Machine Learning in Agriculture: A Review of Farming & Fertilizer Methods

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***Abstract*—Agriculture 4.0 is characterized by the inlaying of advanced technologies like ML, data science, and IoT to improve agricultural yield, sustainability, and efficient resource utilization. Hence, ML can be applied on a large volume of agricultural data to analyse for yield prediction, efficient resource utilization, and evidence-based decision-making. IoT allows for real-time monitoring-interconnected devices like sensors, drones, and satellites that, in turn, allow for efficient management of farming processes. The paper discussed different applications of ML, data science, and IoT in agriculture, ranging from fertilizer application optimization and pest/disease detection to irrigation management and soil health monitoring. Farmers can, therefore, improve yields and minimize harm to the environment by making use of these technologies and, to some extent, contributing to solving global food challenges. The study further outlines emerging trends and challenges, and describes in detail how computational intelligence can be used to turn modern agriculture more resilient and sustainable.**

***Index Terms*—AI in Agriculture, Crop Yield Prediction, Fertilizer Management, Machine Learning in Agriculture.**

I. INTRODUCTION

This era of machine learning, data science, and IoT changes modern agriculture toward more solutions for efficiency, sustainability, and precision farming. With increasing world population and climate changes, these technologies are becoming the fertile ground for optimizing agricultural productivity.

Machine learning is that branch of Artificial Intelligence that allows to scan through large agricultural datasets-provides predictive insights within the decision-making process. Data science combined with machine learning is handling big data, and ML is useful in extracting valuable information from complex agricultural systems.

The usage of ML, data science, and IoT in the most sensitive areas of agriculture like optimized fertilizer application, pest and disease detection, irrigation management, and monitoring the health of the soil will be explained in this review paper. These technologies can help farmers optimize resources, increase yields, and diminish environmental effects. With ML algorithms and IoT devices to monitor soil moisture, fertilizer application is tailored to crop-specific needs, while irrigation is optimized.

Those applications in agriculture will also come into focus with regard to data analytics, computational capacity, and sensor technology. Other emerging trends in the area are included in the paper, which will focus on ML, data science, and IoT great capability to continue revolutionizing agriculture, for the development of more robust and sustainable farming cultures.

II. MOTIVATION OF RESEARCH

Agriculture today is facing the challenge of feeding the rapidly growing population while managing limited resources and adapting to climate change. Traditional farming methods are not sufficient to meet the demands of growing population. Machine learning (ML), data science, and the Internet of Things (IoT) provides solutions by using precise, data-driven agricultural practices. These technologies can analyse vast datasets from sources like soil sensors and satellite images, pest and disease detection, irrigation management, and soil health monitoring.

The motivation for this research is to explore how ML, data science, and IoT can be used to revolutionize farming by making them more efficient and sustainable. By reviewing this current technology and identifying future trends this paper aims to

contribute to the development of smarter agricultural practices to address global food security

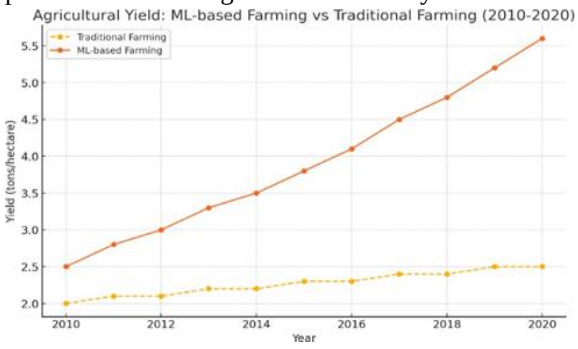

Fig 1- production of crops traditional methods v/s using ML

I. Contribution of Research

This research contributes on the following aspects:

- Machine Learning for Agriculture - A detailed review on the role of ML in crop yield prediction and

optimization; it pinpoints its importance in precision agriculture and resource management.

- Application and Limitations - Extensive discussion on various applications of ML, from fertilizer optimization to pest detection, keeping in view the limitations and further areas of research.
- Technology Integration - How ML, IoT, and Data Science integrate into robust agricultural management systems, with a focus on real-time monitoring,

decision-making, and automation.

