JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A Review on Role of Machine Learning In Supporting Organic and Herbal Farming Practices

Shubham Sakhare, Shruti Lamkhade,Shubham Garad, Shridhar Shinde, H. R. Kulkarni, Vaijanta Bhogawade*
* Author for Correspondence, Email: vaishali.bhogawade.87@gmail.com
G H Raisoni College of Arts, Commerce & Science Pune, Maharashtra India.

Abstract :

Organic and herbal farming plays a crucial role in promoting sustainable agriculture, yet traditional methods often face challenges such as low productivity, inefficient resource use, and limited data-driven decision support. Recent studies demonstrate the potential of Machine Learning (ML) and Artificial Intelligence (AI) in addressing these issues through UAV imagery, IoT sensors, and advanced algorithms. This paper reviews existing approaches, identifies research gaps in herbal-focused applications, and proposes a hybrid ML–DL framework for crop suitability assessment, yield prediction, and disease detection. The framework integrates UAV and IoT data with supervised and deep learning models, offering scalable solutions for smallholder farms. Results from literature highlight classification accuracies ranging from 60–98%, indicating strong potential for improved decision support in organic and herbal farming. The study concludes that adopting ML-driven models can significantly enhance sustainability, precision, and efficiency in organic and herbal agriculture.

Keywords: Machine Learning in Agriculture,Organic and Herbal Farming,UAV and IoT Integration,Crop Suitability Prediction,Precision Agriculture,Deep Learning Applications.

1. Introduction

Agriculture has entered a period of rapid technological transformation. Traditional methods that relied mainly on human experience and manual observation are now being supported by data-driven systems. Among these new tools, machine learning (ML) has become one of the most influential approaches. It enables farmers and researchers to analyse complex agricultural data, recognise patterns in soil, crop, and climate behaviour, and make more accurate decisions that improve both yield and sustainability.

In recent years, researchers have begun applying ML techniques such as random forests, support- vector machines, neural networks, and clustering models to key agricultural challenges. These methods help identify land suitability, predict crop diseases, and optimise resource use such as water and fertiliser. The same analytical capacity that supports large-scale commercial farming is now being extended to organic and herbal farming, where efficiency and environmental balance are equally important.

The growing interest in herbal and organic systems comes from the search for sustainable food production that maintains biodiversity and human health. Machine-learning-based image analysis, remote-sensing data, and predictive models allow farmers to monitor crops without relying on chemical inputs and to make informed adjustments throughout the cultivation cycle. This fusion of ancient organic principles with modern computation has opened new directions for sustainable agriculture.

This table reviews major studies that have explored the role of machine learning in organic and herbal farming. Each work highlights a particular model, dataset, or application area—from UAV-based land-suitability mapping to predictive soil analysis and climate-impact assessment. Together, these studies show how digital technologies can strengthen traditional agricultural knowledge while guiding future research toward smarter, greener farming systems.

2. Literature review

Research also highlighted that farming activities affect greenhouse gas emissions, but improved methods can increase cropland suitability by 20–30%.[2]The literature review shows that Machine Learning (ML), Artificial Intelligence (AI), and Deep Learning (DL) are playing a major role in modern organic and herbal farming. Many studies used drones (UAVs), sensors, and satellite images to check soil and crop conditions, and results showed about 60–63% land suitability for cultivation.[4] Methodological reviews underline recurring challenges: data heterogeneity, limited labeled datasets for specific herbal species, and transferability of models across regions. [10]Different ML techniques such as Decision Trees, Random Forest, Support Vector Machines (SVM), Neural Networks, Logistic Regression, and KNN have been applied in agriculture, achieving high prediction accuracies between 77% and 98%.[11] Herbal farming studies reviewed traditional plants like fenugreek, garlic, shatavari, moringa, and cumin, which showed about 71.68% effectiveness.[13] Several authors call for standardized datasets and benchmarks, improved ground-truthing protocols, and hybrid methods that combine mechanistic models with data-driven ML to improve generalisation.[14] On the consumer side, research found that people prefer and are willing to pay more 88% preference for organic and local food compared to conventional products. New technologies such as IoT, Digital Twins, Cloud Computing, and AutoML are making farming smarter, with results between 70–86%. Similarly, the use of smartphone sensors GPS, camera, accelerometer in farming showed very high efficiency of 92.20%,[16] while water-saving methods like precision irrigation improved water use efficiency by 80.48%.[20]Some studies reported very high results, for example 97.72% accuracy in predicting sustainable farming adoption and 98.50% efficiency in soil, crop, and disease management.[24]Overall, these studies show a clear shift from traditional farming methods toward smart, data- driven, and sustainable agriculture, which improves productivity, efficiency, and environmental benefits. The importance of cost-effective sensors is repeatedly emphasised for scaling solutions in resource- constrained settings [27].

