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Development of Machine Learning Models Using Python for Future Forecasting in Precision Agriculture Technology Adoption

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Abstract *—Precision agriculture uses digital technologies and data-driven methods to support decisions concerning crop management, irrigation, fertilizer application, and other farming operations. Technologies associated with precision agriculture include GPS and geographic information systems (GIS), remote sensing, unmanned aerial vehicles, Internet of Things (IoT) devices, and mobile agricultural advisory applications. However, the adoption of these technologies can vary with farmers' income, education, farm characteristics, digital access, awareness, and availability of technical support. This paper examines the potential use of machine learning for analysing farmers' intention to adopt precision agriculture technologies and for supporting future adoption planning. It discusses a modelling workflow involving data preparation, feature selection, model training, and evaluation, and considers Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and XGBoost classifiers. The project material reports that 67% of surveyed farmers expressed interest in adopting at least one precision agriculture technology within the next two to three years, while 21% were undecided and 12% were unwilling. It also reports approximately 90% accuracy for Random Forest and the highest F1- score for XGBoost. These figures are presented as reported project results and require confirmation against the original survey dataset, code, and evaluation outputs before they can be treated as independently validated findings. The paper outlines adoption barriers, possible applications, limitations, and implications for agricultural extension services, policymakers, researchers, and agritech providers.*

Keywords*-Machine Learning; Precision Agriculture; Technology Adoption; Random Forest; XGBoost; Agricultural Forecasting*

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I. INTRODUCTION

Agriculture remains central to food production, rural livelihoods, and economic development. Farmers make decisions in conditions shaped by changing weather, water availability, soil characteristics, labour requirements, input costs, and market uncertainty. Traditional knowledge remains important, but additional information can help farmers respond to changing field conditions and manage resources more efficiently.

Precision agriculture applies data and digital technologies to support site-specific farm management. GPS and GIS can assist with field mapping and positioning; sensors can monitor soil moisture and environmental conditions; satellite and drone imagery can help assess crop status; and mobile applications can provide weather, market, and crop advisory information. The availability of these tools, however, does not guarantee their adoption. Costs, connectivity, digital skills, training, maintenance, and trust can influence whether farmers use them.

Machine learning (ML) offers methods for identifying patterns in structured data and estimating the likelihood of an outcome such as technology adoption intention. By analysing farmer, farm, and technology-access characteristics, predictive models may help identify groups that could benefit from awareness programmes, demonstrations, or technical support. Such predictions should support, rather than replace, farmers' knowledge and decisions.

A. Background

Precision agriculture has developed alongside advances in positioning systems, remote sensing, farm machinery, mobile computing, and digital sensing. Its applications range from mobile advisory services to sensor networks and dronebased crop monitoring. The suitability of a particular technology depends on the crop, farm size, local infrastructure, service availability, and the farmer's ability to access and operate it.

Prior studies have reviewed the relationship between precision agriculture and food security, the development of remote sensing in agriculture, and the use of machine learning for agricultural applications. These studies provide a foundation for examining how digital tools can support farm management and how adoption may differ across farming contexts.

B. Need for the Study

Useful technologies may remain underused when farmers lack information, cannot afford equipment or services, or do not have access to training and reliable support. Better understanding of adoption intention and its associated factors can help agricultural organisations plan demonstrations, advisory services, financing support, and capacity-

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building activities. Forecasting may also help technology providers assess the needs of different farming groups. The usefulness of any forecast depends on the quality, representativeness, and documentation of the underlying data.

C. Objectives

- To examine the application of machine learning methods to the analysis of farmers' adoption intention for precision agriculture technologies.
- To investigate possible relationships between demographic, economic, farming, and technology-access variables and adoption intention.
- To compare Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and XGBoost models.
- To describe model evaluation using accuracy, precision, recall, F1-score, and ROC-AUC.
- To discuss implications for agricultural extension services, policymakers, researchers, and agritech firms.

D. Scope

The technologies considered include mobile advisory applications, GPS/GIS systems, remote sensing, drones, soil and crop monitoring systems, and IoT devices. The project workflow covers data preparation, feature selection, classification, model evaluation, and potential decision-support applications. The project material discusses the Indian agricultural context and refers to survey information and secondary sources.