- Future Trends - It is in this connection that the paper spells out the emerging trends in the technology of agriculture and discusses the future of those innovations with a view to addressing the challenges that are confronting food security and sustainability.

II. LITRATURE REVIEW

I. Machine Learning for Precision Agriculture

Precision agriculture is what some people call it digital or intelligent farming, which has largely been enhanced to date by the embedment of such advanced technologies as the IoT and ML. Precision agriculture refers to the practice of increasing productivity and sustainability of agriculture by bringing contemporary techniques and methods into traditional farming. IoT has become a cornerstone for that approach through which the automation of data gathering and analysis may be allowed to improve many aspects of farming, ranging from monitoring crops to the detection of diseases and proper use of resources. With this technology, extreme data is acquired on soil characteristics, crop conditions, and weather that enables evidence-based decision-making and planning on issues related to bio-security, farm management, and land-use patterns.[1]

Machine learning plays the vital role in the analysis of agricultural data, which are usually imbalanced, sparse, and noisy. There has been a significant amount of research concerning ML applications to the management of crops, water, and soil; yet, there is a lack of consensus on best practices, and only limited attention has been paid so far to model trustworthiness. Most of the existing works focus solely on accuracy while overlooking interpretability and trustworthiness, two key drivers for the adoption of ML technologies in agriculture.[2]

One of the more exciting studies combined state-of-the-art ML algorithms with new dual methodologies on plant development patterns. The objectives here explore which actual musical frequencies between 1 and 10 kHz have an influence on such plant growth. Ideally, the integration of ancient and modern approaches

will provide new insight into the dynamics of plants and advance precision agriculture. The three major plant species involved in the study are cowpea, cotton, and pigeon pea-all for their agricultural importance. In this research, support vector machines and artificial neural networks were applied to enhance the prediction accuracy, and SVM reached an accuracy of up to 92.10%, performing better than ANN. The aim of this research was to contribute to sustainable agriculture by fusion of traditional farming methods along with modern technologies and also showed the potential of SVM in redefining precision farming. Although varied, the combination of reviewed methodologies underlines the dynamic nature of precision agriculture in developing its contributions to address challenges in global agriculture. Such a wide approach ensures further steps in understanding plant growth and contributes to developing more effective and sustainable agricultural methods of management.

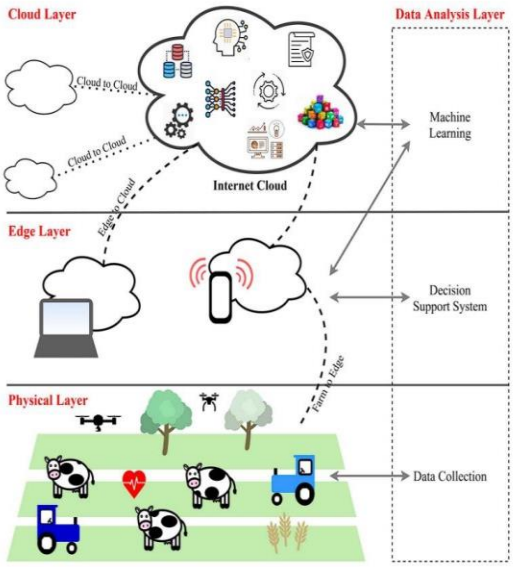

Fig 2 - The Precision Agriculture Ecosystem.

