Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 4, Issue 2, 2026

MACHINE LEARNING AND DEEP LEARNING FOR SUSTAINABLE AGRICULTURE

Muhammad Tayyab[*1], Hammad Ahmad[2], Muhammad Khan[3], Hasnain Kashif[4]

[*1,2,3,4]*Dept, School of Engineering (SEN), University of Management and Technology, Lahore, Pakistan*

[1]f22022019018@umt.edu.p,[2]f2022019012@umt.edu.p,[3]f2022019025@umt.edu.pk,
[4]hasnain.kashif@umt.edu.pk

DOI: https://doi.org/10.5281/zenodo.18608078

Keywords
Machine Learning; Deep Learning; Sustainable Agriculture; Precision Farming;IoT.

Article History
Received: 10 December 2025
Accepted: 25 January 2026
Published: 11 February 2026

Corresponding Author: *
Muhammad Tayyab

Abstract
Recent digitalization has included increasing elements of artificial intelligence and Machine Learning into agriculture and Deep Learning to address the challenges brought about by population growth, Cli- mate change (CC) and Resource Limitation (RL). The present study comprehensively deals with the areas of potential applications of AI techniques. The innovations range from upstream to downstream in agricultural production, with an emphasis on those that conform to Climate-smart (CS) agricultural practices. A review of research articles was carried out, with the Application of Machine Learning and Deep Learning in crop selection, monitoring and land management, water, soil and nutrient malabsorp- tion, management, weed control, harvest and post-harvest practices, managing pests and insects, and soil management. The results highlight that ML and DL enable the analysis of complicated datasets, thereby informing data-driven decision-making, reducing dependence on subjective expertise, and enhancing farm management strategies. Machine Learning and Deep Learning also offer immense opportunities in increasing agriculture productivity, sustainability, and resilience. By highlighting data-driven insights and embracing innovative technologies, the agricultural sector can transition toward more efficient, environmentally sustainable, and economically feasible approaches to farming to contribute towards food globally.

1 Introduction
Sustainable agriculture is vital for a variety of reasons such as increased food and energy prices, climate change, continuing exhaustion and depletion of natural resources, an unprecedented reduction in freshwa- ter availability, and the projected increase in population [1–5]. Agriculture is vital for food security and economic prosperity globally, constituting 6.4% of the total GDP and serving as a significant livelihood source for millions globally [6]. The United Nations' Food and Agriculture Organization (FAO) projects a 70% surge in worldwide food demand by 2050, because of population growth and changing consumption patterns related to increased incomes in many nations [7,8]. These changes in demand exert enormous pressure on the food systems. Despite surpluses in global food production, widespread malnutrition is thought to affect 500 million people, while over 821 million people suffer from hunger. Urbanization trends show that two-thirds of the population will live in urban areas, with a large increase projected in several regions [9,11]. This shift in demographics, along with an approximate 473 million people who are expected to enter the middle class in India and Nigeria, is a challenge to the fulfillment of Sustainable Development Goals (SDGs), specifically the elimination of hunger, by 2030. Meeting 40% of the water demand may be a challenge, with a further 20% of agricultural land that may be degraded [12].Taking into

consideration the impending resource constraints, farmers are encouraged to practice sustainability to increase productivity [13]. Mainly because of increased yields, advanced technologies are required to satisfy the worldwide population's expected demands by 2050 [14,15]. However, the feasibility of achiev- ing these objectives in an environmentally sustainable and socially equitable approach remains uncertain [10,12].

Table 1: Abbreviations and their full forms.

Abbreviation	full forms
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
CC	Climate Change
FAO	Food and Agriculture Organization
SDGs ANNs	Sustainable Development Goals ANN / Artificial Neural Network(s) RF Random Forest
DTs	Decision Trees
SVM	Support Vector Machine
KNN	k-Nearest Neighbors
GAN	Generative Adversarial Networks
CNN	Convolutional Neural Networks
RNN	Recurrent Neural Networks
DNN	Deep Neural Network
LSTM	Long- Short Term Memory
IoT	Internet of Things