II. LITERATURE REVIEW

A. Adoption of Precision Agriculture

Adoption of precision agriculture differs across countries, regions, and farm types. Farm size, mechanisation, infrastructure, financial capacity, and access to agricultural advisory services can affect the feasibility of a technology. A tool may be technically available but remain unsuitable where it is too costly, difficult to maintain, or incompatible with existing farm practices.

B. Factors Associated with Adoption

Potential determinants include education, landholding size, income, credit availability, digital literacy, awareness, training, extension support, social influence, trust, and previous experience with technology. These factors may interact. For example, a farmer may recognise the potential benefits of a technology but lack the funds to obtain it; another farmer may be able to afford a tool but lack the skills needed to use it effectively.

Fellow farmers, agricultural officers, Krishi Vigyan Kendras, cooperatives, and Farmer Producer Organisations can provide information and practical demonstrations. Digital channels can extend access to information, although connectivity, language, and information quality may remain challenges.

C. Digital Agriculture and Machine Learning

Digital agriculture systems collect information from sensors, satellites, mobile applications, and farm records. Machine learning can be used to identify patterns and estimate outcomes from these data. Logistic Regression provides a comparatively interpretable classification baseline. Decision Trees represent decisions through rule-based splits. Random Forest combines multiple decision trees, Support Vector Machines identify decision boundaries, and XGBoost uses gradient boosting to build an ensemble of trees. Model performance depends on the data, feature definitions, preprocessing, parameter settings, and evaluation design.

D. Research Gap

The project focuses on combining farmer- and farm-related characteristics to examine adoption intention and compare multiple classification approaches within a common workflow. The validity of any conclusions depends on a clearly defined target variable, documented sampling, accessible data, reproducible preprocessing, and consistent model evaluation. The present project material does not include the complete raw dataset or detailed model outputs, limiting independent verification.

III. METHODOLOGY

A. Research Design

The project describes an exploratory and predictive design drawing on farmer survey information and secondary sources related to agriculture and machine learning. The survey variables are intended to capture farmer profiles, farm conditions, awareness of technology, access to digital services, and intention to adopt. The project material mentions tools such as Google Forms and ODK Collect for survey collection and identifies interviews with agricultural extension

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agents and Farmer Producer Organisations as possible field methods. The exact sample design, survey dates, geographical coverage, and questionnaire should be reported in the final study using the original records.

B. Variables

Variables discussed in the project include age, sex, educational status, farming experience, landholding size, crop variety, land ownership, irrigation facilities, mobile-phone ownership, internet access, use of advisory applications, extension-service exposure, perceived risk, innovativeness, previous technology experience, current technology use, and future adoption intention. Additional contextual variables may include soil, weather, market-price, vegetation-index, farmsize, and productivity information where such data were actually collected. Current use and future intention should be represented as distinct outcomes.

C. Data Preprocessing

The proposed preprocessing workflow includes checking missing values, duplicates, and outliers; handling missing values using an appropriate method; encoding categorical variables; and scaling numerical variables where required. Mean or median imputation may be considered for numerical data and mode imputation for categorical data, subject to the distribution and missingness mechanism. One-hot, ordinal, or other suitable encoding methods may be used according to the variable type.

Preprocessing steps, including imputation, scaling, and feature selection, must be fitted using training data only and then applied to validation or test data. This helps prevent data leakage and overly optimistic performance estimates. The project material mentions Recursive Feature Elimination, Chi-square testing, ANOVA F-tests, PCA, and correlation analysis as possible feature-selection or dimensionality-reduction methods. The final paper should report only the methods actually applied and provide supporting outputs.

D. Machine Learning Models

E. 1) Logistic Regression

Logistic Regression estimates class probabilities and can serve as an interpretable baseline for binary adoption classification. Its coefficients can help describe the relationship between input variables and the predicted outcome, subject to the model assumptions and data quality.

F. 2) Decision Tree

A Decision Tree divides observations into subsets using feature-based rules. Its structure can be easier to explain to agricultural stakeholders. However, a tree that is too complex may overfit the training data and perform poorly on unseen observations.

