iJRASET
International Journal For Research in Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** XI **Month of publication:** November 2026

DOI: https://doi.org/10.22214/ijraset.2026.85645

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue XI Nov 2026- Available at www.ijraset.com

Machine Learning for Integrated Farmer Advisory and Marketplace Systems: A Literature Survey

Disha D S[1], Disha H Jain[2], Dhruhi Atykar[3], Parth Rawat[4], Vanishree[5]
[1, 2, 3, 4, 5]*Department of Computer Science and Engineering, B.M.S. College of Engineering, Bengaluru, India*

Abstract: ***Farmers have to decide what to plant, what to buy, what to do when the crop goes wrong, and when to sell. Most of the software we found covers one of these decisions and leaves the rest alone. This paper looks at 27 studies, mostly from 2022 to 2026, on crop recommendation, fertilizer and input recommendation, advisory tools and disease detection, crop price prediction, online marketplaces, and a few joined-up platforms. For each one we note the method, the main finding, and what it leaves out if a farmer wants help from planting to sale. Tree-based ensembles turn up often in crop and input work, but price forecasting has no clear winner: ridge regression, LSTM and XGBoost each came out ahead in different studies. A handful of joined-up platforms exist, though they are mostly prototypes judged on benchmark data, and the e-NAM studies we read measure prices and arrivals but say nothing about advising the farmer. We also use our own prototype to show why accuracy figures need a simple baseline and real data before anyone leans on them. The paper ends with the gaps we found and a few things worth trying next.***

Keywords: Literature survey, crop recommendation, crop price prediction, plant disease detection, Random Forest, XGBoost, e-NAM, farmer advisory, precision agriculture.

I. INTRODUCTION

A farmer's year is a string of decisions. What to sow comes first, and it depends on the soil and the season. Then seed and fertilizer have to be bought, preferably at a fair price, and anything that goes wrong with the crop has to be spotted early. At harvest the question is when and where to sell, and to whom. Advice is hard to get at most of these points and price information is patchy. Many farmers end up selling through an intermediary who takes a cut.

Machine learning has been tried on each of these steps, one at a time.

There are crop recommenders, fertilizer recommenders, chatbots for farmer questions, disease detectors, price forecasters and online trading sites, with plenty of papers on each. A few recent papers do try to join some of them up. Even so, a farmer who wants help from sowing to sale would, in most cases, still be switching between separate tools and typing the same soil values in again.

We ran into this ourselves while building a prototype that joins five of these services together [1]. Two things came out of that. The accuracy numbers depend a lot on the data and on what you compare against, and the published studies say little about how well the stages fit together. So we went back to the literature to see what is actually there.

This paper is a literature survey. We read 27 studies, sorted them into six groups, and put the main points side by side in a table. After that we list the gaps we noticed and some possible next steps. Section II explains the scope, Sections III to VIII go through the groups, Section IX compares the studies, and Section X covers the gaps. Our own prototype is in Section XI, next steps are in Section XII, and a short conclusion follows.

II. SCOPE OF THE SURVEY

This is a narrative survey, not a systematic one. We did not follow a formal search protocol or write inclusion criteria beforehand, so the 27 studies are best read as a reasonable sample of recent work and not as everything that exists. Most were published between 2022 and 2026, and Table I gives the year of each. Every study was checked against its published record before we described it, but for some we could only read the abstract, and we say so where it counts. A handful of older or background sources are cited where we needed them. Each study was read for the problem it tackles, the method, the main result, and what it leaves out. That last item needs a word of warning. A crop classifier is not at fault for failing to forecast prices. We only note where a study stops, because a farmer would need whatever comes next. Fig. 1 shows the five stages in the order a farmer meets them.

Two methods come up again and again. Random Forest [2] builds many decision trees on random slices of the data and takes a vote. XGBoost [3] builds trees one after another, each trying to fix the mistakes of the last. Both do well on table-shaped data, which is what most of this field works with.