Agri-technology and precision farming, now encompassed under digital agriculture, have emerged as innovative scientific disciplines leveraging data-concentrated methodologies to enhance agricultural effi- ciency while mitigating environmental influence [17,18]. The modern agriculture landscape uses many sensors to generate data, offering insights into dynamic interactions between crops, soil, weather condi- tions, and machinery performance. This Big Data enables more informed and expedited decision-making processes [19]. The integration of computers into agriculture was documented in 1983 [20]. Since then, a number of approaches, from Decision Support Systems and databases, have been used to cope with agri- cultural problems. Over the past decade, Artificial Intelligence (AI), Deep Learning (DL), encompassing Machine Learning (ML) have been developed [21]. Using High Performance Computing and Big Data technologies, ML and DL have led to a revolution in the analysis of agricultural environments. ML is described as the scientific discipline that makes it possible for machines to learn without explicit program- ming [22].In agriculture, ML and DL have a lot of promise for solving complicated processes, measuring tendencies, and recognizing complicated relationships within an operating environment [19]. ML models are divided into four categories: supervised learning [23], Unsupervised learning [24], Semi-supervised learning [25], and Reinforcement learning [26].

2 Materials and Methods

The structure consists of four basic phases, which are identification, where the studies are carried out; screening, used to eliminate irrelevant literature; eligibility, which includes assessment; and inclusion, which is used to complete the choice of studies to analyze as given in Figure 1 . This structured process promotes the credibility levels of the review, ensuring full coverage within the research domain.

