Dr. G. M. Asutkar, 2026, 14:5
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

AgriVerse: An AI-Driven Agri-FinTech Decision Intelligence Platform

Dr. G. M. Asutkar[1], Sayli Jibhakate[2], Antariksh Mundle[3], Rohit Kadway[4], Rohit Vaidya[5]
Prof. Aarti Dhandare[6]
Department of Artificial Intelligence & Data Science
Priyadarshini College of Engineering, Nagpur

Abstract- Small and marginal landholders continue to make up the majority of the agricultural workforce, yet crop planning and financing decisions are frequently made from scattered and disconnected information. Over the past decade, researchers have applied machine learning (ML) and deep learning (DL) methods to individual pieces of this problem — crop recommendation, yield estimation, leaf-disease diagnosis, credit-risk and loan-eligibility scoring, and commodity price forecasting — with each area independently reaching strong, often benchmark-level accuracy. This paper reviews recent literature across these five research strands and additionally surveys operational Agri-FinTech platforms that attempt to combine agricultural and financial services. The review finds that Random Forest and related ensemble classifiers dominate crop recommendation and yield estimation, typically reporting 91–98% accuracy; MobileNetV2-based transfer learning achieves roughly 94–96% accuracy on standard leaf-disease datasets; ensemble credit-risk models increasingly incorporate agricultural and remote-sensing variables; and LSTM/GRU architectures lead commodity price forecasting. However, very few peer-reviewed systems combine agronomic and financial reasoning into a single, jointly evaluated recommendation, and commercial platforms that do integrate these services rarely publish reproducible model evaluations. Using the AgriVerse decision-intelligence platform as an illustrative case, this review argues that the next research priority is not incremental accuracy gains within any one module, but the unification of agronomic and financial decision layers, the replacement of rule-based financial logic with trained models, and rigorous field-level validation of such integrated systems.

Keywords- Agri-FinTech, Machine Learning, Deep Learning, Small and Marginal Farmers, Crop Recommendation, Crop Yield Prediction, Plant Disease Detection, Agricultural Credit Risk Assessment, Loan Eligibility Prediction, Commodity Price Forecasting, Ensemble Learning, Integrated Agricultural Decision Support Systems, AgriVerse.

I. INTRODUCTION

Agriculture continues to employ a large share of India's rural population, and smallholders cultivating less than two hectares make up the majority of this workforce. Even so, profitability for this group remains inconsistent, largely because decisions about what to grow, how to grow it, and how to finance it are made independently rather than as part of one connected process. A farmer choosing a crop typically has access to soil and weather information, but rarely has simultaneous visibility into cultivation cost, likely return on investment, prevailing market prices, or the loan options that crop would qualify for.

Machine learning has, in fact, been applied to almost every one of these sub-problems on its own.

Recommendation systems use soil chemistry and climate variables to suggest suitable crops. Yield-prediction models translate historical and environmental data into an expected harvest figure. Computer-vision models flag disease symptoms from photographs of leaves. Credit-scoring models estimate a farmer's likelihood of loan repayment from financial and, in newer work, agricultural

© 2026 Dr. G. M. Asutkar. his is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly credited.

indicators. Time-series models project future commodity prices to inform when and where to sell.

Each of these lines of inquiry has matured into a reliable, high-performing body of work, but largely in parallel — published in different venues, tested on different benchmarks, and rarely brought together.
This review surveys the literature across these five strands and, in addition, looks at industry-level AgriFinTech platforms that attempt to combine agricultural and financial services operationally. The intent is to map, strand by strand, what has already been convincingly demonstrated and what specific gap still stands open, so that newer integrated systems — the AgriVerse platform discussed as a case study later in this paper — can be situated clearly within the existing body of research.

Section 2 reviews the literature across six functional clusters: crop recommendation, yield prediction, disease detection, credit-risk and loan-eligibility prediction, commodity price forecasting, and integrated Agri-Fintech platforms. Section 3 consolidates these findings into a comparative table. Section 4 identifies the research gaps that emerge from this review. Section 5 outlines an integrated research direction, using AgriVerse as a working example. Section 6 discusses future research directions, and Section 7 concludes the paper.