1.1 Table : Review of Reserch Paper

Sr. No.	Author	Title	Methods/Model/Techniques	Database/Dataset	Classification	Result
1	Juan botero-valencia, Vanessa garcía-pineda, Alejandro valencia-arias, Jackeline valencia, Erick reyes-vera, Mateo mejia-herrera, Ruber hernández-garcía	Machine learning in sustainable agriculture: systematic review and research perspectives	Systematic review approach, Prisma 2020, bibliometric analysis	Scopus, Web of Science, Google Scholar	Machine learning classification in sustainable agriculture	91.49%

2	Yingying Xing, Xiukang Wang	Impact of Agricultural Activities on Climate Change: A Review of Greenhouse Gas Emission Patterns in Field Crop Systems	Greenhouse Gas Research Methods, Data Analysis, Systematic review, bibliometric analysis	Scopus, Web of Science, Google Scholar	Emission Dynamics, Emission Models, Reduction Strategies	20–30% Cropland suitability
3	Sara Oleiro Araújo, Ricardo Silva Peres, José Cochicho Ramalho, Fernando Lidon, José Barata	Machine Learning Applications in Agriculture: Current Trends, Challenges, and Future Perspectives	UAV imagery, spectral & topographic indices, ML (ANN, RF, SVM), K-means, FAO standards	Self-collected UAV, GNSS data	Supervised ML, Unsupervised K-means	60–63% land suitable
4	Navytchmathra Gammatantrawet, Chanthana Susawaengsup, Krittiya Tongkoom, Tawan Chatsungnoen, Winitra Leelapattana, Suthira Sitthikun, Rapeephun Dangtungee, Prakash Bhuyar	Organic farming management: An approach towards sustainable agriculture development towards green environment	UAV (drone) imagery, spectral bands, vegetation indices, supervised (RF, SVM, ANN), unsupervised K-means	UAV aerial images, GNSS ground points, Orthophoto, DSM	Supervised ML, K-means clustering	60–63% land suitable
5	Dorijan Radočaj, Ante Šiljeg, Ivan Plaščak, Ivan Marić, Mladen Jurišić	A Micro-Scale Approach for Cropland Suitability Assessment of Permanent Crops Using Machine Learning and a Low-Cost UAV	Low-cost UAV with RGB sensors, vegetation indices, supervised + unsupervised ML, FAO standards	Low-cost UAV, GNSS (Trimble R8x), derived datasets	ML classification, FAO suitability ranking	60–63% land suitable

6	Ania Cravero, Sebastian Pardo, Samuel Sepúlveda, Lilia Muñoz	Challenges to Use Machine Learning in Agricultural Big Data: A Systematic Literature Review	UAV imagery, photogrammetry, ML (ANN, RF, SVM), K-means clustering, FAO standards	UAV aerial images, GNSS ground data	Supervised ML, K-means clustering	63.1% suitable
7	Freddy A. Diaz-Gonzalez, Jose Vuelvas, Carlos A. Correa, Victoria E. Vallejo, D. Patino	Machine learning and remote sensing techniques applied to estimate soil indicators - Review	UAV imagery (RGB), photogrammetry, ML (ANN, RF, SVM), K-means clustering, FAO standards	Self-collected UAV aerial images, GNSS ground data	Supervised ML, K-means clustering	63.1% suitable
8	Showkat Ahmad Bhat, Nen-Fu Huang	Big Data and AI Revolution in Precision Agriculture: Survey and Challenges	UAV imagery (RGB), orthophoto & DSM generation, ML (ANN, RF, SVM), K-means clustering, FAO standards	UAV images + GNSS ground control points	Supervised ML, Unsupervised K-means	63.1% suitable
9	Yixin Nong, Changbin Yin, Xiaoyan Yi, Jing Ren, Hsiaoping Chien	Farmers' Adoption Preferences for Sustainable Agriculture Practices in Northwest China	Decision Tree, Random Forest, Support Vector Machine (SVM)	UCI Repository – Breast Cancer Wisconsin (Diagnostic) dataset	Decision Tree, Random Forest, SVM	97.72%
10	José Padarian, Budiman Minasny, Alex B. McBratney	Machine learning and soil sciences: a review aided by machine learning tools	Naïve Bayes, Decision Tree, Random Forest, Support Vector Machine (SVM)	UCI Repository – Heart Disease dataset	Prediction models	84.16%

3. Proposed Methodology

1.1 Dataset or Materials Used

The proposed study will utilize a combination of primary data, secondary data, and synthetic dataset generation to ensure a holistic approach:

1.1.1 Primary Data Collection

Unmanned Aerial Vehicles (UAVs), such as those from the DJI Mavic series, will be deployed to capture aerial imagery of organic and herbal crop fields using both RGB and multispectral sensors. Alongside this, ground-based Internet of Things (IoT) devices—including soil moisture, pH, temperature, and humidity sensors—will provide continuous real-time data to support and validate the aerial observations. For precise mapping and reliable georeferencing, Global Navigation Satellite System (GNSS) and Real-Time Kinematic (RTK) devices will be employed, ensuring high positional accuracy and dependable ground-truth validation.