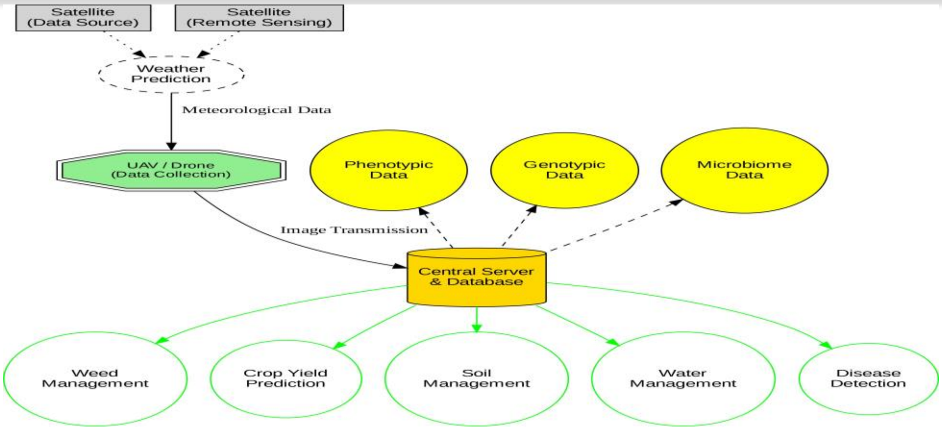

Figure 1: PRISMA Flow Diagram Methodology

Agriculture Land is a critical resource for food production, environment, andregulation . The assess- ment includes evaluation of soil, topography,climate, and other factors to match land properties with crop needs This models are capable of handling a vast amount of data, result in a remarkably high degree ofvul- nerabilities [14].. ML is used to tackle nonlinear problemswith varied data sets, making decisions better and minimizing dependence on user knowledge. DL takes these applications further by"transforming data sets with hierarchical data modeling, automating feature description, ensuring increased accuracy with classificationanalysis.The sustainability and resilience of modern agriculture are fundamentally dependent upon ML and DL models, serving as a predictive control system for crop selection that is informed not by generalized data but rather by vast, heterogeneous datasets ranging from site-specific soil characteristics and hyperlocal climate forecasts to historical yield data and even global market prices. Deep Learning architectures, including RNNs and CNNs, have been invaluable in processing complex inputs such as time- series climate predictions and geospatial imagery in the form of NDVI maps, which identify nonlinear patterns indicative of risk and opportunity. This level of precision control lowers risk by recommending the most resilient crop variety types appropriate to the particular farm environment, directly influencing resource use efficiency, such as irrigation and fertilizer application. The ML/DL pairing serves to ensure ahead of planting that the crop selection decision is optimized for yield, farmer income stabilization, and a drastic reduction of the operational footprint, thus driving genuine green technology adoption in farm- ing.Machine Learning (ML)/Deep Learning (DL) segues as the necessary control system for optimizing soil management, thereby transforming agricultural practices from generalized resource inputs to hyper- localized precision farming. This control is enabled via the merging of massive, disparate data inputs such as IoT soil sensors (for moisture, pH, nutrients), topographic maps, and high-resolution satellite imagery, which is modeled via Random Forest Regressors and Artificial Neural Networks (ANNs). The result is the highly precise prediction of exact nutrient and water requirements for each small area of farmland, thereby allowing control for fertilizer application only when necessary, thus significantly minimizing fer- tilizer runoff, precluding the pollution of waterways (eutrophication), and minimizing the energy profile of agriculture. Machine learning and deep learning are part of the critical control system in modern crop nutrient management, enabling the shift from expensive, uniform application to highly sustainable variable rate technology. This intelligence enables the fusing of large, complex datasets comprising real- time soil nutrient readings, such as from IoT sensors, multispectral satellite and drone imagery on plant health and hyperlocal weather forecasts, which are analyzed by algorithms such as Random Forest Re- gressors and ANNs. Models can thus predict site-specific nutrient demand at every point in the field and at different growth stages, serving as prescription maps for automated machinery. Precise and efficient control mechanisms are central to sustainability. It achieves up to savings in fertilizer and drastically cuts environmentally destructive nitrogen runoff into waterways reduces input costs, boosts and mini- mizes the environmental footprint of global food production Additionally, the strength of the predictive control system of ML/DL is used within crop yield prediction, which is fundamental for economic sus- tainability and worldwide food safety. The ML/DL predictive model is extremely useful for studying complicated temporal (time-series) data sets such as past crop yields, weather changes, soil conditions, even the genetic makeup of the crop used, with RNNs/LSTM models proving particularly adept at such tasks. Through the continuous learning of the complicated, non-linear relationship existing within a set of diverse inputs used to produce a certain desired result, the control system is capable of making highly accurate, real-time crop yield predictions. This predictive advantage gives the farming community highly valuable, real-time control inputs, such as irrigation, critical mid-season nutrient spurts, even optimized harvest delivery systems, which significantly reduces crop waste while ensuring maximization of resource utilization, thus ensuring agricultural profitability as well as commodity chain efficiencies.ML and DL are increasingly making Pest and Disease Management a highly effective and sustainable control system, which replaces broad-spectrum, scheduled chemical treatments with targeted, early intervention. This is primarily driven by models of Deep Learning, particularly Convolutional Neural Networks, analyzing huge amounts of visual data in the forms of high-resolution images from drones, fixed field cameras, and smartphone applications to make real-time image classification and object detection of pathogens, pests, and the subtle visual symptoms they cause on foliage. This advanced control capability lets the system identify not only what the threat is, but precisely where it is, very often detecting outbreaks in their nascent stages days or weeks before a human scout could. The resultant output is a prescription map, feeding autonomous robotic sprayers or targeted applications, reducing pesticide and fungicide use, in some cases up to 90. Such a huge reduction minimizes the development of chemical resistance and pro- tects useful insects, like pollinators, and ecosystem health while considerably lowering the environmental footprint of crop protection.

3 Literature Review

The following table summarizes the key research findings from the reviewed studies (2023–2025).

Table 2: Summary of literature review on ML and DL applications in agriculture.

No.	Reference Study	Domain	Model	Key Findings
1	Li et al. (2023) [31]	Land Quality	RF & DNN	RF outperformed DNN for land quality assessment.
2	Azadnia (2022) [32]	Soil Mgmt	CNN	High accuracy soil texture classification via mobile.
3	Singh et al. (2022) [33]	Land Monitoring	U-Net & RF	Superior performance in mapping land usage types.
4	Sarma et al. (2022) [34]	Disease Mgmt	VGG16 (CNN)	Effective disease detection integrated with IoT.
5	El Hoummaidi (2021)	Land Mapping	UAV + DL	Precise vegetation mapping in arid environments.
6	Ma et al. (2021) [35]	Yield Prediction	LSTM	93.77% accuracy in early-season crop mapping.
7	Koul (2021)	Crop Selection	ML/DL	Optimized crop recommendations based on soil health.
8	Hüppi et al. (2020) [36]	Yield Prediction	RF	Successful regional yield forecasting across Europe.

