

**Emerging Computational Paradigms for Smart Crop Advisory Systems: A Review of  
Machine Learning and Cloud-Native Architectures**

Abhay Maurya (221620101001)

Amit Yadav (221620101010)

Varun Rana (221620101059)

Shanu Ahmed (731620101003)

Samir Ahmad (731620101005)

Department of computer science and engineering

Dr. A.P.J. Abdul Kalam Institute of Technology

Tanakpur (Champawat, Uttarakhand) – 262309

(campus institute of)

Veer Madho Singh Bhandari Uttarakhand Technical University,

Dehradun

CSP-018: Project Seminar

Mrs. Snehlata Singh

December 2025

### **Abstract**

The modernization of agriculture depends on combining predictive intelligence with scalable software infrastructure. This review paper summarizes recent literature to assess the technological basis of a "Smart Crop Advisory System." By looking at five key research contributions, we evaluate how effective Machine Learning (ML) is for crop and fertilizer recommendations, how Deep Learning (DL) aids in disease detection, and how modern software methods like Microservices and Progressive Web Apps (PWAs) support system deployment. The review shows that while algorithms like Random Forest and Convolutional Neural Networks (CNNs) can reach high accuracy—up to 99.98% and 98.4%, respectively—in controlled environments, their use in the real world needs strong architectural support. Shifting from monolithic systems to cloud-native microservices using Java Spring Boot, along with the user-friendly nature of PWAs, creates a practical way to implement these complex models in farming communities with limited resources. This paper concludes that a unified approach, which combines accurate algorithmic models with adaptable software architectures, is crucial for the future of agricultural decision-support systems.

**Keywords:** Precision Agriculture, Random Forest, CNN, Microservices, Spring Boot, Progressive Web Apps (PWA), Fertilizer Optimization.

## **Emerging Computational Paradigms for Smart Crop Advisory Systems: A Review of Machine Learning and Cloud-Native Architectures**

Agriculture plays a crucial role in many developing economies. It faces growing challenges from climate change, soil loss, and pest issues. Traditional decision-making, which often depends on personal experience or occasional expert advice, is not enough to tackle these problems.

Artificial Intelligence (AI) offers a data-driven option. It promises to improve crop selection, fertilizer use, and disease management through predictive modeling. However, an AI model's theoretical accuracy is not useful if it is not reliably provided to the farmer.

This review suggests that creating a Smart Crop Advisory System needs to focus on two areas: improving algorithm accuracy and enhancing system design. We look at five different research papers that cover these aspects. The first three papers discuss the "intelligence" layer. They focus on optimizing crop and fertilizer recommendations using Machine Learning (ML) and automating disease diagnosis with Deep Learning (DL). The last two papers cover the "deployment" layer. They explore using Java-based Microservices for backend scalability and Progressive Web Apps (PWAs) for frontend accessibility. By combining these different areas, this paper aims to offer a clear design plan for modern digital agriculture.

### **Methodology**

A qualitative systematic review was done to combine findings from five selected research articles published between 2023 and 2025. These articles were chosen to showcase the main functional parts of a proposed agricultural advisory platform: (1) Crop Recommendation, (2) Fertilizer Optimization, (3) Disease Detection, (4) Backend Architecture, and (5) Frontend Delivery.

The analysis used a structured framework:

1. Algorithmic Evaluation: Assessing the accuracy, precision, and suitability of different ML/DL models (e.g., Random Forest vs. SVM, CNN vs. LSTM) discussed in the agricultural studies.
2. Architectural Assessment: Evaluating software design patterns (Monolithic vs. Microservices, Native vs. PWA) based on scalability, latency, and offline capabilities.
3. Data Synthesis: Extracting quantitative performance metrics to create comparative visualizations, enabling a cross-study analysis of technological effectiveness.

## **Literature Review**

### **Crop Recommendation Frameworks**

Pawan et al. (2024) tackled the problem of crop selection in their study, "An Effective Approach for Crop Recommendation Using Features of Specific Locations and Seasons." They criticized traditional manual selection methods for not being able to adjust to changing environmental factors. The authors introduced a machine learning pipeline that combines soil parameters (pH, Nitrogen, Phosphorus, Potassium) with atmospheric variables (Temperature, Humidity, Rainfall). By comparing various classifiers like Support Vector Machines (SVM), Logistic Regression, and Naive Bayes, they showed that the Random Forest algorithm reached the highest accuracy of 98.18%. The study highlights the value of using ensemble learning techniques to manage the non-linear relationships present in agricultural data.