II. Fertilizer Application Optimization

Fertilizers are crucial for agricultural production. Fertilizers are widely used because they provide essential nutrients effectively. However, fertilizers are based on exhaustible resources: natural gas, phosphate rock, and potash. They contribute to global warming and degradation of the environment. Overuse of fertilizers like these also lead to nutrient loss in the soil, eutrophication, among many other environmental problems. Europe imports nutrients for its agriculture, which epitomizes some of the issues with mineral fertilizers. However, bio-based fertilizers promise an alternative source of useful nutrients from biomass and agricultural waste through composting, anaerobic digestion, and production of biochar. But if bio-based fertilizers are to become more widely used, then their cost must come down to that of mineral fertilizers. The complete change could be initiated only by a thought of farmers, who require financial support in the form of subsidies or taxes on mineral fertilizers.[3]

In Northeastern China, rice cultivation in black soil regions has rapidly increased since the conditions are ideal. However, the inferior irrigation techniques and improper rainfall have resulted in the utilization of over 90% of farmland water by the rice fields. Additionally, the application of excessive fertilizers in these regions exceeds the international safety limits, resulting in greenhouse gas emissions and soil degradation. Using biochar, along with good irrigation and fertilization methods, offers a hopeful answer to these problems. Biochar is highly carbonaceous, with a sponge-like structure, which improves the quality of the soil and reduces greenhouse gas emissions, improving crop yields and water use efficiency.

Traditional experimental designs, such as orthogonal tests, have been utilized for the optimization of a mix represented by water, fertilizer, and biochar. However, it is difficult for such methods to handle complexity and changes in agricultural systems. The RAGA model has cropped up to deal with a complex and nonlinear problem arising in agriculture. The RAGA model is applied in field experiments as an efficient regressor within multiobjective formulations. The best mixes of water, fertilizer, and biochar are estimated to be able to achieve higher yields with reduced water losses and lower emissions. Therefore, this methodology will be useful for growing rice in cold regions with high productivity, reducing environmental damage.[4]

III. Pest and diseases Detection

Diseases and pests are enemies of the plants, since they can interrupt the function of the plant and probably may cause its death. They are natural parts, and these problems affect the plant at each stage of development starting from seed production, to seedling and mature plant growth. From the point of view of machine vision, there are no mathematically defined diseases or pests of plants but are derived from human experience and sight-classification, localization, and segmentation. First is classification, which is determining what disease or pest is in an image. Which is like grouping the problem by its outward appearance.[6] The next step is localization, where the program detects precisely in the picture where the disease or a pest is. This is the most important stage since this is where the problem is actually determined, usually by boxing out the infected area. At an even finer level of detail, the final stage is segmentation. It consists of all that tedious work of isolating the diseased or pest- infested sections of the picture, pixel by pixel. That makes it easy to measure and analyse, such as how big that is, its area, how bad the damage is. All three phases are related, since one leads to another. For instance, localization is a kind of classification, and segmentation is a kind of localization. So, despite the

fact that each stage has its very unique function, they all work in concert to achieve an ultimate objective: the diagnosis and appraisal ofdiseases and pests of plants.[7]

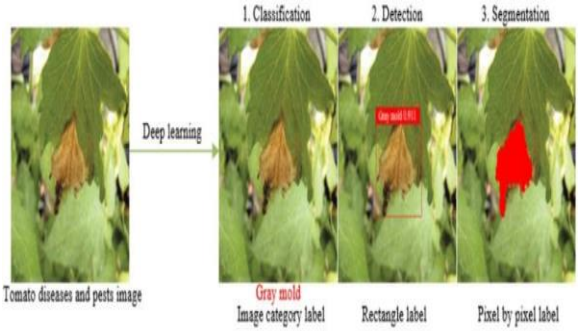

Fig 3 - Agricultural Plant Diseases Identification

IV. Irrigation management

Irrigation management deals with water use efficiency as a means of attaining certain goals, which include saving money, conserving water, and increasing crop production, among other factors. To achieve this, there is an urgent need to study and evaluate various irrigation systems to meet these needs. There are three major types of irrigation systems: sprinkler, surface, and micro-irrigation, each with advantages and disadvantages, pending the type of crops, terrain, and water availability.