II. LITERATURE REVIEW

1. Crop Recommendation Systems

Machine learning-based crop recommendation is one of the more mature branches of agricultural AI. Comparative studies typically train classifiers such as Random Forest, Decision Tree, K-Nearest Neighbours, and Support Vector Machines on soil nutrient levels (nitrogen, phosphorus, potassium), pH, temperature, humidity, and rainfall, with the publicly available Kaggle crop-recommendation dataset — spanning 22 crop categories — serving as a de facto benchmark [1], [3], [7], [8].

Random Forest and its ensemble variants consistently outperform simpler baselines, with reported accuracy generally falling between 91% and 98% [1], [4], [6].

More recent work pushes past single-crop suggestions toward mixed-cropping recommendations built on explainable-AI frameworks combined with ant-colony optimization [6], while other studies feed live IoT soil-moisture and nutrient readings into a cloud-hosted Random Forest model so that recommendations track real-time field conditions rather than static averages [5], [7], [9].

Despite this progress, the systems reviewed optimize almost exclusively for agronomic fit; none of them factor cultivation cost, expected market price, or credit access into the recommendation itself, so a crop judged agronomically ideal can still be financially out of reach for a smallholder. Therefore, for our project, AgriVerse's crop-recommendation module extends this line of work by pairing a Decision Tree classifier for agronomic suitability with a downstream financial-ranking layer, so that profitability and risk are weighed alongside soil and climate fit rather than left out entirely.

2. Yield Prediction Models

Yield-prediction research has converged in much the same direction, with Random Forest regression emerging as a strong default that generally outperforms linear regression and holds its own against Gradient Boosting and XGBoost on error metrics such as MAE, RMSE, and R^2 [10]-[14].

A frequently cited global-scale study reported Random Forest RMSE values of 6–14% of average yield, against 14–49% for multiple linear regression across wheat, maize, and potato [10], [17], a pattern later confirmed on region-specific datasets from Switzerland and the U.S. cotton belt, where R^2 regularly exceeded 0.95 [11], [13].

Two systematic reviews spanning the wider field confirm Random Forest, Neural Networks, and Gradient Boosting Trees as the most common algorithms, with CNNs and LSTMs used mainly for remote-sensing and time-series-based estimation, and note that no single feature set or model is best across all crops and regions [15], [16]. Even so, this literature almost always stops at the predicted

number: it rarely connects a yield estimate to expected revenue, net profit, or ROI, or feeds it into a farmer-facing decision layer.

Therefore, for our project, AgriVerse's Random Forest yield module is designed to feed directly into the financial-estimation engine, turning a raw tonnage figure into a profitability estimate rather than leaving it as a standalone output.

3. Plant Disease Detection

CNN-based transfer learning is the standard route to automated leaf-disease diagnosis. MobileNetV2, pretrained on ImageNet and fine-tuned on the roughly 54,000-image, 38-class PlantVillage dataset, is a common choice because it balances accuracy against the light computational footprint needed for mobile deployment, with reported validation accuracy around 94% [19]-[21], [25].

Later studies benchmark MobileNetV2 against heavier networks such as DenseNet121, ResNet50, EfficientNetB0, and VGG, generally finding that the larger models gain only marginal accuracy at a much higher computational cost [22], [26], [28], while hybrid architectures — a concatenated DenseNet121–MobileNetV2 model with attention, for instance — attempt to close that gap without sacrificing efficiency [22].

Separate work has examined robustness under adversarial perturbation such as FGSM and PGD attacks, raising reliability concerns for field-deployed agricultural AI [23], and multi-model ensembles combining MobileNetV2, NASNetMobile, and InceptionV3 have been proposed for resource-constrained edge devices [24].

Nearly all of this research, however, trains and tests on PlantVillage or similarly curated, clean-background images, which limits how well it generalizes to cluttered field photographs, co-occurring stress factors, or regional diseases outside the 38 labelled classes; disease detection is also uniformly treated as a standalone vision task, disconnected from any downstream cost or risk estimate. Therefore, for our project, AgriVerse applies the same MobileNetV2-on-PlantVillage approach reported in the literature, while explicitly treating this dataset-coverage limitation as a priority for future field-data collection.

