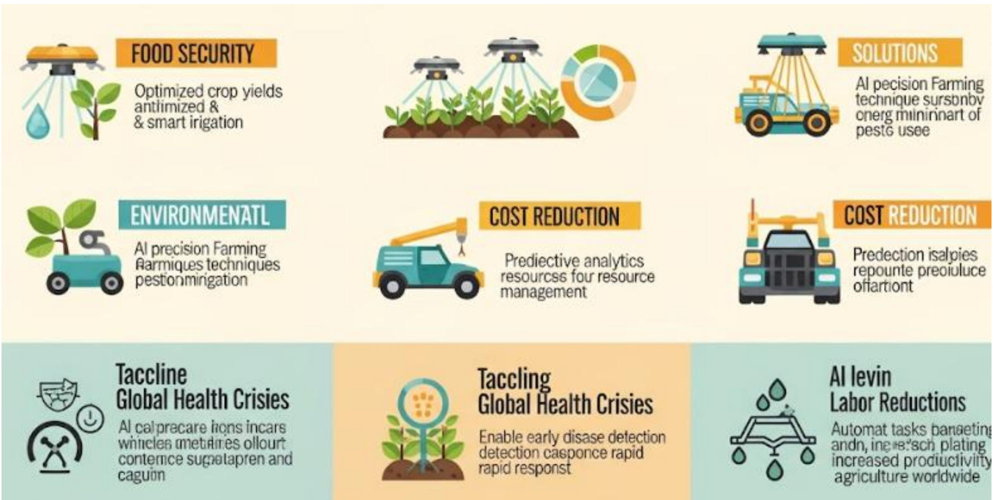

Fig 10 . 3 : AI Revolutionizing Agriculture

10.7.1. Summary and Future Directions for AI in Agriculture

Once neglected from modernization in a developing world, agriculture has come out to be the backbone for the survival of humans and their habitat with the integration of novel ideas and practical realization of scientific principles. Farmers' main concerns are to ensure food security by preventing the crop/plant diseases to ensure food security. Artificial Intelligence (AI), a remarkable computerised technology which facilitates machines that can learn from experience and simulate human intelligence processes such as learning, cognition and reasoning, is invited into agriculture to foster the industry at every stage. Of particular interest to many researchers, scientists and developers are dealing with the recognition of different leaf diseases of plants or their classification. Towards this, many review papers have been published, but these works fall short of comprehensively providing a synopsis of the state-of-the-art studies. Our work is devoted to a complete pipeline of insight and suggestion that may in turn facilitate the design of experimental research and furtherance in application in the wider field of AI in plant leaf disease detection. This work considered not only historic and contemporary research issues and directions but also imported contextuality by comparing plant leaf disease detection with other kinds of visual recognition research. The summary of our work includes a complete pipeline for the task of plant leaf disease detection in terms of the dataset and typical experimental setting, pre-processing, modelling, transfer-learning based, and post-processing, novel methodological research directions, and the methodological contextuality of the task. We hope that this work can become a useful guide to future experimental studies in the task and therefore help build AI in agriculture step by step. Although significant and fruitful growth has been witnessed in AI-based plant leaf disease detection, there exists urgent necessity for further advancement and commercialisation due to still existing notable limitations. In particular, the current achievements are limited to specific illnesses of specific plants.

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