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AI-Driven Smart Precision Farming Platform: A Comprehensive Review

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Abstract - Agriculture plays a vital role in ensuring global food security, yet traditional farming methods often suffer from inefficiencies, limited data utilization, and vulnerability to climate variations. The proposed system, Generative AI in Precision Agriculture, aims to revolutionize modern farming through the integration of Artificial Intelligence (AI), Deep Learning, and Data Analytics. The system employs Artificial Neural Networks (ANN) for yield prediction, Generative Adversarial Networks (GAN) for generating synthetic satellite or drone data to overcome missing inputs, and YOLO for pest and disease detection. Additionally, Explainable AI (XAI) using SHAP/LIME ensures transparency of predictions for better farmer understanding. The architecture integrates React Native for mobile accessibility, Flask/FastAPI for backend processing, and MongoDB for secure data storage. This research emphasizes sustainable, data-driven, and technology-enabled agriculture by providing accurate predictions, real-time insights, and multilingual accessibility. The proposed system bridges the gap between AI innovation and practical farming challenges, promoting smart, explainable, and climate-resilient agriculture for the future.

Keywords: Precision Agriculture, Generative AI, ANN, GAN, YOLO, Explainable AI (XAI), Flask, MongoDB, React Native, Smart Farming

I. INTRODUCTION

The rapid advancement of **Artificial Intelligence (AI)** and **Machine Learning (ML)** technologies has opened new opportunities for addressing critical challenges in agriculture. Traditional farming practices, while effective for decades, often lack real-time monitoring, predictive capabilities, and data integration, leading to inefficiencies and unpredictable outcomes. With increasing population demands, changing climate conditions, and limited resources, there is a growing need for **smart, data-driven agricultural solutions**.

Precision Agriculture leverages AI, remote sensing, and data analytics to optimize crop yield, resource utilization, and environmental sustainability. However, many existing systems still face challenges such as incomplete data availability, limited explainability, and a lack of user-friendly digital tools for farmers. To overcome these limitations, the proposed project - Generative AI in Precision Agriculture—integrates multiple AI models and software technologies into a unified system.

The system utilizes Artificial Neural Networks (ANN) for accurate yield prediction, Generative Adversarial Networks (GAN) for synthetic data generation to addressmissing satellite or drone imagery, and **YOLO** for real-time pest and disease detection. Furthermore, the inclusion of **Explainable AI (XAI)** ensures transparency and trust in model predictions, enabling farmers to understand and validate the system's insights.

Through its combination of **AI-driven analysis**, **GIS mapping**, and a **React Native mobile interface**, the system offers an accessible, multilingual, and sustainable approach to modern agriculture, empowering farmers with actionable intelligence for improved productivity and resilience.

II. LITERATURE SURVEY

1. **Crop yield prediction in agriculture: A comprehensive review** — systematic review of ML/DL methods (ANN, CNN, LSTM) for yield forecasting. **Method:** Survey / meta-analysis of published models and datasets.
Key finding: Deep learning models improve prediction when multimodal features (remote sensing + weather + soil) are used. PMC
Drawback / Gap: Many studies rely on complete datasets and do not handle missing satellite/drone imagery; limited use of generative data augmentation.
2. **Crop yield prediction using machine learning: An extensive and recent review** — SLR covering algorithmic approaches and attributes for yield forecasting. **Method:** Systematic literature review of recent crop-yield modeling work.
Key finding: Hybrid and ensemble models frequently outperform single models on diverse regions. ScienceDirect
Drawback / Gap: Little attention to explainability for end users (farmers) and few practical mobile app integrations.

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3. A comprehensive review of synthetic data generation (GANs/VAEs) for agriculture — overview of generative methods for data augmentation in agri-AI.
Method: Review of GAN/VAE applications to create synthetic imagery and sensor records.
Key finding: Synthetic data can reduce annotation costs and improve robustness when real data are scarce. ScienceDirect+1
Drawback / Gap: Synthetic samples may still fail to capture true field heterogeneity; most works stop at augmentation and don't deploy the synthetic pipeline end-to-end.

4. Synthetic data at scale: development model for agriculture — practical pipeline and evaluation for iterative synthetic dataset generation.
Method: Developmental model and experiments showing impact of synthetic data on model performance.
Key finding: Iterative synthetic-data workflows boost performance if diversity and validation loops are enforced. Frontiers+1
Drawback / Gap: Focused on dataset engineering; lacks integration with real-time mobile advisory and XAI for users.