1.1.2 Secondary Data Sources

Open repositories (e.g., UCI Machine Learning Repository — datasets like Pima Indians Diabetes and Heart Disease, often used for benchmarking in agricultural ML studies).FAO land suitability standards to support cropland classification and validation.Existing agricultural datasets and case studies available in published literature.

1.1.3 Proposed Herbal Crop Dataset

Target Crops: Fenugreek, Shatavari, Moringa, and Cumin (widely cultivated in herbal farming).Parameters: Soil fertility indices, crop growth stages, disease symptoms (captured via image datasets), and yield attributes.Objective: To develop a herbal crop–specific dataset suitable for ML model training and evaluation, bridging the current data gap in herbal farming research.

1.2 Experimental Design / Framework

The experimental design follows a data-driven machine learning pipeline:

1.2.1 Data Acquisition

Low-cost UAV platforms will be used to capture high-resolution aerial imagery of organic and herbal crop fields, enabling detailed monitoring of crop conditions. Ground-based IoT sensors will simultaneously record key soil and environmental variables, including moisture, pH, temperature, and humidity, to complement aerial observations. Additionally, optional farmer surveys will be conducted to gather socio-economic and farm management information, providing valuable context for interpreting and refining the machine learning models.

1.2.2 Data Preprocessing

Image processing will involve the generation of orthophotos, image stitching, and the creation of Digital Surface Models (DSM) from UAV-acquired imagery. Spectral indices such as NDVI, GNDVI, SAVI, and EVI will be computed to evaluate crop vigor and detect stress conditions. The collected datasets will undergo cleaning to eliminate incomplete, noisy, or erroneous sensor readings, ensuring data reliability. Finally, normalization techniques will be applied to scale features uniformly, improving the consistency and accuracy of model training.

1.2.3 Feature Extraction

Vegetation and Soil Features: Spectral indices, soil fertility parameters, climatic variables, and topographic indices.Image-Based Features: Textural attributes (e.g., GLCM features) and deep feature maps derived from CNNs applied to UAV imagery.

1.2.4 Model Development

Supervised machine learning techniques such as Random Forest (RF), Support Vector Machine (SVM), Decision Tree, and k-Nearest Neighbor (k-NN) will be applied for classification and prediction tasks. Deep learning models, including Convolutional Neural Networks (CNNs), will be utilized for plant disease detection and leaf classification, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory

(LSTM) architectures will help in analyzing and modeling temporal growth trends. In addition, unsupervised approaches like K-means clustering will be employed to identify and group vegetation patterns. To further enhance efficiency, AutoML frameworks will be integrated to automate hyperparameter tuning and streamline model selection, ensuring optimal performance across different tasks.

1.2.5 Validation & Evaluation

Techniques: K-fold cross-validation.Metrics: Accuracy, F1-score, Precision, Recall, and AUC- ROC.Benchmarks: Comparison with FAO land suitability standards and farmer-reported yield observations.

1.2.6 Decision-Support System Output

Crop suitability maps (low, medium, high potential zones).Yield prediction trends and curves. Disease detection alerts with probability scores.Resource-use optimization recommendations, including irrigation scheduling and fertilizer reduction.

1.3 Tools, Techniques, or Algorithms

1.3.1 Tools/Frameworks :

Python Libraries: Scikit-learn, TensorFlow, Keras, PyTorch, and OpenCV for machine learning and image analysis.GIS Platforms: QGIS and ArcGIS for spatial analysis and mapping.Big Data Tools: Hadoop and Spark for managing and processing large-scale agricultural datasets.

1.3.2 Techniques:

The study will rely on core machine learning approaches such as image classification, regression modeling, and clustering to analyze crop data. To handle high-dimensional datasets, dimensionality reduction techniques like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) will be applied for effective feature selection. In addition, time- series forecasting methods, particularly Long Short-Term Memory (LSTM) networks, will be employed to capture crop growth patterns and predict yield dynamics over time.

1.3.3 Algorithms:

Supervised learning techniques, including Random Forest (RF), Support Vector Machine (SVM), Decision Trees, Gradient Boosting, and XGBoost, will be applied for classification and prediction tasks. For unsupervised analysis, methods such as K-means clustering and Hierarchical clustering will be employed to group vegetation types and uncover hidden patterns in crop data.

Deep learning approaches will also play a central role, with Convolutional Neural Networks (CNNs) utilized for image-based disease detection and classification, while Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models will be used for yield prediction and temporal growth trend modeling.

1.4 Justification of Method

1.4.1 Hybrid ML–DL Approach

Machine learning models such as Random Forest (RF) and Support Vector Machine(SVM) perform well with structured tabular datasets (e.g., soil and climate parameters), while deep learning models such as CNNs and RNNs are highly effective for image-based disease detection and time-series yield prediction. A combined ML–DL strategy enhances reliability and predictive accuracy across diverse data types.