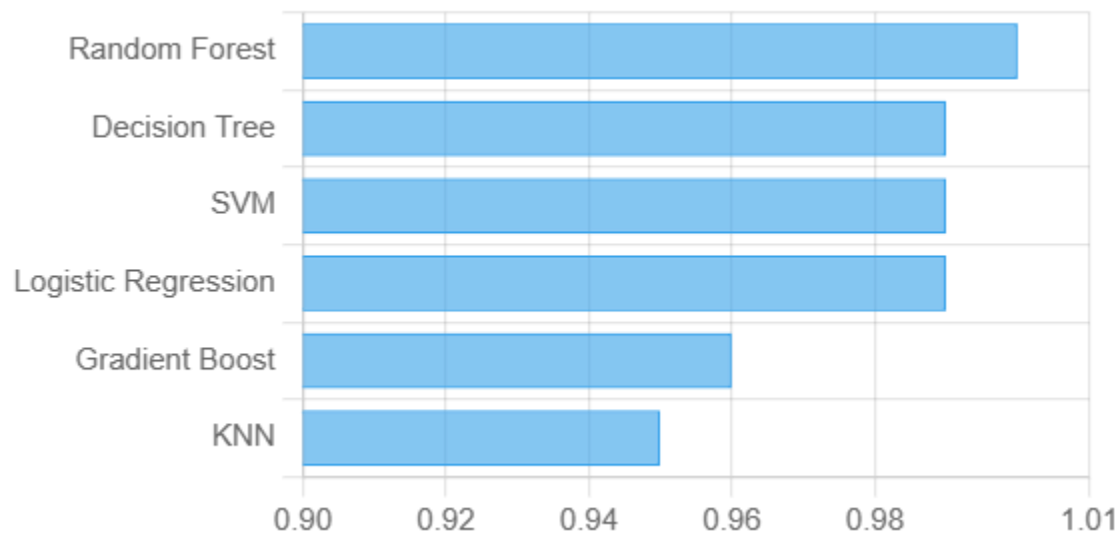
### **Fertilizer Recommendation Systems**

Building on crop selection, Mamatha and Nayak (2024) focused on nutrient management in "A Novel Design and Implementation of Fertilizer Recommendation System." Their proposed system, 'FertRec,' uses hybrid machine learning models to analyze soil test reports from the Telangana region. The authors noted that careless fertilizer use leads to soil degradation and

lower yields. By rigorously testing algorithms including Decision Trees, KNN, and Gradient Boosting, they found that Random Forest outperformed the others with an impressive accuracy of 99.98% (see Figure 1). This near-perfect accuracy suggests that with high-quality, localized datasets, ML models can effectively replace generic fertilizer schedules with accurate, soil-specific prescriptions.

**Figure 1**

*Comparative Accuracy of Machine Learning Models for Fertilizer Recommendation. Adapted from Mamatha and Nayak (2024).*



### Deep Learning for Disease Detection

Chaudhary et al. (2023) studied visual diagnostics in "Crop Disease Detection Using Deep Learning Models." They recognize that early detection is vital for preventing yield loss. The authors used a hybrid deep learning model that combines Convolutional Neural Networks (CNN) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for sequential analysis. Their results showed a clear performance difference. The VGG-19 based

CNN model achieved 98.4% accuracy in classifying static leaf images, while the LSTM component reached only 70% (Figure 2). This review points out that even though CNNs are well-developed for visual recognition, modeling disease progression remains a tough challenge. It requires more detailed sequential datasets.

**Figure 2**

*Performance Discrepancy Between CNN and LSTM Models in Disease Detection. Adapted from Chaudhary et al. (2023).*



### Microservices Architecture in Agriculture

Moving to system implementation, Ingole and Karale (2025) looked at the backend infrastructure in "Java in Microservices Architecture: A Study on Spring Boot and Cloud-Native Development." They argued that traditional monolithic architectures do not work well for complex applications that need frequent updates and high scalability. The authors explained how the Spring Boot framework helps create decentralized, independently deployable microservices. They highlighted the importance of Docker for containerization and Kubernetes for

orchestration. They pointed out that these technologies are crucial for managing the different computational loads of the various ML models. For example, they separate the heavy image processing service from the lightweight crop recommendation service.