4. Credit-Risk and Loan-Eligibility Prediction

Machine-learning approaches to loan-eligibility and credit-risk scoring began largely in general consumer and small-business banking, where Random Forest, Gradient Boosting, and Logistic Regression are applied to income, credit-history, and repayment-capacity features [6], [8], [9].

Farm-specific credit research has since folded in agricultural variables — regional output, land-yield capacity, crop performance, and even climate and remote-sensing indicators. One hybrid ensemble combining Adaptive Synthetic Sampling with a Local Cascade Ensemble was designed specifically to counter the class imbalance typical of farmer-default data, flagging marital status and regional agricultural output as strong predictors [29]; other work has examined severe-weather signals in peer-to-peer farmer loan-default prediction [30] and proposed indicator-optimization frameworks validated on thousands of real bank records [31].

A particularly relevant study folds multi-source remote-sensing data — temperature and precipitation volatility among them — into explainable ML models for agricultural loan-default prediction, directly targeting the climate-related risk that traditional credit assessment tends to miss [34].

Closest in spirit to an integrated system, a 2025 study proposes deriving loan eligibility and sanction amount directly from AI-predicted land-yield capacity combined with blockchain transaction records [32], while a systematic review of AI-based agricultural loan-recommendation systems flags bias, poor data interoperability, and weak interpretability as unresolved barriers to equitable access [33].

Across this body of work, though, models are built and judged from the lender's side — accurate default prediction, not farmer-facing decision support — and even the yield-linked loan-appraisal system treats loan approval as a terminal output

rather than one factor weighed jointly against crop choice and cultivation cost. Therefore, for our project, this gap motivates moving AgriVerse's present rule-based financial-risk logic toward a trained model informed by the ensemble techniques surveyed here.

5. Agricultural Commodity Price Forecasting

Commodity-price forecasting has been studied through both classical time-series and deep-learning methods, with comparative studies repeatedly finding that LSTM and GRU architectures outperform ARIMA, SVR, and XGBoost at capturing volatile, nonlinear price movements, including during disruptive periods such as the COVID-19 pandemic [45], [47], [48].

A large-scale evaluation across 23 commodities and a decade of daily wholesale prices confirmed that LSTM/GRU models consistently beat traditional statistical and machine-learning baselines [48]. More recent work explores hybrid and optimization-augmented models — genetic-algorithm-tuned LSTM and Extreme Learning Machine variants, and swarm-intelligence-weighted ensembles of ARIMA, SVR, and recurrent networks — generally reporting further gains during high-volatility periods [45], [49], [54], while Graph Neural Network approaches attempt to capture spatial and temporal relationships across correlated commodities at once, addressing a known weakness of single-variable LSTM forecasting [52].

Despite this technical maturity, integrated agricultural decision-support systems in the literature and in practice still lean on live or recent market-price feeds rather than a trained forecast, which means profitability and ROI estimates are computed against today's price rather than the price likely to prevail at harvest — understating both the upside and the risk tied to price movement over the growing season. Therefore, for our project, this points to forecast-driven pricing, built on the LSTM/GRU methods reviewed here, as a natural next addition to AgriVerse's financial-estimation engine.

6. Integrated AgriFinTech Platforms

A smaller and less academically documented body of work concerns platforms that combine agricultural and financial services operationally. Commercial products such as DeHaat, Jai Kisan, Ant Group'ssatellite-and-AI lending offering, and newer entrants such as Soluta bundle advisory services, credit access, input procurement, and market linkages into a single application, typically scoring credit from satellite imagery, IoT sensor data, and digital transaction history rather than from a published, peer-reviewed model pipeline [37], [38], [43].

Industry analyses describe these platforms as bundling risk-reduction tools — weather-based advisory, crop-diversification modelling, and parametric insurance triggered by measurable variables such as rainfall — alongside more conventional lending and payment features [40], [41].

Academic evaluation of this kind of integration, though, remains thin: most available sources are market-sizing reports, feature-requirement write-ups, or conceptual overviews of how AI, IoT, and blockchain might be combined in an agri-fintech setting, rather than empirically evaluated systems reporting accuracy, F1-score, or error metrics comparable to the single-task studies discussed above [39], [42], [44].