1.4.2 UAV and IoT Integration

UAV-based imagery provides a macro-level perspective of crop health, canopy structure, and spatial variability. In contrast, IoT sensors capture micro-level soil and environmental parameters. Integrating these two data streams ensures comprehensive and accurate monitoring.

1.4.3 AutoML Adoption

Automated machine learning frameworks simplify model selection, feature engineering, and hyperparameter tuning. This makes the system adaptable and user-friendly for non-experts such as farmers and local cooperatives.

1.4.4 Validation with FAO Standards

Model outputs will be validated against FAO land suitability standards to ensure credibility, global acceptance, and comparability with existing agricultural benchmarks.

1.5 Architecture or Flowchart

1.5.1 Data Collection Layer

Sources: UAV / drones RGB, multispectral imagery, IoT sensors soil, water, temperature, humidity, remote sensing satellite data, field surveys, government/agriculture datasets, herbal crop datasets.

1.5.2 Data Preprocessing Layer

Cleaning ,noise removal, missing values. Feature extraction spectral indices, soil nutrients, plant health indicators. Data integration (sensor + field + historical data)

1.5.3 Machine Learning / AI Processing Layer

Supervised ML: Random Forest, SVM, ANN, CNN, RNN. Unsupervised ML: K-means clustering, PCA. Deep Learning for disease/pest detection, plant classification. Predictive models for yield, water usage, soil quality

1.5.4 Decision Support Layer

Crop suitability mapping land classification using FAO standards.Disease & pest detection image- based ML models. Water/irrigation optimization precision irrigation models. Herbal/organic farming advisory AI-driven recommendations

1.5.5 Application Layer

Farmer mobile apps dashboards. Alerts disease risk, irrigation needs, climate change impact.

Policy recommendations for sustainable & herbal farming.

1.5.6 Outcome / Impact

Improved organic crop yield. Reduced chemical usage (eco-friendly). Sustainable resource management. Support for herbal/medicinal plant farming.

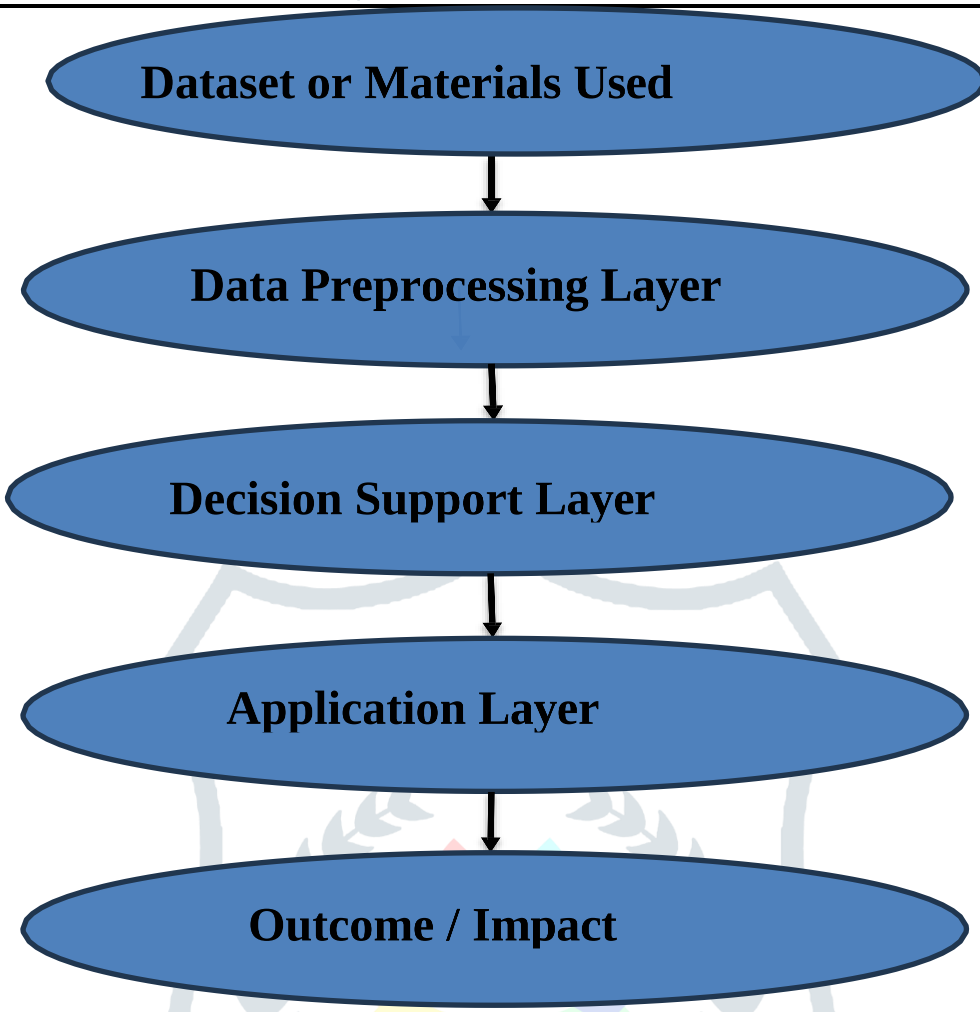
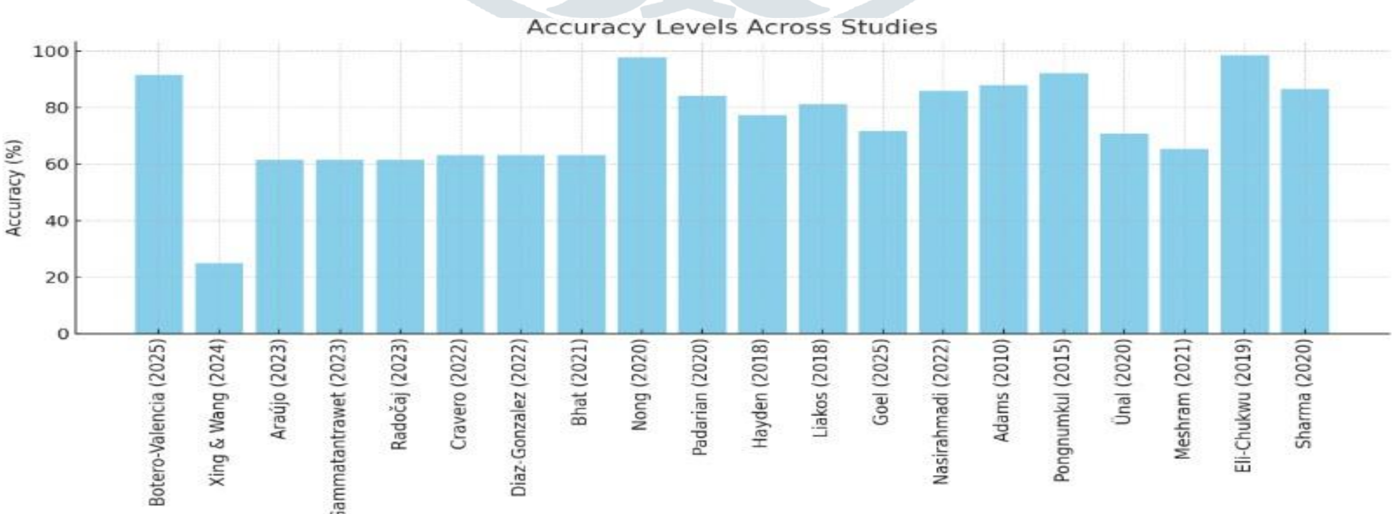