©IJRASET: All Rights are Reserved

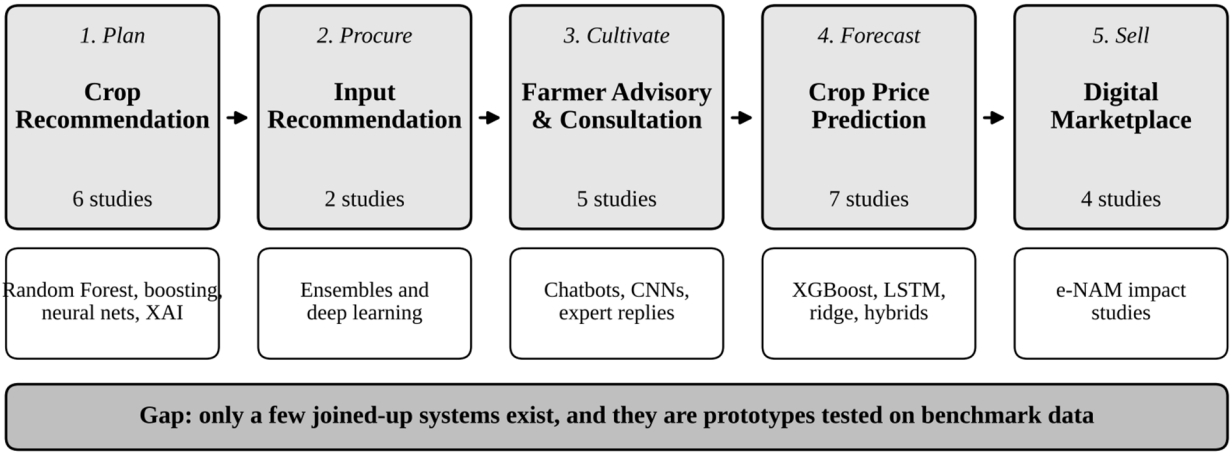


Fig. 1 The five stages covered in this survey and the number of studies in each. Three joined-up platforms are discussed separately in Section VIII.

III. CROP RECOMMENDATION

Crop recommendation is almost always treated as classification. You give the model soil nutrients, weather and sometimes location, and it names a crop.

Tree-based ensembles show up in much of this work, though not all of it. Dey et al. [4] trained five models (SVM, XGBoost, Random Forest, KNN and a decision tree) on 11 agricultural and 10 horticultural crops from India, and XGBoost came out on top with precision around 99% in each case. Shastri et al. [5] paired supervised learning with explainable AI so that the reasons behind a recommendation can be looked at, and their best model was Gradient Boosting.

Neural networks appear too. Bhola and Kumar [6] work at farm level in two steps: an artificial neural network filters the suitable crops from local inputs (they report 99.10% accuracy), and a Random Forest then estimates yield for the shortlisted ones. Kathoon et al. [7] go fully to deep learning, with a hybrid framework over the usual soil and weather inputs.

Dahiphale et al. [8] compared seven algorithms (Random Forest, Naive Bayes, KNN and SVM among them) and a four-layer neural network on a Kaggle dataset of 2,200 records covering 22 crops. Random Forest and Naive Bayes both reached 99.5% accuracy, and the neural network reached 97.73% validation accuracy. A plain Naive Bayes keeping up with Random Forest is in line with what we saw in our own prototype. The authors suggest linking such models to IoT sensors and language models later on.

A review by Umamaheswari and Kavitha [9] covers both crop recommendation and plant disease detection and lists Random Forest, SVM and CNNs among the usual tools.

Accuracy figures from these papers cannot really be compared with each other, because the datasets, the features and the validation set-ups all differ and the winner changes from paper to paper. Most of them also stop at the planting decision. Once the crop is chosen, the farmer is on their own.

IV. INPUT RECOMMENDATION

Once the crop is picked, the next job is deciding what to put on it. We found fewer recent studies here than for crops. Singh et al. [10] compared Random Forest, gradient boosting, SVM, logistic regression, KNN and a deep learning model on about ten thousand samples (soil nutrients, moisture, humidity, temperature, crop and soil type), scored by mean average precision at 3. Random Forest did best, though its score was only 0.2805, so fertilizer prediction looks much harder than crop prediction. Patel and Patel [11], a little older, built a recommender that suggests a crop and the fertilizers for it, for both the kharif and rabi seasons, using several criteria together.

Neither one tells the farmer where to buy anything, which is a bigger omission than it sounds. A recommendation for a product the farmer cannot find nearby, or can only get at a higher price, does not help much. It also depends on lists of approved products and suppliers being kept up to date by someone. In our own prototype [1] we typed those lists in by hand as demonstration data and could not check them against official sources, so we know first hand that this part is awkward.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

V. ADVISORY TOOLS AND DISEASE DETECTION

The advisory work we found is mostly about chatbots. Mzumara and Mulepa [12] propose an advisory system for smallholder farmers in Malawi growing maize and sweet potato, with a knowledge base of crop guidelines and a chatbot for questions the knowledge base does not cover. It is a project report, so there are no field results to quote. IDinsight [13] ran a scoping study of how digital tools can be made to work for farmers.

Chatbots have moved on a bit. Farmer.Chat [14], from Digital Green and Microsoft Research, uses generative AI with retrieval over a curated knowledge base, works in several languages and in more than text, and has been deployed in Kenya, India, Ethiopia and Nigeria. The authors report more than 15,000 farmers and over 300,000 queries.

Still, some farm problems are hard to judge from a description. A leaf can be yellow for several reasons, and the right call may depend on the soil, the variety and the week. One alternative keeps a person in the loop: the farmer sends photos and a short description, and a registered expert replies on the platform, which also keeps a record. That is slower and does not scale the way a chatbot does. It also raises questions about how many experts there are, how fast they answer and how good the answers are. We did not measure any of these in our own prototype [1].