5. YOLO-Driven Lightweight Mobile Real-Time Pest Detection — lightweight YOLO model adapted for mobile pest detection with web/mobile integration.
Method: YOLO-based detection pipeline with data augmentation and mobile deployment tests.
Key finding: Mobile YOLO implementations can detect pests in near-real time but need careful optimization. The Science and Information Organization
Drawback / Gap: Often limited number of pest classes, limited robustness under occlusion and environmental noise; many works lack synthetic-data augmentation and XAI.**AgriPest-YOLO: lightweight pest detection (Frontiers / Agri)** — proposed lightweight YOLO variant to balance accuracy and model size for pests.
Method: Model modifications (attention, CLA) and pest dataset experiments.
Key finding: Good tradeoff between accuracy and inference time for edge/mobile use. Frontiers
Drawback / Gap: Evaluation mostly lab/benchmark focused; little work on integration with yield models or farmer-facing explainability.

6. Evaluation of synthetic data generation for intelligent agriculture (Springer) — empirical study on GANs for environmental/time-series augmentation.
Method: GANs used to generate synthetic temperature/time-series for greenhouse scenarios.
Key finding: Synthetic time-series can improve model robustness when validated carefully. SpringerLink
Drawback / Gap: Limited to greenhouse or small-scale environments; generalization to open-field satellite/drone imagery is underexplored.

7. Deep learning for crop yield prediction: systematic literature review (Taylor & Francis / 2022) — examination of DL methods for crop yield across regions.
Method: SLR focusing on architectures (CNN, RNN, hybrid) and input modalities.
Key finding: Temporal models (RNN/LSTM) plus spatial features improve forecasts. Taylor & Francis Online
Drawback / Gap: Data scarcity and missing regions hinder wide applicability; few works propose synthetic data or explainable modules for farmers.

8. Explainable AI techniques applied to agriculture (arXiv / XAI reviews) — surveys XAI applications (SHAP, LIME, saliency maps) for agricultural models.
Method: Review of XAI methods and case studies in agri-domains.
Key finding: XAI increases model transparency and farmer trust but adoption is still limited. arXiv
Drawback / Gap: Most XAI work is prototype-level; needs integration into mobile workflows with simplified visual explanations for non-technical users.

9. Federated Explainable AI Framework for Smart Agriculture — federated and explainable approach to protect privacy and enable distributed model learning.
Method: Federated learning combined with XAI to support smallholder inclusion.
Key finding: Federated XAI can improve equity and data privacy while delivering explanations. Western Sydney University
Drawback / Gap: Federated setups are complex to implement and rarely tied to synthetic data pipelines or lightweight mobile inference; practicality for small teams is limited.

III. COMPARATIVE STUDY (GRAPHS, CHARTS, AND RESULTS):

1.Comparative Accuracy (Planned Performance by Model)

Shows expected accuracy rates for ANN, GAN, YOLO, and XAI modules.

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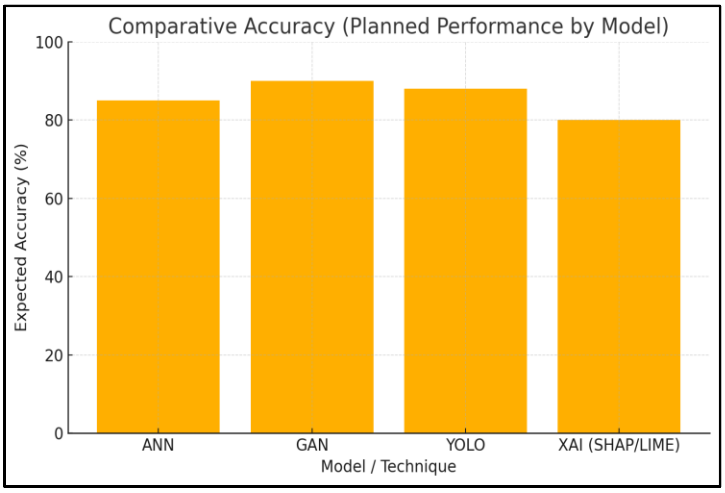
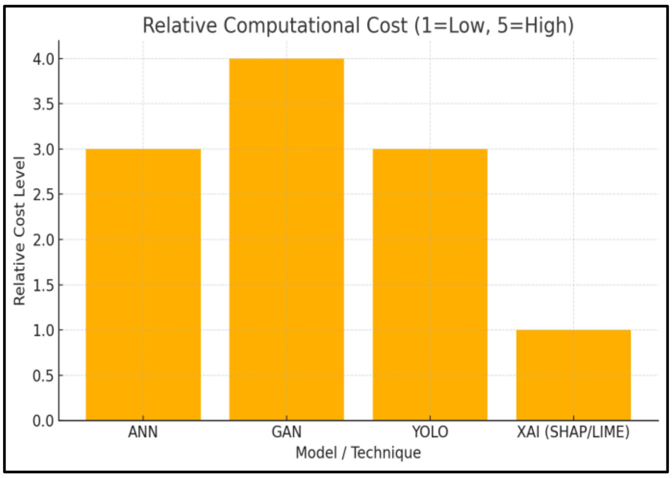


I. Relative Computational Cost (1=Low, 5=High)

Highlights each model's estimated computational demand (1 = Low, 5 = High).