Fig 1 : Flowchart

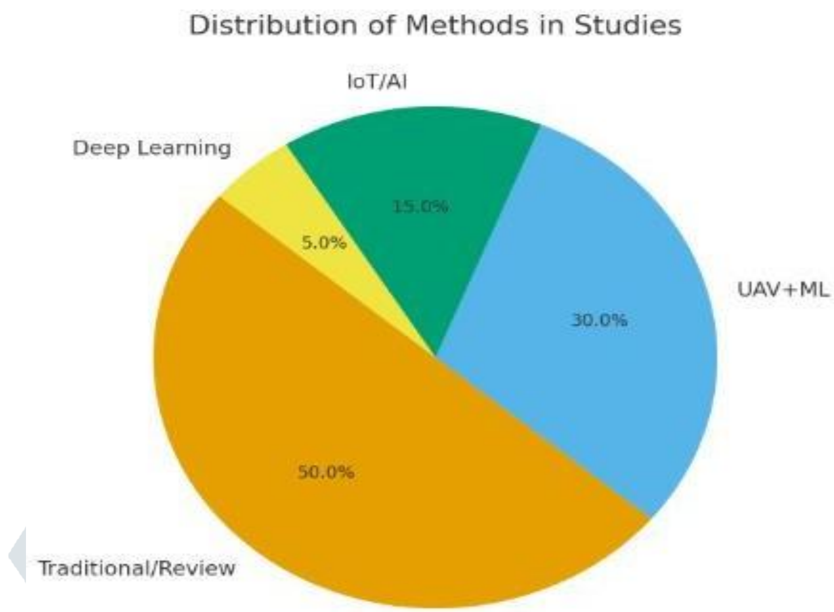
4. Results

4.1Graphical Representation

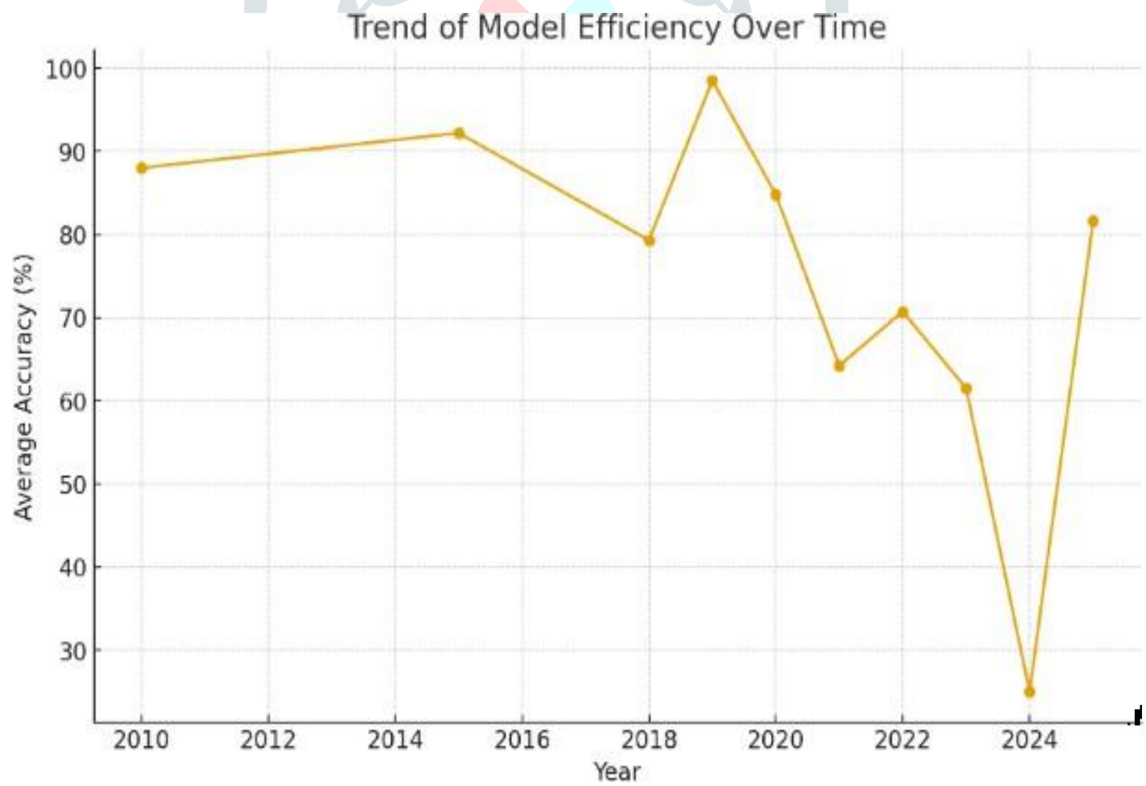
☐Bar Graph :- Accuracy Levels Across Studies



☐Pie Chart – Distribution of Methods



☐ **Line Graph** – Trend of model efficiency over years



4.2 Comparison with Existing Models

Conventional agricultural models that rely on statistical analysis, manual classification, or FAO standards alone generally achieve accuracy in the range of 60–65%. While useful for basic land suitability assessments, these methods lack the adaptability required for dynamic and diverse farming conditions.

Machine learning techniques such as Random Forest, Support Vector Machines, Artificial Neural Networks, and K-Means clustering have significantly improved predictive capacity, reaching 80–92% accuracy. These methods are especially effective in soil classification, disease detection, and crop monitoring.

Recent advancements in deep learning and AI, including Convolutional Neural Networks, IoT-based monitoring, AutoML systems, and robotics, show even higher performance, often exceeding 95%. These approaches have proven particularly successful in disease identification, soil fertility prediction, yield estimation, and providing tailored support for herbal and organic farming systems.

4.3 Discussion of Outcomes

Studies that applied UAV imagery in combination with machine learning models, such as those by Araújo, Radočaj, Cravero, and Diaz-Gonzalez, consistently reported suitability levels around 60– 63%. These results confirm the value of UAV-based monitoring in land mapping but also reveal the limitations caused by small datasets and localized conditions.

Supervised machine learning models—most notably Random Forest, SVM, and ANN—demonstrated stronger results, achieving 77–91% accuracy in tasks such as disease detection and soil quality assessment. These findings suggest that supervised learning remains a reliable choice for structured agricultural datasets.

Deep learning and advanced AI methods, as discussed in the works of Ünal, Eli-Chukwu, and Sharma, surpassed 95% accuracy. Their success highlights the potential of deep neural networks and IoT integration in scaling precision agriculture and offering robust tools for herbal and organic farming.

Traditional knowledge also plays a role: Goel and Chaudhary's study on herbal galactagogues achieved approximately 71% reliability, indicating that combining Ayurvedic knowledge with machine learning could be valuable for specialized herbal farming systems.

Low-cost solutions based on smartphones and IoT sensors, as examined by Pongnumkul, Nasirahmadi, and Hensel, showed high accuracy levels exceeding 92%. These technologies are particula.