A third route is automatic disease detection from photos, and the literature here is large. Mohanty et al. [15] trained deep networks on tens of thousands of labeled leaf images and got very high accuracy on held-out images from the same collection. They also found that accuracy dropped sharply on images taken under different conditions. Three recent reviews say much the same thing. Jelali [16] found that results on the PlantVillage dataset, collected under laboratory conditions, are over-optimistic, and that only a few studies use real field data. Shafay et al. [17] report accuracy of 95-99% in the laboratory against 70-85% in the field, with transformer models holding up better than CNNs. Nyawose et al. [18] review machine learning and deep learning methods with a focus on real-time use in uncontrolled farm conditions. Photo-based detection can work, but a score on a tidy benchmark says little about a phone photo taken in a field.

VI. PRICE PREDICTION

There is no clear winner here, which is the first thing to say. In Khare's review [19], LSTM models pick up time-dependent patterns while ensembles and XGBoost reach high accuracy on standard datasets. Zhao et al. [20] stack a temporal convolutional network with XGBoost to forecast agricultural prices. On Malaysian commodity prices, LSTM beat ARIMA, SVR, Prophet and XGBoost in the comparison by Chen et al. [21].

Several Indian studies use AGMARKNET or state portal data. Manogna et al. [22] tested ARIMA, SVR, XGBoost, MLP, LSTM, GRU and an echo state network on daily wholesale prices of 23 commodities. Nayak et al. [23] added weather as an outside input for tomato, onion and potato prices and compared statistical, machine learning and deep learning models. Patil et al. [24] looked at onion prices in the Bengaluru market and found LSTM clearly ahead of SARIMA and Holt-Winters (RMSE of 429.58 against 958.66 and 749.25 for the Local variety), although they did not include a machine learning or naive baseline.

The most useful study for us was Balantrapu et al. [25], who used AGMARKNET records for wheat and maize in India. They trained eight algorithms (ridge regression, SVR, Random Forest, extremely randomized trees, gradient boosting, XGBoost, ARIMA and SARIMA) and added a naive persistence benchmark. Ridge regression on lagged prices beat everything else, with MAPE of 2.75% for wheat and 2.59% for maize. Tree-based models and SVR fell apart on the trending test window. Against the naive forecast, though, ridge's lead was small for wheat and mixed for maize, where persistence matched it on MAE and MAPE.

Two things stood out. First, the forecast is where these papers end. A farmer who is told what the price might be in three weeks still has to decide whether to sell now, which market to use, and whether the number is any good. Turning a forecast into a sell or hold call, after transport and storage costs, is the step we did not find.

Second, a high score does not mean much without something to compare it to. Weekly prices move slowly, so a naive forecast that just repeats last week's price is hard to beat over short horizons, and the forecasting literature has said for a long time that such a benchmark should be included [26]. Balantrapu et al. found this on real data. We found the same on generated data in our own prototype [1]: the naive forecast scored $R^2 = 0.9816$ against 0.9808 for XGBoost, one week ahead.

VII. ONLINE MARKETPLACES

India already has a large government platform, e-NAM, which links existing APMC mandis for electronic trading. The government reports 1,656 mandis in 23 States and 4 Union Territories by March 2026 [27].

Most of what we found on marketplaces is about e-NAM, and the findings lean positive. In Rajasthan, Swain [28] looked at price realization and market arrivals after e-NAM was adopted. Haryana has two studies. Mahto and Patil [29] cover 2015-16 to 2020-21 and report significant changes in arrivals and prices after implementation, while noting that infrastructure problems remain and that

earlier studies gave mixed results; Singh et al. [30] compared growth rates before and after e-NAM at the Sirsa APMC and concluded the overall effect there was positive. Chaudhary and Suri [31] turned to wholesale prices of selected commodities and the effect of e-trading on them.

All four measure what happened to prices and arrivals. Advising the farmer on when to sell is a different job, and in the parts we read nobody takes it on.

Bidding lets buyers compete instead of accepting a listed price, and that brings its own trouble. Our prototype [1] has no payment handling, no identity checks, no way to settle disputes and no protection against buyers who agree among themselves. A real marketplace would need all of that sorted out first.

VIII. JOINED-UP PLATFORMS

Some recent papers do put several of these services behind one interface, and we found three. Krishna et al. [32] combine crop recommendation and plant disease identification, using IoT soil sensors and camera images, and report CNN accuracy of almost 99.98%. Sribharathi et al. [33] describe a web application where the farmer enters location, soil type and land area and gets weather forecasts, crop suggestions and financial estimates, plus a chatbot that advises on crop choice, timelines and cost and profit. Their abstract mentions piloting but gives no details.