These include single sprinkler, solid-set, and moved lateral sprinkler irrigation systems. Single-sprinkler systems irrigate an area with a single sprinkler, which may be moved manually or automatically. These systems are relatively easy to install, and once installed, they can serve irregular areas; however, improper positioning leads to the unnecessary loss of water. In solid-set systems, sprinklers.[8]

Surface irrigation This includes basin, border and furrow irrigation. Basin and border systems are used where the area is divided into sections and then thoroughly waterlogged; this system is ready to go for flat or gently sloping lands. These systems are of lower cost but do require good management to prevent wastage of water. Furrow irrigation supplies water via a series of small grooves that supply water throughout the field between rows of crops. This is, however, a simple and low-cost method, whereas uniformity can be poor if it is not closely monitored. Surface irrigation has problems like runoff, labour-intensive operations, and the possibility of non-uniform application.[8]

Micro-irrigation systems include drip irrigation, micro-sprinklers, and subsurface drip irrigation (SDI). Drip irrigation supplies water directly to the plant roots through small tubes and dramatically cuts down on water usage and evaporation, though it is quite costly in terms of investment and maintenance. Micro-sprinklers irrigate only a small area-one tree, one bush-hence are very appropriate for gardens and other high-value crops. However, these usually need constant maintenance because of the susceptibility to clogging. SDI keeps drip lines underground, sheltered from injury,

and delivers water directly to the roots. While highly effective, SDI is very expensive to install.

V. Soil Health Monitoring

In this regard, soil health is being debated as a base for successfully implementing ecosystem restoration and furthering sustainability pursuits. It does not pertain to agricultural productivity alone but plays a critical role in maintaining ecological balance on the whole. The review highlights the role of various biological indicators for monitoring soil, which includes microbial biomass, enzyme activities, soil organic matter, and earthworm populations.[9]

Key messages coming out of this review emphasized that there was an intrinsic linkage between soil health and functioning to a range of essential ecosystem functions. In sum, prudent monitoring of these indicators in order to improve soil quality will not only enhance biodiversity and increase retention capacity but, more importantly, carbon sequestration-parameters germane to sustaining the environment. It means that an integrated approach, for instance, will ensure that such restoration of soils is effective and contributes to long-term environmental sustainability through the development of resistant and healthy ecosystems.[10]

To this end, the review finds a growing need for new methods of real-time monitoring of soil health facilitated by recent technological advances in conjunction with data analytics. This will be important in trying to mitigate the huge challenges involved in the variation of climate change but also ensuring that this process of soil restoration is kept effective even within a none-too-predictable environment. In a nutshell, the review calls for an approach to monitoring soil health that is proactive and adaptive-in fact, one that will continue to evolve

with the demands placed upon it by sustainable ecosystem management.

VI. Future Trends in Machine Learning for Agriculture

Very soon, ML in agriculture could experience transformative developments with emerging technologies and the ever-growing need for sustainability. Another point at which the trend will converge is with the Internet of Things: sensors implanted in fields, machinery, and even the environment gather real-time data. That would facilitate more precise farming based on information at regular time intervals in detail about crop health, soil conditions, and weather patterns, hence making the process of decision-making highly responsive and automated.

With edge computing, this complements the IoT, as the data will be processed locally on the farms. This reduces latency and thus provides faster and more efficient ML applications. That, too, is very valuable for real-time tasks like irrigation management or pest control.[11]

Deep learning and computer vision will continue to move forward in order to achieve better accuracy of crop monitoring, disease detection, and yield prediction even at variable conditions.

Lastly, ML will again play a leading role in climate-resilient agriculture development, resource-use optimization, and enhancing sustainability for agriculture to meet food security challenges across the globe with environmental consciousness.

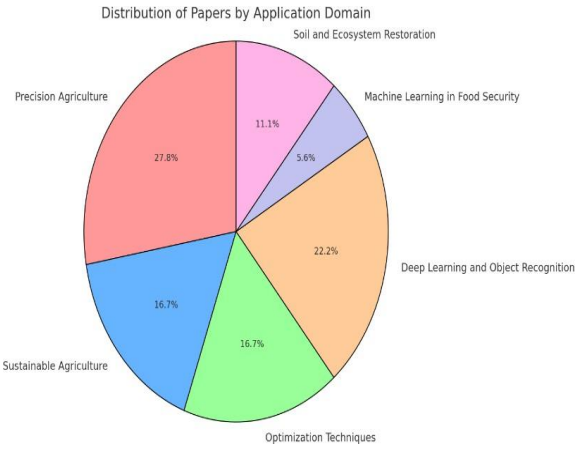

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Fig 4 - Pie chart presenting the papers according tothe application domains