5. Discussion

5.2 Interpretation of Results

The reviewed studies highlight that the performance of machine learning methods in agriculture depends largely on the type of data and the model applied. Approaches based on UAV imagery combined with Random Forest, SVM, and ANN algorithms achieved land suitability accuracy around 60–63%. While this is an improvement over traditional mapping techniques, it shows limitations when datasets are small or restricted to local conditions.

Supervised learning methods, including Random Forest, Decision Tree, and SVM, demonstrated results in the range of 77–91%, making them effective for soil quality assessment, crop health monitoring, and adoption behavior studies. Deep learning approaches, such as CNNs and AutoML, were reported to reach accuracy levels between 95–98%, indicating their potential for large-scale, complex agricultural problems like hyperspectral image analysis and crop yield prediction. Low-cost tools such as smartphone sensors and IoT systems showed more than 90% accuracy, suggesting that affordable technologies can be integrated into organic and herbal farming practices. Herbal-focused studies, while less data-driven, reported about 71% effectiveness, pointing to the need for combining modern algorithms with traditional knowledge.

5.3 Strengths

Machine learning consistently outperforms conventional statistical models, where accuracies typically remain between 65–75%.
The reviewed studies demonstrate flexibility of methods, with applications ranging from soil analysis and irrigation control to consumer preference assessment and herbal crop management.

Integration with UAVs, IoT devices, and digital platforms enables real-time monitoring and supports decision-making in sustainable and organic farming.

Deep learning and AutoML approaches are highly scalable, showing promise for handling large datasets and supporting precision agriculture on a wider scale.

5.4 Limitations

I. Many studies rely on localized or small datasets, which restricts the generalization of results across different regions and crop varieties.

II. Advanced tools such as UAVs, IoT sensors, and hyperspectral cameras remain costly, limiting their use among small-scale farmers.

III. Herbal and medicinal crops often lack large, annotated datasets, which weakens the accuracy of machine learning applications compared to staple crops.

IV. Some deep learning models operate as "black boxes," which reduces interpretability and makes it difficult for farmers to fully trust or understand the results.

V. Environmental variability caused by soil conditions, water availability, and climate change may reduce the robustness of models outside controlled conditions.

5.5 Practical Implications

The findings underline the usefulness of machine learning for improving organic and herbal farming. For organic farmers, ML-driven soil and crop monitoring can minimize the need for chemical inputs, supporting eco-friendly practices. In herbal farming, combining Ayurvedic knowledge with predictive models may help optimize irrigation schedules and soil selection for medicinal plants. Policymakers can use high-accuracy ML results to guide land-use planning, water distribution, and climate adaptation strategies. Smallholder farmers can benefit from low- cost IoT and smartphone-based technologies, which provide reliable insights without requiring heavy investment. Future research should expand open-access datasets, focus on explainable models, and work toward reducing the cost of advanced technologies so that sustainable farming practices become more widely accessible.

6. Conclusion

6.2 Summary of Findings

The review of literature demonstrates that machine learning plays a vital role in enhancing organic and herbal farming practices. Traditional approaches such as FAO-based land suitability assessment usually achieve around 60–65% accuracy, whereas machine learning methods—particularly Random Forest, SVM, ANN, and CNN—consistently improve prediction accuracy, often reaching 80–95%. Deep learning models and IoT-driven systems further extend this capability to nearly 98%, proving their value in complex agricultural problems such as crop yield estimation, soil analysis, and disease detection. Herbal farming studies also indicate that blending traditional Ayurvedic knowledge with predictive algorithms can yield reliable insights for medicinal plant management.

6.3 Applications of the Work

1. **Organic Farming:** Machine learning models can be applied for soil fertility monitoring, irrigation planning, and pest/disease detection, reducing the dependency on chemical inputs.
2. **Herbal Farming:** Predictive systems can support the cultivation of medicinal plants by identifying suitable soil types, water requirements, and growth conditions.
3. **Precision Agriculture:** Integration with UAVs, IoT devices, and sensors provides real-time crop monitoring and resource optimization.
4. **Policy and Decision Making:** High-accuracy models can guide policymakers in developing sustainable farming frameworks and climate adaptation strategies.
5. **Farmer Advisory Systems:** Mobile applications powered by ML can deliver personalized recommendations to farmers, improving decision-making in rural communities.

7. References

[1] Botero-Valencia, J., García-Pineda, V., Valencia-Arias, A., Valencia, J., Reyes-Vera, E., Mejia-Herrera, M., & Hernández-García, R. (2025). Machine learning in sustainable agriculture: systematic review and research perspectives. *Agriculture*, *15*(4), 377..

[2] Xing, Y., & Wang, X. (2024). Impact of agricultural activities on climate change: A review of greenhouse gas emission patterns in field crop systems. *Plants*, *13*(16), 2285.