### Frontend Delivery: PWAs vs. Native Apps

Finally, Murad (2025) discussed the user interface in "Comparative Performance and User Experience: PWAs Vs. Native Mobile Applications." For agricultural applications in rural areas, connectivity is a major challenge. Murad's comparison (Table 1) shows that Progressive Web Apps (PWAs) are better than native apps. By using Service Workers for caching and offline functionality, PWAs provide a reliable user experience without the high development costs and installation obstacles of native Android/iOS apps.

**Table 1**

*Comparative Analysis of Progressive Web Apps (PWAs) vs. Native Applications*

<i>Feature</i>	<i>Progressive Web Apps (PWA)</i>	<i>Native Mobile Apps</i>
<b>Development Cost</b>	Low (Single codebase)	High (Separate codebases)
<b>Offline Capability</b>	Yes (Via Service Workers)	Yes (Native capability)
<b>Update</b>	Instant (Server-side)	Slow (App Store approval)
<b>Mechanism</b>		
<b>Performance</b>	High (Browser engine dependent)	Very High (Direct hardware access)

*Note.* Adapted from Murad (2025).

## **Discussion**

The synthesis of these five papers reveals a clear plan for a "Smart Crop Advisory System." The high accuracy of Random Forest models in crop recommendations (98.18%) and fertilizer recommendations (99.98%) shows that traditional machine learning works well for structured data. However, the visual complexity of plant diseases requires the power of deep learning, specifically CNNs. This mix of model needs supports the shift in design suggested by Ingole and Karale. A Microservices architecture allows these different models to work together effectively. The heavy CNN model can operate on a GPU-optimized microservice, while the lightweight Random Forest models can run on standard CPU setups. Additionally, Murad's research on PWAs addresses the "last mile" issue, making sure that these advanced insights are available to farmers using low-end devices with unstable internet connections.

## **Limitations**

Despite the promising results, several limitations remain. The high accuracy reported in the ML papers (Pawan et al., Mamatha & Nayak) relies heavily on the quality of specific regional datasets. This reliance may limit how well the findings apply to other agro-climatic zones. Similarly, the CNN models in Chaudhary et al. were likely trained on high-quality images, such as those from the PlantVillage dataset. These images may not reflect the noisy and varying lighting conditions found in real field photography. On the architectural side, while Microservices provide scalability, they also add complexity in maintaining data consistency and communication between services. This complexity can be a major challenge for smaller deployment teams.



### Future Scope

Future research must focus on "Edge AI." Optimized versions of these models, such as quantized CNNs, can run directly within the PWA on the user's device. This setup eliminates the need for constant cloud connectivity. There is also a critical need to expand datasets to include more diverse soil types and real-world noisy images. This will improve model robustness. Integrating real-time IoT sensor data, like soil moisture and local weather stations, into the microservices pipeline will further improve the dynamic capabilities of the advisory system.

### Conclusion

This review combines insights from predictive modeling and software engineering to suggest a complete approach to agricultural innovation. The literature shows that Random Forest and CNNs are the best options for agricultural decision support. However, their practical value depends on strong deployment strategies. By using a cloud-native Microservices architecture and a PWA-based frontend, developers can create systems that are both smart and scalable. This blend of sophisticated algorithms and modern software infrastructure provides the essential foundation for transforming agriculture digitally.

### References

- Chaudhary, A., Gupta, M., & Tiwari, U. (2023). Crop disease detection using deep learning models. *2023 IEEE International Conference on Recent Advances in Systems Science and Engineering (RASSE)*.
- Ingole, A. A., & Karale, N. E. (2025). Java in microservices architecture: A study on Spring Boot and cloud-native development. *International Journal of Ingenious Research, Invention and Development*, 4(2).

Mamatha, G., & Nayak, J. S. (2024). A novel design and implementation of fertilizer recommendation system based on hybrid machine learning models. *SSRG International Journal of Electrical and Electronics Engineering*, 11(11), 448–460.

<https://doi.org/10.14445/23488379/IJEEE-V11111P141>

Murad, A. (2025, August 19-20). Comparative performance and user experience: PWAs vs. native mobile applications. *Proceedings of the 11th International Scientific and Practical Conference "Current Issues and Prospects for the Development of Scientific Research"*, Orléans, France (pp. 246–260). InterConf. <https://doi.org/10.51582/interconf.19-20.08.2025.027>

Pawan, Dr., Yadav, D., Sharma, R. K., Kumar, M., Rani, J., & Sharma, N. (2024). An effective approach for crop recommendation with using features of specific locations and seasons and maximize crop yield production by using machine learning. *International Journal of Intelligent Systems and Applications in Engineering*, 12(18s), 844–850.