III. METHODOLOGY

I. Machine Learning Applications In Agriculture

Machine learning transforms agriculture into wiser and more efficient farming. The most significant use of ML also lies in precision agriculture, wherein data gathered from sensors, satellites, and drones improve crop management. The ML algorithms analyse environmental and crop data and make recommendations on irrigation, fertilization, and pest control in real time, thereby increasing yield and reducing the use of resources.

Another important application is crop health monitoring. It involves the processing of images taken from drones and satellites using ML models, which detect the early signs of disease, pests, or nutrient deficiencies in crops. These models are also able to identify problems that can be well ahead of human- eye visibility, enabling their early treatment and reducing crop loss.[12]

On yield prediction, ML uses analysis of historic data on weather patterns and current conditions to make a forecast about crop productivity. This helps farmers prepare for harvest accordingly and use their resources in an efficient manner.

Soil health management is another area where ML performs extremely well. By analysing data on soil, the ML models can deduce nutrient levels of the same and do targeted treatments, helping improve soil fertility and reduce the overuse of fertilizers and pesticides.[13]

These ML applications have been helping farmers conserve on resources while enhancing efficiency with the use of environmentally friendly methods. While ML technology will continue to evolve, its implementation in agriculture will also do so, therefore paving the way toward a more resilient and productive farming future.

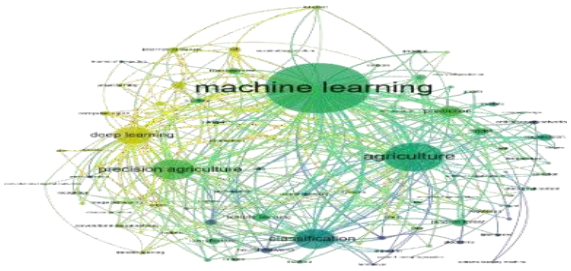

Fig 5 - Machine Learning in Agriculture

II. Data science

Data science further revolutionizes agriculture by enabling data- influenced decision-making and optimization in farming. Included among its major applications is precision farming, where such tools analyse the surrounding environment in terms of soil composition, weather conditions, and health of crops to make decisions on farming. By applying machine learning models and predictive analytics, farmers can receive real-time recommendations on irrigation, fertilization, and pest control to improve crop yield and reduce the loss of resources.

Crop monitoring is yet another area in which data science does excel. The processing of data from satellite imagery, drones, and sensors through algorithms allows for early detection of stress in crops, diseases, and nutrient deficiencies. Therefore, farmers can take interventions pretty on time, preventing any potential loss and allowing for better optimization of field management.[14] Overall, data science applications in agriculture promote efficiency, sustainability, and profitability. Moving ahead, with uninterrupted advancement in technological aspects, data science is bound to remain an instrumental intervention to attain the challenges of modern agriculture and improve global food security.[15]

III. IOT (Internet Of Things)

IoT promotes global connectivity which provide ease of sense, share and communicate over worldwide. This important to know how this impacts on Pakistan. Pakistan underdeveloped country and having very dense areas where IoT cannot work more efficiently due to harsh and remote regions i-e Hilly, desert or mountainous regions where connectivity with internet is very difficult. IoT sensing devices can sense temperature, steam in mining area where most of the critical condition is faced on regular basis. Agriculture industry now has been smarter than ever before due to advance development of technology. This technology has greater impacts in crop production with several new tools and techniques. In agricultural technology many new advanced technology concepts are introduced. The water control and saving water drip irrigation is introduced for irrigation management. Another concept of smart farming with several