This is, in many ways, the most consequential gap surfaced by this review: commercial platforms show that integration is operationally and commercially workable, but rarely publish transparent model evaluation, while the academic literature is rigorously evaluated but confined to single-purpose tasks. Therefore, for our project, this gap is precisely the space AgriVerse is positioned to occupy — an academically evaluated system that still functions as a single, jointly ranked, farmer-facing recommendation pipeline.

7. Comparative Analysis

Table I consolidates the six clusters reviewed above, listing a representative paper from each, the technique it uses, what it found, the gap it leaves

open, and how that gap connects to the proposed AgriVerse pipeline.

Sr. No.	Research Paper / Reference	Year	Main Focus	Method / Approach	Key Findings	Research Gap / Limitation	Relevance to Proposed System
1	A Comprehensive Study on Crop Recommendation System Using Machine Learning [1]	2025	Crop recommendation	Comparison of Random Forest, Decision Tree, KNN and SVM on soil-nutrient and climate features	Random Forest consistently the strongest performer, 91-98% accuracy across comparative studies	No cultivation cost, ROI, or credit factors included in the recommendation	Supports AgriVerse's Decision Tree crop-recommendation module as an agronomic baseline
2	Random Forests for Global and Regional Crop Yield Predictions [10]	2016	Yield prediction	Random Forest regression benchmarked against multiple linear regression	RF RMSE 6-14% of average yield vs. 14-49% for linear regression across wheat, maize and potato	Yield output is not linked to revenue, profit, or a farmer-facing decision layer	Supports AgriVerse's Random Forest yield-estimation module feeding the financial engine
3	Plant Leaf Disease Detection using MobileNetV2 [25]	2025	Disease detection	MobileNetV2 transfer learning fine-tuned on the PlantVillage dataset (38 classes)	Reported validation accuracy of approximately 94%	Trained and tested on curated, clean-background images; not linked to financial impact	Supports AgriVerse's disease-detection module and its acknowledged dataset-coverage limitation
4	Farmers' Credit Risk Evaluation with an Explainable Hybrid Ensemble Approach [29]	2024	Credit-risk prediction	Adaptive Synthetic Sampling combined with a Local Cascade Ensemble to address class imbalance	Marital status and regional agricultural output identified as strong default predictors	Built and evaluated from the lender's perspective; not tied to crop or cultivation decisions	Motivates a future trained financial-risk engine within AgriVerse
5	Enhancing Agricultural Commodity Price Forecasting with Deep Learning [48]	2025	Price forecasting	LSTM and GRU architectures evaluated across 23 commodities using a decade of daily prices	LSTM/GRU consistently outperform ARIMA, SVR and XGBoost baselines	Integrated advisory systems generally use live prices rather than a trained forecast	Motivates forecast-driven, rather than snapshot, pricing in AgriVerse's financial engine
6	A Farmer Friendly AI Powered Smart Agriculture Loan Appraisal System [32]	2025	Integrated agri-finance	Loan eligibility and sanction amount derived from AI-predicted land-yield capacity with blockchain-based records	Demonstrates that loan appraisal can be driven directly by an agronomic prediction	Loan appraisal is treated as the terminal output rather than one input weighed against crop choice	Closest existing analogue to AgriVerse's goal of a single, jointly ranked recommendation

III. RESEARCH GAPS

- Agronomic recommendations ignore financial viability: Crop-recommendation systems optimize almost exclusively for soil-climate suitability; none of the systems reviewed factor

cultivation cost, expected price, or credit access into the recommendation, so an agronomically sound crop can still be financially out of reach.