Table 2 – *Continued from previous page*

No.	Reference Study	Domain	Model	Key Findings
9	Vogel et al. (2019) [37]	Soil Health	RF & SVM	Predicted tillage status using microbiome data.
10	Osorio et al. (2020) [38]	Weed Control	YOLOv3	Targeted weed spraying through visual identification.
11	Yu et al. (2019) [39]	Weed Detection	Deep CNN	Effectively identified specific weeds in turfgrass.
12	Hussain et al. (2020)	Weed Detection	SVM, KNN	Proved the efficacy of ML for precision weeding.
13	Wu et al. (2019) [40]	Weed Coverage	Mask R-CNN	Precision estimation of lettuce weed coverage.
14	Zhu et al. (2018) [41]	Smart Agriculture	Deep Learning	Evaluated real-time classification for target detection.
15	Arad et al. (2020) [42]	Pest Mgmt	ANN, SVM	Detected insect pests in corn and wheat crops.
16	Li et al. (2021) [43]	Pest Mgmt	CNN	Improved results using data augmentation techniques.
17	Zhu et al. (2021) [44]	Disease Mgmt	VGG-19	98.7% accuracy for potato/sugar beet diseases.
18	Abbas et al. (2021) [45]	Disease Mgmt	DenseNet	99.75% accuracy in multi-crop disease detection.
19	Melesse (2022) [46]	Post-Harvest	Digital Twin	Monitored fruit quality evolution and shelf-life.
20	Ashtiani (2021) [47]	Post-Harvest	DL Models	Detected mulberry ripeness stages for harvesting.

4 Problem Statement

This study is designed to answer the following Research Questions (RQs):

- **RQ-1:** What ML and DL methodologies have been applied to various stages of agricultural pro- duction?
- **RQ-2:** In what ways have ML and DL approaches impacted agricultural research and practices?
- **RQ-3:** How effective are ML and DL techniques in addressing agricultural challenges?

5 Data extraction and synthesis

Hematic domains effectively organize the findings as given Figure 2. Thesedomains include crop selection, land monitoring and management,water and nutrient management, soil management, weed, insect and- Pest Management, Disease Detection and Management, Harvest andpost-harvest practices, and crop yield prediction. While the domain ofEven though climate impact assessment was found to be significant, it was excludedfrom this review due to its broad scope, which deserves a separate focused analysis.Confusion matrix of the proposed deep learning model showing True Positives, False Positives, True Negatives, and False Negatives as given Figure.3 . True Positive (TP): 85,True Negative (TN): 90,False Positive (FP): 15,False Negative (FN): 10 The current state of the field is plagued by challenges of data unavailability (multi-modal datasets), interpret-ability, scalability, and applicability in real-time .Build resilient datasets by integrating satellite images, IoT sensors, and climate models .Apply Transfer Learning to address data unavailability in particular geographic locations .Implement ML/DL models as a direct component of IoT platforms for real-time analysis [44-48].