Dwibedy et al. [34] go furthest. Their Kisan AI adds market price as an input to a Random Forest crop recommender (99.3% accuracy on a benchmark dataset augmented with a price variable), uses Prophet for six-month price forecasts and MobileNetV2 for disease detection (96.2% validation accuracy on 16 classes), and ties it together with a multilingual chatbot. It is a preprint, and the evaluation is on benchmark data and not on farms.

These are closer to what a farmer needs than a single model. As far as we could tell, none of the three has a marketplace or a sell or hold layer, and none reports a trial with real farmers that we could read about. Joined-up systems are not missing from the literature. Evidence that they work in the field is.

IX. COMPARING THE STUDIES

Table I lists all 27. The last column says what each study leaves out for someone who needs help across the whole cycle. It is not a judgement of the study itself.

TABLE I
SUMMARY OF THE REVIEWED STUDIES

Ref.	Year	Area	Method	Main finding	What it leaves out
[4]	2024	Crop recommendation	SVM, XGBoost, Random Forest, KNN, decision tree	XGBoost best, precision about 99%	Stops at the planting decision
[5]	2025	Crop recommendation	Supervised ML with explainable AI	Reasons for a recommendation can be inspected; Gradient Boosting did best	Stops at the planting decision
[6]	2025	Crop recommendation	ANN to filter crops, then Random Forest for yield	99.10% crop accuracy; yield R^2 0.99	Stops at the planting decision
[8]	2025	Crop recommendation	Seven algorithms plus a four-layer neural network, 2,200 records	Random Forest and Naive Bayes 99.5%; neural network 97.73%	Stops at the planting decision
[7]	2025	Crop recommendation	Hybrid deep learning framework	Deep learning on soil and weather inputs	Stops at the planting decision
[9]	2026	Review: crop and disease	Review of ML classification (RF, SVM, CNN)	Covers crop recommendation and disease detection	Review; no single end-to-end system
[11]	2023	Input recommendation	Multi-criteria ML recommender	Suggests crop and fertilizers for kharif and rabi	No link to suppliers
[10]	2026	Input recommendation	Six ML and DL models on about 10,000 samples	Random Forest best, MAP3 of 0.2805	No link to suppliers

Ref.	Year	Area	Method	Main finding	What it leaves out
[12]	2025	Advisory	Knowledge base and AI chatbot (project report)	Proposed for Malawian smallholders; no field results	Advice only; no link to prices or inputs
[14]	2024	Advisory	Generative AI with retrieval, multilingual	Used in four countries; 15,000+ farmers, 300,000+ queries	Advice only; no link to prices or inputs
[16]	2024	Disease detection	Review of deep learning on tomato field datasets	PlantVillage results over-optimistic; few field studies	Diagnosis only; no link to advice, prices or sale
[17]	2025	Disease detection	Systematic review of 11 benchmark datasets	Lab 95-99% vs field 70-85%; transformers held up better	Diagnosis only; no link to advice, prices or sale
[18]	2025	Disease detection	Narrative review of ML and DL methods	Focus on real-time use in uncontrolled conditions	Diagnosis only; no link to advice, prices or sale
[19]	2026	Price prediction	Review of ML price prediction	LSTM suits time patterns; ensembles and XGBoost accurate on standard data	Forecast only; no sell or hold advice
[25]	2026	Price prediction	Eight algorithms plus persistence, AGMARKNET data	Ridge best; trees and SVR failed on trending data; persistence close	Forecast only; no sell or hold advice
[20]	2025	Price prediction	Temporal convolutional network with XGBoost	Hybrid aimed at agricultural price volatility	Forecast only; no sell or hold advice
[21]	2021	Price prediction	ARIMA, SVR, Prophet, XGBoost, LSTM on Malaysian data	LSTM best of the five	Forecast only; no sell or hold advice
[22]	2025	Price prediction	Seven models on 23 commodities, AGMARKNET	Compares statistical, ML and deep learning models	Forecast only; no sell or hold advice
[23]	2024	Price prediction	ML and DL with weather inputs for tomato, onion, potato	Tests weather as an outside input	Forecast only; no sell or hold advice
[24]	2025	Price prediction	SARIMA, Holt-Winters, LSTM on Bengaluru onions	LSTM clearly ahead of both; no naive or ML baseline	Forecast only; no sell or hold advice
[28]	2022	Marketplace (e-NAM)	Price and arrival analysis in Rajasthan	Looks at price realization and arrivals after e-NAM	Measures prices and arrivals; no advice to the farmer
[29]	2025	Marketplace (e-NAM)	Longitudinal comparison in Haryana, 2015-16 to 2020-21	Significant changes in arrivals and prices; infrastructure problems remain	Measures prices and arrivals; no advice to the farmer
[30]	2023	Marketplace (e-NAM)	Growth rates before and after, Sirsa APMC	Overall positive effect on arrivals and prices	Measures prices and arrivals; no advice to the farmer
[31]	2022	Marketplace (e-trading)	Effect of e-trading on wholesale prices	Analyses price effects of electronic trading	Measures prices and arrivals; no advice to the farmer
[32]	2024	Joined-up platform	IoT sensors and camera; crop recommendation plus disease detection	CNN accuracy almost 99.98%	No marketplace or sell/hold layer; evidence on benchmark data
[33]	2025	Joined-up platform	Web app: weather, crops, finances, chatbot	Abstract mentions a pilot; no details	No marketplace or sell/hold layer; evidence on benchmark data
[34]	2026	Joined-up platform	RF with price input, Prophet, MobileNetV2, chatbot (preprint)	99.3% on augmented benchmark data; disease module 96.2% on 16 classes	No marketplace or sell/hold layer; evidence on benchmark data