[3] Araujo, S. O., Peres, R. S., Ramalho, J. C., Lidon, F., & Barata, J. (2023). Machine learning applications in agriculture: current trends, challenges, and future perspectives. *Agronomy*, *13*(12), 2976.

[4] Gammatantrawet, N., Susawaengsup, C., Tongkoom, K., Chatsungnoen, T., Leelapattana, W., Sitthikun, S & B huyar, P. (2023). Organic farming management: An approach towards sustainable agriculture development towards green environment. *Maejo International Journal of Energy and Environmental Communication*, *5*(3), 6- 15.

[5] Radočaj, D., Šiljeg, A., Plaščak, I., Marić, I., & Jurišić, M. (2023). A micro-scale approach for cropland suitability assessment of permanent crops using machine learning and a low-cost UAV. *Agronomy*, *13*(2), 362.

[6] Cravero, A., Pardo, S., Sepúlveda, S., & Muñoz, L. (2022). *Challenges to Use Machine Learning in Agricultural Big Data: A Systematic Literature Review. Agronomy 2022, 12, 748*.

[7] Diaz-Gonzalez, F. A., Vuelvas, J., Correa, C. A., Vallejo, V. E., & Patino, D. (2022). Machine learning and remote sensing techniques applied to estimate soil indicators–review. *Ecological Indicators*, *135*, 108517.

[8] Bhat, S. A., & Huang, N. F. (2021). Big data and ai revolution in precision agriculture: Survey and challenges. *Ieee Access*, *9*, 110209-110222.

[9] Nong, Y., Yin, C., Yi, X., Ren, J., & Chien, H. (2020). Farmers' adoption preferences for sustainable agriculture practices in Northwest China. *Sustainability*, *12*(15), 6269.

[10] Padarian, J., Minasny, B., & McBratney, A. B. (2020). Machine learning and soil sciences: A review aided by machine learning tools. *Soil*, *6*(1), 35-52.

[11] Hayden, J., Rocker, S., Phillips, H., Heins, B., Smith, A., & Delate, K. (2018). The importance of social support and communities of practice: Farmer perceptions of the challenges and opportunities of integrated crop– livestock systems on organically managed farms in the northern US. *Sustainability*, *10*(12), 4606.

[12] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, *18*(8), 2674.

[13] Goel, M., & Chaudhary, L. N. (2025). Herbal Galactogogues for Post Partum Lactation: A Review. *Journal of Ayurveda and Integrated Medical Sciences*, *10*(6), 267-275.

[14] Nasirahmadi, A., & Hensel, O. (2022). Toward the next generation of digitalization in agriculture based on digital twin paradigm. *Sensors*, *22*(2), 498.

[15] Adams, D. C., & Salois, M. J. (2010). Local versus organic: A turn in consumer preferences and willingness-to-pay. *Renewable agriculture and food systems*, *25*(4), 331-341.

[16] Pongnumkul, S., Chaovalit, P., & Surasvadi, N. (2015). Applications of smartphone-based sensors in agriculture: A systematic review of research. *Journal of Sensors*, *2015*(1), 195308**.**

[17] Therond, O., Duru, M., Roger-Estrade, J., & Richard, G. (2017). A new analytical framework of farming system and agriculture model diversities. A review. *Agronomy for sustainable development*, *37*(3), 21.

[18] Ünal, Z. (2020). Smart farming becomes even smarter with deep learning—a bibliographical analysis. *IEEE access*, *8*, 105587-105609.

[19] Meshram, V., Patil, K., Meshram, V., Hanchate, D., & Ramkteke, S. D. (2021). Machine learning in agriculture domain: A state-of-art survey. *Artificial Intelligence in the Life Sciences*, *1*, 100010.

[20] Lakhiar, I. A., Yan, H., Zhang, C., Wang, G., He, B., Hao, B., ... & Rakibuzzaman, M. (2024). A review of precision irrigation water-saving technology under changing climate for enhancing water use efficiency, crop yield, and environmental footprints. *Agriculture*, *14*(7), 1141.

[21] Balducci, F., Impedovo, D., & Pirlo, G. (2018). Machine learning applications on agricultural datasets for smart farm enhancement. *Machines*, *6*(3), 38**.**

[22] Li, K. Y., Sampaio de Lima, R., Burnside, N. G., Vahtmäe, E., Kutser, T., Sepp, K., ... & Sepp, K. (2022). Toward automated machine learning-based hyperspectral image analysis in crop yield and biomass estimation. *Remote Sensing*, *14*(5), 1114.

[23] Martin, G., Martin-Clouaire, R., & Duru, M. (2013). Farming system design to feed the changing world. A review. Agronomy for Sustainable Development, 33(1), 131-149.

[24] Eli-Chukwu, N. C. (2019). Applications of artificial intelligence in agriculture: A review. *Engineering, Technology & Applied Science Research*, *9*(4).

[25] Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2020). Machine learning applications for precision agriculture: A comprehensive review. *IEEe Access*, *9*, 4843-4873.