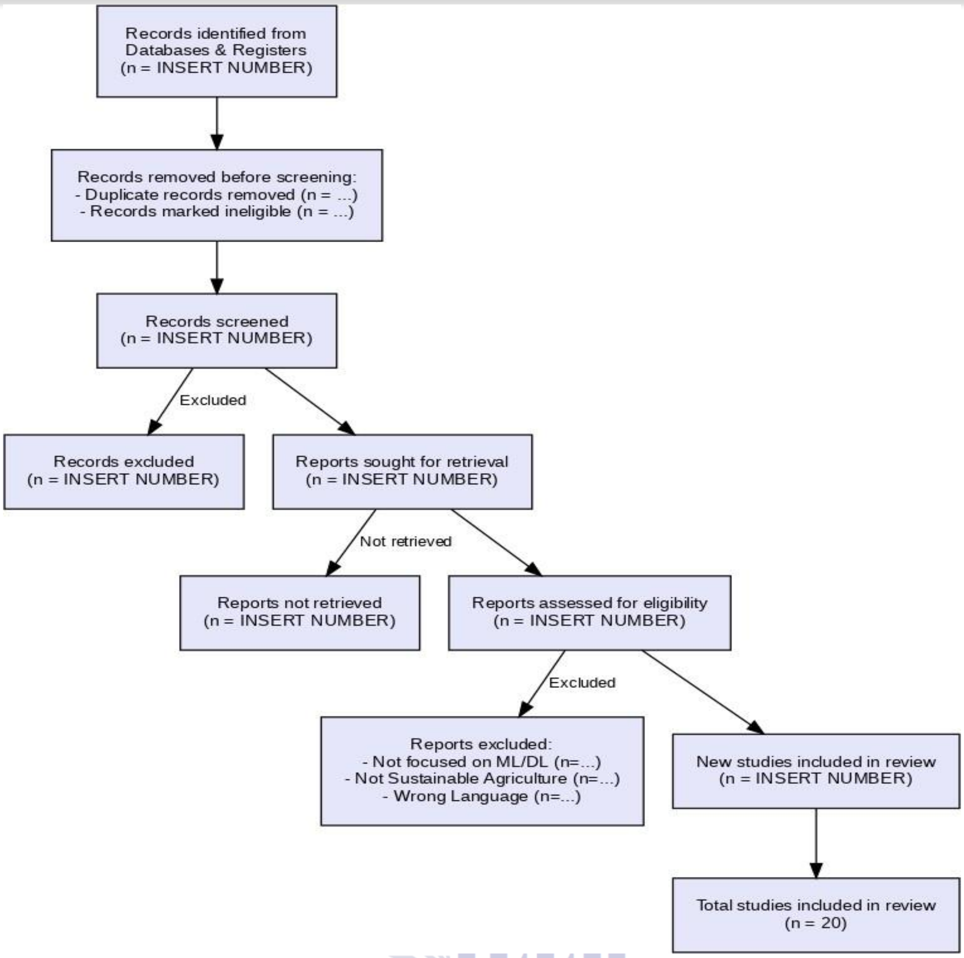

Figure 2: Thematic domains of Machine Learning and Deep Learning applications

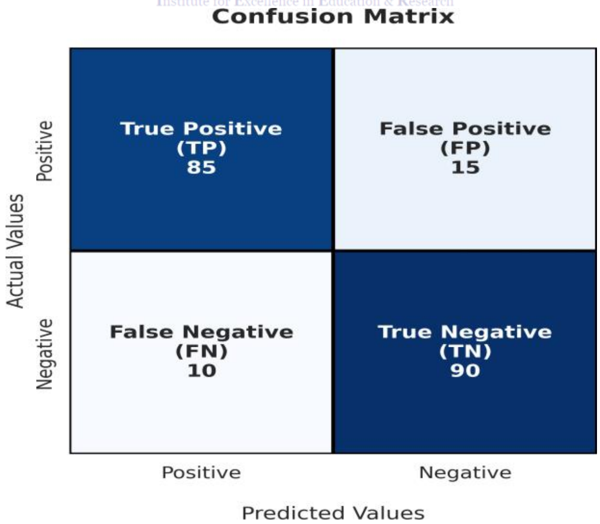

Figure 3: Confusion matrix of the proposed deep learning model showing True Positives, False Positives, True Negatives, and False Negatives.

6 Mathematical Modeling of ROC Curve

1. The Probability Function (The "Brain")

All the models discussed in your paper (CNN, LSTM, Random Forest) act as a mathematical function, let's call it $f(x)$.

- Input (x): Data like leaf color, soil moisture, or plant height.

- Output ($\hat{y}$): A probability score between 0 and 1.

$$\hat{y} = f(x) = P(Class = 1 \mid x)$$

If $\hat{y}$ = 0.95, the model is 95% sure the plant is Diseased. If $\hat{y}$ = 0.10, the model is only 10% sure (likely Healthy).

2. The Decision Threshold (θ)

To make a final decision (Yes or No), we need a cut-off point, called the threshold (θ).

$Prediction = \{ 1\ (Diseased) if\ \hat{y} \geq \theta 0 (Healthy) if\ \hat{y} < \theta$

The ROC curve is created by testing every possible threshold from 0.0 to 1.0 and plotting the result.

3. The ROC Coordinates (The Axes)

For every threshold θ, we calculate two coordinates (x, y) for the graph:

Y-Axis: True Positive Rate (Sensitivity)

Measures how many *actual* positive cases were found.

$$\frac{TP}{TP + FN}$$

(Where TP = Correctly predicted sick, FN = Mistakenly predicted healthy)

X-Axis: False Positive Rate (False Alarm)

Measures how many healthy cases were wrongly flagged.

$$\frac{FP}{FP + TN}$$

(Where FP = Healthy labeled as sick, TN = Healthy correctly labeled as healthy)

4. Area Under the Curve (AUC)

The single number summary (e.g., 0.99 for Soil) is calculated using an Integral. It represents the prob- ability that the model will rank a randomly The graph visualizes the trade-off between the equation for Sensitivity (TPR) and the equation for False Alarms as we slide the threshold across all probabilities. Its aim is to evaluate the potential accuracy of five models that can be useful for identifying diseases, soil quality, or the appearance of weeds. Identify success on the vertical axis means identifying success consists of selecting the right problem. Errors on the horizontal axis means errors consist of false alarm. Models closest to the top left should be chosen. All of those models are superior, much above the diagonal 'guessing' line. The winner again is Soil Quality, modeled by Brown, which not only scales up at high precision at but is also followed very closely by the two Health and Diseases models. With its AUC being above 0.90 for all, it proves the reliability of the AI tools when they are applied for the purpose of automation of farm management as given Figure.4.