- Yield prediction stops at the number: Yield models are evaluated purely on regression accuracy and are rarely connected to revenue, profit, or a farmer-facing decision layer.
- Disease detection is trained on curated, not field, imagery: Almost every disease-detection study relies on PlantVillage-style, clean-background datasets, limiting generalization to cluttered real-world photographs and regional disease variants, and disease diagnosis is never linked to a downstream cost or risk estimate.
- Credit-risk models are built for lenders, not farmers: Loan-eligibility research optimizes for default prediction rather than farmer-facing decision support, and even the most integrated appraisal systems treat loan approval as a terminal output rather than one input among several.
- Price forecasting exists but integrated systems don't use it: Well-validated LSTM/GRU forecasting methods are rarely incorporated into decision-support platforms, which instead rely on today's price, understating both the opportunity and the risk tied to price movement before harvest.
- Operational integration outpaces academic evaluation: Commercial AgriFinTech platforms achieve agricultural-financial integration in practice but seldom publish reproducible model evaluations, while academic literature remains confined to single tasks.
- Validation stays confined to historical benchmarks: Almost all reviewed systems, single-task and integrated alike, are validated on historical or curated datasets rather than through longitudinal, multi-season field deployment.

IV. PROPOSED INTEGRATED RESEARCH DIRECTION

Motivated by the gaps identified above, the proposed direction is not a claim of experimentally superior single-module accuracy, but an end-to-end decision pipeline that keeps agronomic and financial reasoning connected at every stage:
Farmer Profile & Location Input → Soil & Climate Data Retrieval → Data Validation → Crop-Suitability Prediction (Decision Tree) → Yield Estimation (Random Forest Regressor) → Leaf-Image Upload (optional) → Disease Detection (MobileNetV2 Transfer Learning) → Cost, Revenue, ROI & Risk Computation (AgriFinTech Engine) → Joint Ranking by Profitability, Risk & Sustainability → Loan / Scheme Recommendation → Farmer-Facing Output. Soil and climate inputs, along with location metadata, are first validated to reject incomplete or malformed records.

A Decision Tree classifier scores agronomic suitability across candidate crops, and a Random Forest regressor estimates expected yield for each. Where a leaf photograph is available, a MobileNetV2 model, fine-tuned on the PlantVillage dataset, flags visible disease symptoms so that a revised, risk-adjusted yield can feed into later stages. These agronomic outputs are then passed to a financial-estimation engine that converts them into cultivation cost, expected revenue, net profit, ROI, and a composite risk score, before crops are ranked jointly by profitability, risk, and sustainability rather than agronomic fit alone. A final layer maps the top-ranked crop or crops onto loan-eligibility and scheme-recommendation logic, so the farmer sees a single, prioritized output rather than separate agronomic and financial answers.

Critical distinction. Agronomic suitability and financial viability are not the same thing, and a system that reports only the former risks recommending crops a smallholder cannot actually afford to grow. In the current AgriVerse implementation, the agronomic layer — Decision Tree crop recommendation and Random Forest yield estimation — is a trained model evaluated against held-out data, reporting 97.95% crop-recommendation accuracy and a yield-prediction Mean Absolute Error of 1.819 tonnes per hectare across data representative of more than 12,000 farmers across ten districts; the disease-detection layer likewise reports a trained-model accuracy of 95.80%.

The financial-estimation layer, however, remains rule-based rather than trained, which is consistent with the general immaturity of jointly evaluated agronomic-financial modelling identified in Sections 2.4 and 2.6, rather than a shortcoming unique to this system. Replacing that rule-based layer with models trained on real farm-level financial and repayment data, following the ensemble credit-risk techniques reviewed in Section 2.4, is therefore the most direct next step toward a fully learned pipeline.

1. Future Research Directions

- Joint agronomic-financial optimization: fold cultivation cost, market price, ROI, and credit access into the recommendation model itself rather than treating them as a post-hoc calculation.
- Field-representative disease datasets: build broader, field-collected datasets spanning more crops, regional disease variants, and cluttered real-world backgrounds beyond PlantVillage.
- Trained, not rule-based, financial and risk modules: migrate financial-risk and loan-eligibility logic toward models trained on real farm-level financial and historical-risk data.
- Forecast-driven rather than snapshot-driven pricing: incorporate LSTM/GRU-class forecasting into profitability estimates so they reflect expected harvest-time prices rather than today's price.
- Transparent, peer-reviewed evaluation of integrated systems: publish metric-reported evaluations of fully integrated platforms to close the gap between rigorously evaluated single-task research and operationally integrated but rarely evaluated commercial products.
- Longitudinal, real-world field validation: move beyond historical or benchmark datasets toward multi-season, multi-region field deployment and evaluation.