implementation of latest equipment in the region is also arise deep interest in agriculture industry. The major part of technology includes IoT enabling devise, WSN, RFID which brought advanced sensing devices for senses data even minor variations in respective applications. Sensing devices itself are just for sensing where further it needed to be process and analyses for experimentation. Crop management is broad area which is used to produce crop yield with effective monitoring. The cost of monitoring and reduction of operational costs can efficiently manage by IoT enabled devices. Precision agriculture depends on different factors such as soil properties, irrigation management, environmental changes and nitrogenous fertilizers management.[16] Sensing technology gives effectively acquisition of spectral data can improve data accuracy (Patrício & Rieder, 2018). Remote sensing and spatial variations in water, soil and environmental condition can be improved via applying air born It is due to accurate and timely input data is needed to measure over remote regions from different regions of crop.[17]

IV. RESULT

The graph is the number of various models of machine learning that have been cited throughout different papers of research concerning precision agriculture. Deep Learning is the most frequent use model and found in five papers, giving a proof for its important usage in modern agricultural research for predictive modelling, crop growth analysis, and plant disease detection. Convolutional Neural Networks were also very widely used, being applied in three works, most of which had to deal with image recognition tasks, such as the detection of plant disease. Other models are mentioned less often: Predictive Models, Neural Networks, and General Surveys, appearing in 2 or fewer articles. It only applies in niche applications like Decision Trees, SVMs, and specific algorithms such as RAGA. But in those niches, it does prove the relevance of such models in specific scenarios within precision agriculture.

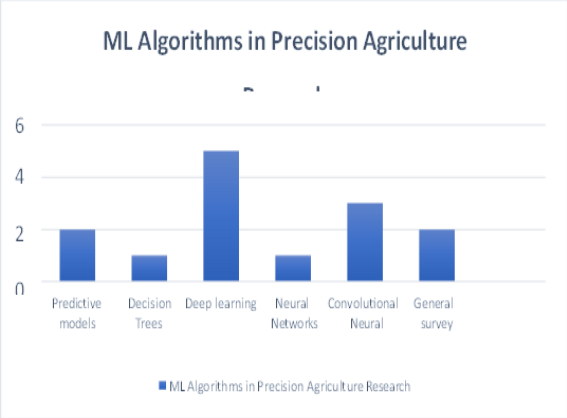

Fig 6 - ML Algorithms in Precision Agriculture Research

Application graph Although the areas of application for these machine learning models are many, the application graph identifies particular differences in the areas of application. In
particular, primarily predictive tasks, optimizations in respect to resource allocation (water and fertilizers), and improvements in the efficiency of real-time agricultural data processing systems are carried out by these models. Deep Learning and CNNs are mostly used in the application domain of images to perform disease detection and segmentation, and Optimization Models and real-time data systems are focused on selecting better agricultural practices using data.

These results show that, although Deep Learning dominates the machine learning landscape of precision agriculture, other models are used for the precisely targeted applications.

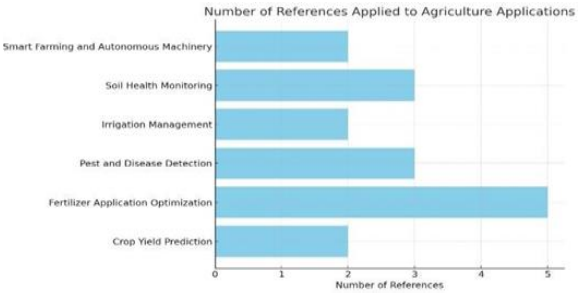

Fig 7 - Applications of ML Algorithms in Precision Agriculture

V. CONCLUSION

ML, data science, and IoT are transforming agriculture through efficiency, data-driven approaches, and ecologically friendly models for high productivity with minimal impacts on the environment. These technologies optimize the main practices of fertilizer application, disease diagnosis, irrigation, and soil health, which improve productivity while minimizing impacts on the environment. Data in real time and predictive models are critical in food security and resource depletion. Although challenges remain with data quality and cost, advances in computational power, sensors, and ML will drive further efficiency and sustainability. The future edge computing and deep learning innovations will more strongly enhance agricultural production in feeding a larger population under a constantly changing climate condition.

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