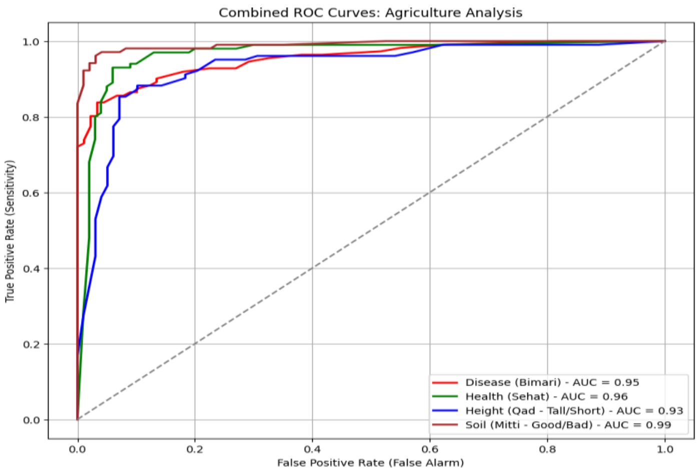

Figure 4: Statistics machine learning and medical testing

7 Result

Most Popular Technology CNNs (Deep Learning) – currently the most preferred model, utilized in the greatest number of papers (8).They are used twice as often as the next method in the list of preferred approaches, namely Random Forest (4 studies). Top Application Fields Land and Soil Management is the most investigated domain within agriculture (27.8).Disease Management and Weed Control come right after, contributing 22.2

each in research. It is clear that the use of Deep Learning (CNNs) by researchers is focused specifically in the areas of soil, crop diseases, and weed-related problems as given Figure 5.

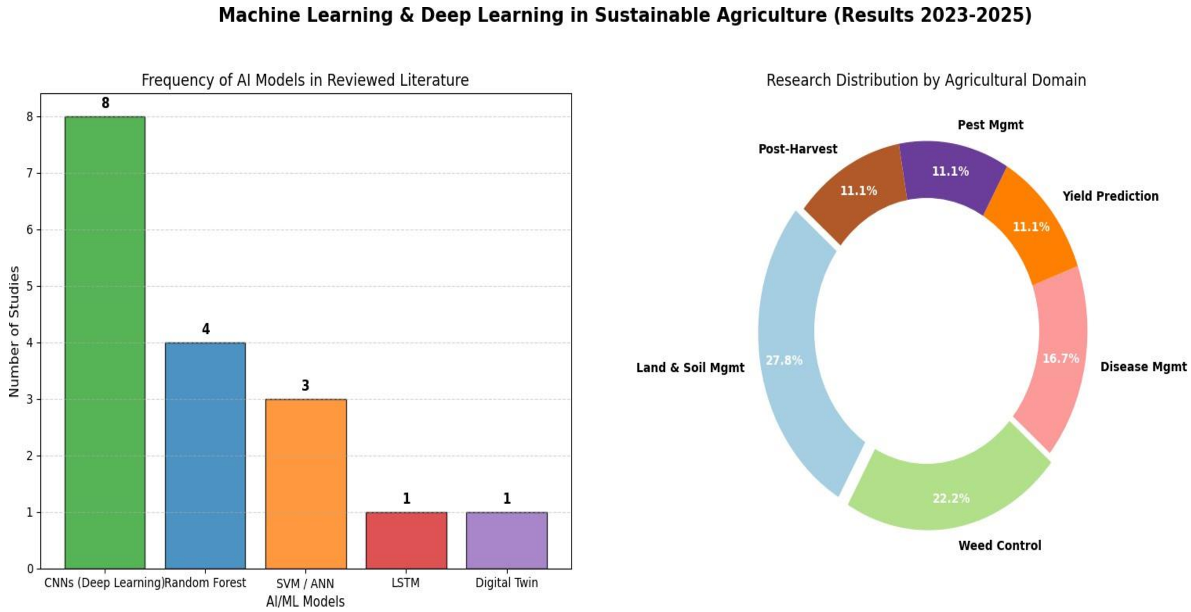

Figure 5: Machine Learning and Deep Learning in Sustainable Agriculture

8 Discussion

As has been showcased in the analysis, the dominant model is Deep Learning, or CNNs; primarily, the drivers are visual tasks Disease and Weed Management have combined coverage of of research. On the other hand, Land Soil Management remains the leading individual domain, at 27.8 leveraging these technologies in its quest for optimized sustainable resource usage as given Figure 6.