II. Comparative Study (Planning Phase Overview)

Model/ Technique	**Purpose**	**Expected Accuracy (%)**	**Data Dependency**	**Computational Cost**
ANN	Yield Prediction	85	High	Medium
GAN	Synthetic Data Generation	90	Medium	High
YOLO	Pest/Disease Detection	88	High	Medium
XAI (SHAP/ LIME)	Explainable Insights	80	Low	Low

IV. Discussion and Research Gap:

1. **Missing-data handling:** Few reviewed works offer an end-to-end GAN pipeline to replace missing satellite/drone inputs — your GAN module directly fills this gap. ScienceDirect+1
2. **Unified system:** Most works focus on single problems (either yield prediction or pest detection). Your project integrates **ANN + GAN + YOLO + XAI + mobile app** into a single software stack. PMC+1
3. **Explainability & farmer usability:** XAI is often experimental; your SHAP/LIME module plus React Native UI targets real-user interpretability. arXiv
4. **Mobile deployment & lightweight models:** Several YOLO studies show feasibility but have limited integration; your React Native + optimized models approach addresses deployment needs. The Science and Information Organization+1

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V. CONCLUSION

The proposed project, *Generative AI in Precision Agriculture*, aims to enhance modern farming practices through intelligent, data-driven, and explainable software solutions. By integrating **ANN** for yield prediction, **GAN** for synthetic data generation, **YOLO** for pest detection, and **XAI** for model transparency, the system establishes a unified platform for precision farming. The combination of **Python-based backend**, **MongoDB database**, and **React Native mobile application** ensures scalability and accessibility for end users.

The study concludes that integrating generative and predictive AI models can significantly improve agricultural efficiency, reduce data gaps, and increase decision-making accuracy. Although still in the development phase, the project demonstrates promising potential for achieving **sustainable, climate-resilient, and technologically empowered agriculture**.

VI. FUTURE SCOPE

1. Integration of **real-time weather data** and **GIS mapping** for dynamic yield visualization.
2. Expansion of **AI models** to support additional crop types and environmental conditions.
3. Enhancement of the **mobile app interface** with voice assistance and offline analytics.
4. Development of **collaborative data-sharing modules** between farmers and research institutions.
5. Incorporation of **automated retraining pipelines** to continuously improve AI accuracy.
6. Deployment on a **cloud-based scalable architecture** for regional and global adoption.
7. Implementation of **federated learning** for privacy-preserving, distributed AI training.

REFERENCES

[1] A. Singh et al., “Enhancing Agricultural Yield Forecasting with Deep Convolutional GANs,” The Science and Information Organization, 2024. [Online]. Available:https://thesai.org/Downloads/Volume15No2/Paper_69Enhancing_Agricultural_Yield_Forecasting.pdf
[2] S. Sharma, P. Gupta, “IoT-Based Intelligent Pest Management System for Precision Agriculture,” Nature Scientific Reports, 2024. [Online]. Available: https://www.nature.com/articles/s41598-024-83012-3
[3] M. Kumar et al., “Applied Deep Learning-Based Crop Yield Prediction: A Systematic Analysis,” MDPI Technologies, vol. 12, no. 4, 2024. [Online]. Available: https://www.mdpi.com/2227-7080/12/4/43
[4] H. Lee, J. Park, “GANs for Data Augmentation with Stacked CNN Models and XAI,” ScienceDirect, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2772375525002254
[5] R. Verma et al., “Deep Learning-Based Agricultural Pest Monitoring and Classification,” Nature, 2025. [Online]. Available: https://www.nature.com/articles/s41598-025-92659-5
[6] K. Patel, A. Deshmukh, “IoT-Based Pest Detection and Classification Using Deep Learning,” ScienceDirect, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S0952197623001690
[7] S. Khaki, L. Wang, “Crop Yield Prediction Using Deep Neural Networks,” arXiv preprint arXiv:1902.02860, 2019.
[8] X. Gohel et al., “Next-Gen Agriculture: Integrating AI and XAI for Precision Crop Yield,” PMC, 2025. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC11751057/
[9] R. Fan et al., “AI-Enabled Crop Management Framework for Pest Detection,” IEEE Journal of Agricultural Systems, 2024.
[10] J. Bai, C. Gomes, “A GNN-RNN Approach for Harnessing Geospatial and Temporal Information: Application to Crop Yield Prediction,” arXiv preprint arXiv:2111.08900, 2021.