V. CONCLUSION

This review surveyed machine-learning and deep-learning research across crop recommendation, yield prediction, plant-disease detection, loan-eligibility and credit-risk assessment, and agricultural commodity price forecasting, alongside existing commercial AgriFinTech platforms. Each of these sub-tasks has reached a mature research stage on its own: Random Forest and related ensembles, MobileNetV2-based transfer learning, and LSTM/GRU architectures all report strong, well-documented performance on their respective benchmarks. Yet a consistent gap runs through this literature — agronomic and financial decision-making remain largely siloed, evaluated separately in academic work and integrated only operationally, rarely with transparent model evaluation, in commercial practice. Integrated decision-intelligence platforms such as AgriVerse represent an early step toward closing that gap, evaluating agronomic and financial modules with reported metrics while still combining them into a single, farmer-facing recommendation. Future work should prioritize joint agronomic-financial optimization, field-representative datasets, trained rather than rule-based financial reasoning, forecast-driven pricing, transparent peer-reviewed evaluation, and longitudinal, real-world validation of such integrated systems.

Acknowledgment

The authors thank Dr. G. M. Asutkar, Vice Principal, Priyadarshini College of Engineering, Nagpur, for his guidance throughout this review, and the Department of Artificial Intelligence and Data Science for its continued support.

REFERENCES

1. "A Comprehensive Study on Crop Recommendation System Using Machine Learning," Springer Nature Link, 2025.
2. "Crop Recommendation System using Random Forest Algorithm in Machine Learning," ResearchGate, 2023.
3. "Machine learning based recommendation of agricultural and horticultural crop farming in India under the regime of NPK, soil pH and three climatic variables," ScienceDirect, 2024.
4. "An Efficient Crop Recommendation System Using Optimized Random Forest Approach," Springer Nature Link.

5. "Internet of Things- and Machine Learning-Based Soil Parameter Monitoring System for Optimal Crop Recommendation," Applied Fruit Science, Springer Nature Link, 2026.
6. "Advancing crop recommendation system with supervised machine learning and explainable artificial intelligence," Scientific Reports, 2025.
7. "A Comprehensive Crop Recommendation System Leveraging Internet of Things and Machine Learning," Springer Nature Link.
8. "Affordable Precision Agriculture: A Deployment-Oriented Review of Low-Cost, Low-Power Edge AI and TinyML for Resource-Constrained Farming Systems," arXiv, 2026.
9. "Real-time soil fertility analysis, crop prediction, and insights using machine learning and deep learning algorithms," Frontiers in Soil Science, 2025.
10. "Random Forests for Global and Regional Crop Yield Predictions," PLOS ONE, 2016.
11. "Crop Yield Prediction Using Random Forest Algorithm and XGBoost Machine Learning Model," International Journal of Research and Innovation in Social Science, 2025.
12. "Crop Yield Time-Series Data Prediction Based on Multiple Hybrid Machine Learning Models," arXiv, 2025.
13. "Analysis of Crop Yield Prediction Using Random Forest Regression Model," ResearchGate, 2023.
14. "Crop Yield Prediction Using Improved Random Forest," ITM Web of Conferences, ICDSAC, 2023.
15. "Crop yield prediction using machine learning: A systematic literature review," ScienceDirect, 2020.
16. "Crop yield prediction using machine learning: An extensive and systematic literature review," ScienceDirect, 2024.
17. "Random Forests for Global and Regional Crop Yield Predictions" (extended citation), Harvard DASH repository.
18. [Crop yield prediction systematic review (extended citation), ScienceDirect, 2024.
19. "Plant-Disease-Detection-with-MobileNetV2," GitHub repository.
20. "Plant-Disease-Detection-with-ML-and-Android," GitHub repository.
21. "Leveraging Transfer Learning for Plant Disease Detection with MobileNetV2," Medium, 2025.
22. "A robust and light-weight transfer learning-based architecture for accurate detection of leaf diseases across multiple plants using less amount of images (LeafDoc-Net)," PMC.
23. "LeafyVGG-16: Transfer Learning for Plant Disease Detection with Cyber Risk Analysis," bioRxiv, 2026.
24. "Dynamic Meta-Ensemble Framework for Efficient and Accurate Deep Learning in Plant Leaf Disease Detection on Resource-Constrained Edge Devices," arXiv, 2026.
25. "Plant Leaf Disease Detection using MobileNetV2," ITM Web of Conferences, KEIS, 2025.
26. "Plant Disease Detection with Transfer Learning: Evaluating the Impact of Various Loss Functions and Explainable AI," Journal of Agricultural, Biological and Environmental Statistics, Springer, 2025.
27. "Using Transfer Learning to Adapt MobileNet for General Plant Disease," CS231N Project Report, Stanford, 2025.
28. "Comparative Analysis of Deep Learning Models for Crop Disease Detection: A Transfer Learning Approach," arXiv, 2025.
29. "Farmers' credit risk evaluation with an explainable hybrid ensemble approach: A closer look in microfinance," ScienceDirect, 2024.
30. "Severe weather and peer-to-peer farmers' loan default predictions: Evidence from machine learning analysis," ScienceDirect, 2023.
31. "Growth potential of machine learning in credit risk predicting of farmers in the industry 4.0 era," International Journal of Finance & Economics, Wiley, 2025.
32. "A Farmer Friendly AI Powered Smart Agriculture Loan Appraisal System by Considering Their Land Yield Capacity," Springer Nature Link, 2025.
33. "Revolutionizing agricultural loan recommendation systems via machine learning and artificial intelligence: A systematic literature review," ScienceDirect, 2025.
34. "Optimizing Risk Profiling of Agricultural Loans: Default Prediction Using Multi-Source Remote Sensing Digital Footprints," MDPI, 2026.
35. "Artificial Intelligence in Sustainable Agricultural Lending: Enhancing Credit Access for Smallholder Farmers," Springer Nature Link.