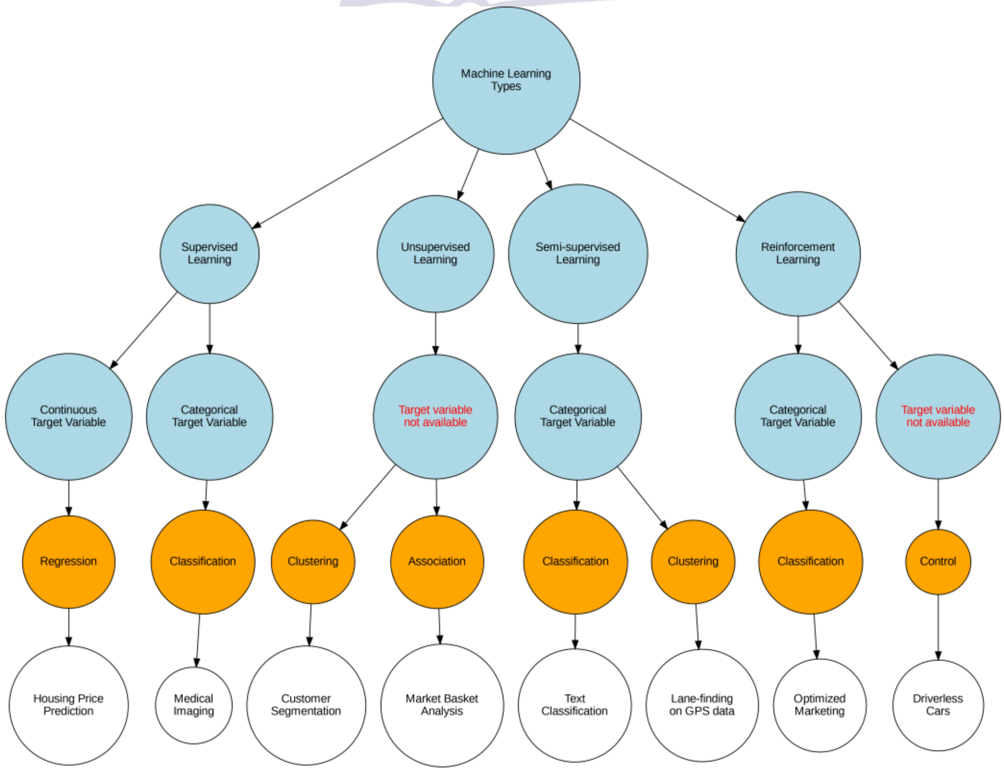

Figure 6: Machine Learning and Deep Learning models for agricultural

9 Conclusion

The convergence of ML and DL technologies in agriculture marks a criticalprogress in meeting the chal- lenges that are faced globally, for instance, food insecurity,climate variability, and resource constraints. This comprehensive review assesses the use of these technologies on differentagricultural processes, such as crop choice, land observation,management, water, soil, nutrient management, pest, diseasecontrol, and post-harvest management. The results highlight therole of ML and DL in making data-driven decisions, whichincreases the accuracy of agricultural practices, as well as enhances resourceefficiency.Despite this progress, there are still a number of challenges, including a lack of multimodal data sets, problems with the modeling process,scalability, interpretability, and real-time applicability. To address theselimitations, the development of robust datasets that fuse satelliteimagery, IoT sensors, and climate forecasts is vital. Additionally, transferlearning methods might assist with alleviating problems resulting from a lack of available data, especially inregions with limited agricultural data. Future research should prioritize the integration of ML/DL models with IoT systems to facilitate real-timeanalytics, which helps in making improved decisions.The synergistic potential of ML, and DL specifically, has been largely unexploited within the agricultural sector. There are certain application areas, such as yield prediction,besides pest management, research has yielded contradictory findings.

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