A few patterns are easy to see. Tree-based ensembles are common in the crop and input work, though neural networks and deep learning appear as well, and the winner changes with the dataset. For prices there is no agreement at all: ridge regression, LSTM and XGBoost each came out on top in different studies. Most single-stage studies stop at their own output, and the three joined-up platforms are the only ones that pass anything along.

The evidence is also uneven. Metrics come from different data and different validation set-ups, so ranking the studies by accuracy would not mean much. The strongest evidence we saw about field performance is the disease detection reviews, and it points to a drop once the data leaves the laboratory.

X. GAPS WE NOTICED

The main gap is not that nobody has joined the stages up. Three papers have, at least in part. The gap is what comes after: those systems are prototypes, judged on benchmark data, and none that we could find has a bidding marketplace or a sell or hold layer. Everything else in the literature is built to solve one problem and then left alone. A farmer who wants crop advice, input guidance, expert help, price forecasts and a place to sell mostly has to use separate platforms.

Crop recommenders go quiet once the crop is in the ground. Input recommenders do not link to suppliers. Price predictors stop at a number. The marketplace studies measure what happened to prices but, in what we read, say nothing about helping a farmer decide when to list or what to ask. Then there is the evidence. Prototypes built on generated or benchmark data say more about the data than about real farms. In our own experience simple baselines scored about as well as the chosen models [1], the one real-data forecasting study we read found much the same [25], and the disease detection reviews report a clear fall in accuracy from laboratory to field [17]. A fair evaluation would use real data, time-ordered splits for forecasting, naive baselines, some report of how uncertain the predictions are, and trials with real users. Marketplaces also need payments, identity checks and a way to handle disputes. Access is the last gap. Language, signal and digital skills decide whether a farmer can use any of this. A very accurate model that works only in English on a fast connection helps few farmers.

TABLE II
GAPS AND POSSIBLE DIRECTIONS

No.	Gap	What we saw in the reviewed work	Possible direction
1	Joined-up systems are thin	Three platforms join some services; none has a marketplace or sell or hold advice	Join forecasting, advice and marketplace in one platform and test it with farmers
2	No route to suppliers	Input systems do not link farmers to manufacturers or suppliers	Link recommendations to verified, government-approved sources
3	Thin advice	Chatbots handle routine questions; photo-specific problems need an expert or a field-tested image model	Expert channel with response time and quality measured; image-based diagnosis checked on field photos
4	Forecast without a decision	Predictions stop at a price, and no model type wins consistently	Sell or hold and best-market advice; compare against a naive baseline
5	Marketplace without advice	The e-NAM studies measure prices and arrivals, not advice to farmers	Combine bidding with price forecasts; add payments, identity checks and dispute handling
6	Little real-world evidence	Integrated prototypes tested on generated or benchmark data; lab accuracy drops in the field	Real-data validation, field trials, user studies

XI. OUR PROTOTYPE

To see what joining the stages involves, we built a prototype called IFAMS [1]. It has five services behind one dashboard: Random Forest crop recommendation with a confidence score, seed and fertilizer guidance linked to suppliers, expert advice (the farmer sends photos and a human agronomist replies), XGBoost weekly price forecasts with a sell or hold and best market suggestion, and a bidding marketplace. It runs as a three-tier web application with separate logins for farmers, buyers, experts and administrators.

The results need careful reading. Both models were trained on generated data that follows the layout of public datasets. Simpler classifiers scored about the same as the Random Forest (98.05% accuracy), and the naive forecast matched XGBoost one week ahead. The sell or hold backtest depended on an assumed holding cost and used a substitute gradient boosting model, and the workflow was only tried with seeded demonstration accounts.

None of this shows that joining the stages is a bad idea. It shows that such systems need real data, simple baselines and field trials before anyone draws conclusions.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

XII. POSSIBLE NEXT STEPS

The first job is a dull one: repeat the model evaluations on real crop and market data, and try the platforms with real farmers, experts and buyers.