36. "Farmer Loan Default Risk Prediction Based on Imbalanced Data Processing and Weighted Soft Voting Heterogeneous Ensemble Model," 2026.
37. "Revolutionizing Agricultural Finance: The Rise of Agrifintech," ResearchGate, 2023.
38. "Agri-Fintech Market Insights Report 2026: The Rise of Digital Lending and Insurance for Farmers," GlobeNewswire, 2026.
39. "AGRI-FINTECH," C4S Courses, 2025.
40. "Building a Robust Agri-Fintech Platform: Key Features for Success," Code & Pepper, 2024.
41. "Agri-Fintech Innovations: Crop Insurance, Lending, Payments & Risk Mitigation For Small Farmers," EnFuse Solutions, 2026.
42. "Agri-Fintech: Bridging Gap between Farmers & Financial Services," TraceAgTech, 2023.
43. "What Is Agrifintech and Why It Matters for Modern Farmers?," Soluta, 2026.
44. "Integrating Agri-Fintech Technologies For Smarter Farm Management," The Farming Insider, 2025.
45. "Various optimized machine learning techniques to predict agricultural commodity prices," Neural Computing and Applications, Springer, 2024.
46. "Automated Agriculture Commodity Price Prediction System with Machine Learning Techniques," arXiv.
47. "Hybrid forecasting of agricultural commodity prices: Integrating machine learning, time series, and stochastic simulation models," ScienceDirect, 2025.
48. "Enhancing agricultural commodity price forecasting with deep learning," Scientific Reports, 2025.
49. "A novel agricultural commodity price prediction model integrating deep learning and enhanced swarm intelligence algorithm," PLOS ONE, 2025.
50. "Predicting Agricultural Commodities Prices with Machine Learning: A Review of Current Research," arXiv, 2023.
51. "A novel agricultural commodity price prediction model integrating deep learning and enhanced swarm intelligence algorithm," PMC.
52. "RNN and GNN based prediction of agricultural prices with multivariate time series and its short-term fluctuations smoothing effect," Scientific Reports, 2025.
53. "Enhancing agricultural commodity price forecasting with deep learning," Scientific Reports, 2025 (extended citation).
54. "A novel agricultural commodity price prediction model integrating deep learning and enhanced swarm intelligence algorithm," PLOS ONE, 2025 (extended citation).