Language comes next. Our prototype has English and Kannada interfaces [1], which is a start; other regional languages and voice input would reach more people, and Farmer.Chat shows that multilingual, multimodal advice is workable at scale. Offline use is needed in places with poor signal.

Typing soil values by hand is tedious and easy to get wrong. Soil sensors and satellite soil data might remove that step, and Krishna et al. already use IoT sensors for this. Photo-based disease detection could sit alongside human experts instead of replacing them, as long as it is tested on field photos. For marketplaces, payments, delivery tracking, identity checks and dispute handling all need work. Regional training data for crop and price models would help, and forecasts should come with some sign of how uncertain they are.

XIII. CONCLUSION

We looked at 27 studies on crop recommendation, input recommendation, advisory tools and disease detection, price prediction, online marketplaces, and joined-up platforms. Tree-based ensembles are common in crop and input work, price forecasting has no agreed winner, advisory tools lean on chatbots, and the marketplace studies are mostly about e-NAM.

Each area has been worked on, and a few platforms now join several of them. What we could not find was evidence from real farms, or a platform that adds a marketplace and a sell or hold layer. That is where we would look next. The survey is narrative and covers a limited set of papers, so there are probably relevant studies we missed.

XIV. ACKNOWLEDGMENT

The authors thank the Department of Computer Science and Engineering, B.M.S. College of Engineering, Bengaluru, for their support.

REFERENCES

[1] Disha D S, Disha H Jain, Dhruhi Atykar, Parth Rawat, and Vanishree, "IFAMS: An integrated farmer advisory and marketplace system using Random Forest crop recommendation, XGBoost price forecasting, and direct farmer-buyer bidding," Int. J. Res. Appl. Sci. Eng. Technol. (IJRASET), vol. 14, no. X, pp. 2055-2063, Oct. 2026.

[2] L. Breiman, "Random forests," Mach. Learn., vol. 45, no. 1, pp. 5-32, 2001.

[3] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2016, pp. 785-794.

[4] B. Dey, J. Ferdous, and R. Ahmed, "Machine learning based recommendation of agricultural and horticultural crop farming in India under the regime of NPK, soil pH and three climatic variables," Heliyon, vol. 10, no. 3, Art. no. e25112, 2024, doi: 10.1016/j.heliyon.2024.e25112.

[5] S. Shastri, S. Kumar, V. Mansotra, and R. Salgotra, "Advancing crop recommendation system with supervised machine learning and explainable artificial intelligence," Sci. Rep., vol. 15, 2025, doi: 10.1038/s41598-025-07003-8.

[6] A. Bhola and P. Kumar, "Farm-level smart crop recommendation framework using machine learning," Ann. Data Sci., vol. 12, no. 1, pp. 117-140, Feb. 2025, doi: 10.1007/s40745-024-00534-3.

[7] K. S. Kathoon, N. V. Naik, T. V. Kumar, K. Narasimha, A. V. Srinivasulu, and E. H. S. N. Goud, "Crop recommendation system using machine learning," in Proc. 1st Int. Conf. Res. Dev. Inf., Commun., Comput. Technol. (ICRDICCT), vol. 3, 2025, pp. 5-9, doi: 10.5220/0013890800004919.

[8] D. Dahiphale, P. Shinde, K. Patil, and V. Dahiphale, "Smart farming: Crop recommendation using machine learning with challenges and future ideas," Artif. Intell. Appl., vol. 4, no. 3, pp. 323-335, 2025, doi: 10.47852/bonviewAIA52026214.

[9] M. Umamaheswari and D. Kavitha, "Machine learning classification techniques for smart agriculture: A review of disease detection and crop recommendation," Front. Artif. Intell., vol. 9, Art. no. 1878006, 2026, doi: 10.3389/frai.2026.1878006.

[10] S. P. Singh, G. K. Saini, R. K. Arora, and P. Dabas, "Predicting optimal fertilizers using machine learning and deep learning," in Proc. Int. Conf. Intell. Syst. Sustain. Future (ISSF 2026), Atlantis Press, 2026, pp. 338-345, doi: 10.2991/978-94-6239-693-7_34.

[11] K. Patel and H. B. Patel, "Multi-criteria agriculture recommendation system using machine learning for crop and fertilizers prediction," Curr. Agric. Res., vol. 11, no. 1, 2023, doi: 10.12944/CARJ.11.1.12.

[12] H. W. Mzumara and J. Mulepa, "Agricultural advisory management system with AI powered chat-bot," Int. J. Innov. Sci. Res. Technol., vol. 10, no. 11, Nov. 2025, doi: 10.38124/ijisrt/25nov004.

[13] IDinsight, "Making digital tools work for farmers in Africa," scoping study funded by IDRC, Apr. 2025. [Online]. Available: https://www.idinsight.org/publication/making-digital-tools-work-for-farmers-in-africa/

[14] N. Singh et al., "Farmer.Chat: Scaling AI-powered agricultural services for smallholder farmers," arXiv:2409.08916, 2024.

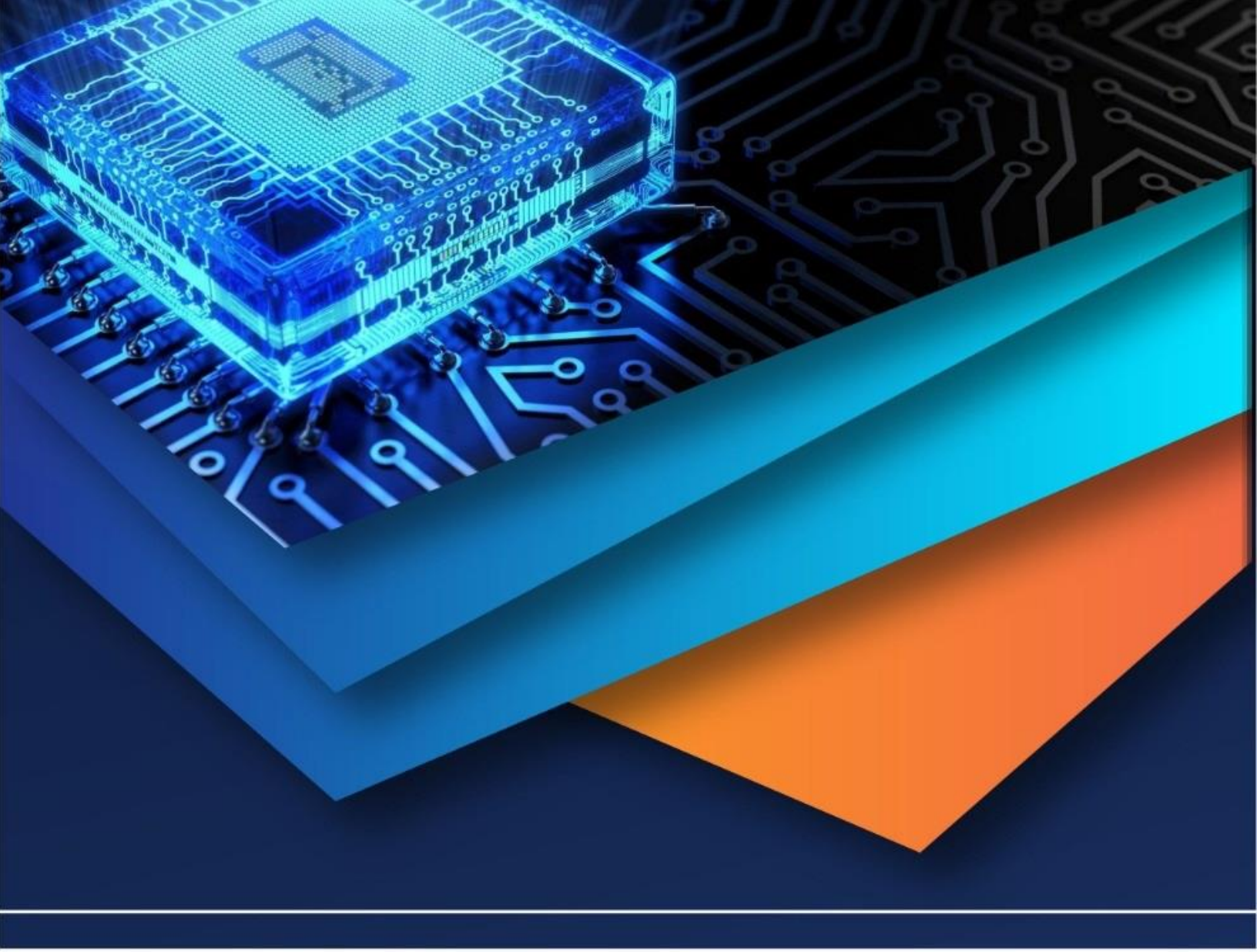
[15] S. P. Mohanty, D. P. Hughes, and M. Salathe, "Using deep learning for image-based plant disease detection," Front. Plant Sci., vol. 7, Art. no. 1419, 2016.

[16] M. Jelali, "Deep learning networks-based tomato disease and pest detection: A first review of research studies using real field datasets," Front. Plant Sci., vol. 15, Art. no. 1493322, 2024, doi: 10.3389/fpls.2024.1493322.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

[17] M. Shafay, T. Hassan, M. Owais, I. Hussain, S. G. Khawaja, L. Seneviratne, and N. Werghi, "Recent advances in plant disease detection: Challenges and opportunities," Plant Methods, vol. 21, no. 1, Art. no. 140, 2025.
[18] T. Nyawose, R. C. Maswanganyi, and P. Khumalo, "A review on the detection of plant disease using machine learning and deep learning approaches," J. Imaging, vol. 11, no. 10, Art. no. 326, 2025, doi: 10.3390/jimaging11100326.
[19] S. Khare, "Machine learning enabled crop price prediction: A review," Indian J. Comput. Sci., vol. 11, no. 1, pp. 31-37, 2026, doi: 10.17010/ijcs/2026/v11/i1/175963.
[20] T. Zhao, G. Chen, S. Suraphee, T. Phoophiwfa, and P. Busababodhin, "A hybrid TCN-XGBoost model for agricultural product market price forecasting," PLOS ONE, vol. 20, no. 5, Art. no. e0322496, May 2025, doi: 10.1371/journal.pone.0322496.
[21] Z. Chen, H. S. Goh, K. L. Sin, K. Lim, N. K. H. Chung, and X. Y. Liew, "Automated agriculture commodity price prediction system with machine learning techniques," Adv. Sci. Technol. Eng. Syst. J., vol. 6, no. 4, pp. 376-384, 2021, doi: 10.25046/aj060442.
[22] R. L. Manogna, V. Dharmaji, and S. Sarang, "Enhancing agricultural commodity price forecasting with deep learning," Sci. Rep., 2025, doi: 10.1038/s41598-025-05103-z.
[23] G. H. H. Nayak, M. W. Alam, K. N. Singh, G. Avinash, R. R. Kumar, M. Ray, and C. K. Deb, "Exogenous variable driven deep learning models for improved price forecasting of TOP crops in India," Sci. Rep., vol. 14, no. 1, 2024, doi: 10.1038/s41598-024-68040-3.
[24] M. Patil, L. Achoth, and K. B. Vedamurthy, "Onion price forecasting: A comparative analysis of SARIMA, Holt-Winters and LSTM models in the Bengaluru market," Mysore J. Agric. Sci., vol. 59, no. 2, pp. 195-205, 2025.
[25] S. P. Balantrapu, G. R. Raju, S. S. Mudigonda, and L. A. Kalur, "Forecasting minimum support price-anchored mandi prices for wheat and maize in India: A comparative machine-learning and time-series framework," Agric. Sci. Digest, vol. 46, pp. 129-135, 2026, doi: 10.18805/ag.D-6567.
[26] R. J. Hyndman and A. B. Koehler, "Another look at measures of forecast accuracy," Int. J. Forecasting, vol. 22, no. 4, pp. 679-688, 2006.
[27] Press Information Bureau, Government of India, "National Agriculture Market (e-NAM): Digital transformation of agricultural trade in India," Apr. 13, 2026. [Online]. Available: https://static.pib.gov.in/WriteReadData/specificdocs/documents/2026/apr/doc2026413845801.pdf
[28] P. K. Swain, "Impact of development of National Agriculture Market (e-NAM) on farmers," Indian J. Agric. Sci., vol. 92, no. 12, pp. 1484-1489, Dec. 2022, doi: 10.56093/ijas.v92i12.127701.
[29] R. K. Mahto and C. Patil, "Assessing the impact of e-NAM on arrivals and prices of agricultural commodities: A case study in Haryana, India," Mysore J. Agric. Sci., vol. 59, no. 4, pp. 305-318, 2025.
[30] A. Singh, Kiran, and S. Sihag, "Changing pattern of prices and arrivals of agricultural commodities through e-NAM: A case study of Sirsa APMC in Haryana," Econ. Reg. Stud., vol. 16, no. 4, pp. 694-707, Dec. 2023, doi: 10.2478/ers-2023-0042.
[31] S. Chaudhary and P. K. Suri, "The impact of digitalisation on the agricultural wholesale prices to aid agrarian income," Agric. Econ. (Czech), vol. 68, no. 10, 2022, doi: 10.17221/113/2022-AGRICECON.
[32] P. A. Krishna, N. Padhy, and A. Patnaik, "Applying machine learning for sustainable farm management: Integrating crop recommendations and disease identification," Eng. Proc., vol. 67, no. 1, Art. no. 73, Nov. 2024.
[33] B. Sribharathi, V. Cibirajan, S. Harikishore, S. Sakthivel, and B. Thulasidharan, "AI-driven platform for crop optimization, weather forecasting and agricultural innovation," in Proc. 1st Int. Conf. Res. Dev. Inf., Commun., Comput. Technol. (ICRDICCT), 2025, pp. 304-311, doi: 10.5220/0013897100004919.
[34] D. Dwibedy, A. Nishtala, P. Mukku, and D. Snehaja, "Smart profit-aware crop advisory system: Kisan AI," arXiv:2605.00133, 2026.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)