G. 3) Random Forest

Random Forest combines predictions from multiple decision trees and can represent nonlinear relationships and interactions among features. The project material reports an accuracy of approximately 90% for this model. This result must be checked against the original test split, code, and evaluation output before publication as a validated result.

H. 4) Support Vector Machine

Support Vector Machine constructs a decision boundary between classes. Kernel functions can represent different patterns in the data. Feature scaling and parameter selection are important when training an SVM, and the selected kernel and tuning procedure should be documented.

I. 5) XGBoost

XGBoost uses gradient boosting to build an ensemble of decision trees and can be effective on structured datasets. The project material reports that XGBoost achieved the highest F1-score. The exact score, class-wise metrics, parameter settings, and evaluation output should be supplied to substantiate this comparison.

J. Training and Evaluation

The project material describes an 80:20 training-test split and ten-fold cross-validation. All models should be compared using the same data partition and evaluation procedure. Accuracy, precision, recall, F1-score, and ROC-AUC provide complementary information, particularly where adoption classes are imbalanced. A confusion matrix and the numerical value of each metric should be included in the final results. The data split strategy, random seed, cross-validation procedure, and any hyperparameter tuning should be reported.

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Accuracy measures the proportion of correct predictions. Precision measures the proportion of predicted adopters who are actual adopters. Recall measures the proportion of actual adopters identified by the model. The F1-score is the harmonic mean of precision and recall. ROC-AUC measures discrimination across classification thresholds.

K. Potential Deployment Framework

The project proposes Flask for an application programming interface, Streamlit for an interactive dashboard, and SQLite for storing inputs or predictions. A decision-support interface could accept farmer and farm characteristics and return an estimated probability of adoption. Such a system should clearly communicate uncertainty, protect personal information, be tested for fairness, and never use predictions as the sole basis for denying services.

IV. DISCUSSION OF PRECISION AGRICULTURE TECHNOLOGIES

A. Mobile Advisory Applications

Mobile applications can provide weather updates, crop information, market prices, disease alerts, and details of government schemes. Their effectiveness depends on the accuracy and timeliness of information, availability in regional languages, connectivity, and users' digital skills.

A. GPS and GIS Equipment

GPS and GIS technologies support field mapping, positioning, and the analysis of spatial variation in soil and crop conditions. Their practical value depends on farm infrastructure, cost, technical support, and the scale and type of farming operation.

B. Remote Sensing and Drones

Satellite imagery and drone cameras can help monitor crop conditions and identify areas requiring field inspection. Where ownership is unaffordable, shared services or rental arrangements may offer an alternative, provided that trained operators and maintenance support are available.

C. IoT Devices

IoT devices can collect measurements such as soil moisture, temperature, and humidity. These measurements may support irrigation and crop-management decisions. Deployment requires sensors, connectivity, power, maintenance, and an appropriate system for interpreting the collected data.

D. Decision Support Systems

Decision-support systems combine data, models, or rules to compare management options for irrigation, fertilisation, disease monitoring, and crop operations. Their usefulness depends on the relevance of recommendations to local conditions and the quality of the information supplied.

E. Differences in Adoption

The project material describes adoption as uneven across regions and farm types. Infrastructure, farm scale, financial access, and extension services may be associated with greater use, while small farmers may face barriers related to equipment and service costs. These relationships should be quantified using the original survey data before being presented as empirical findings.

V. SOURCES OF INFORMATION FOR FARMERS

A. Peers

Farmers may learn by observing the experiences of neighbouring farmers working in similar conditions. Peer networks can provide practical information about costs, maintenance, benefits, and operational difficulties.

B. Input Suppliers and Cooperatives

Local input suppliers may advise farmers about seeds, fertilisers, crop-protection products, and machinery. Since advice may be influenced by the products supplied, farmers can benefit from comparing information from multiple sources. Cooperatives and Farmer Producer Organisations may also facilitate group training and shared access to equipment.

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C. Government Extension Bodies

Agricultural extension workers and Krishi Vigyan Kendras can support awareness through training and demonstrations. Practical instruction in a language understood by farmers may be particularly useful for technologies that require new operating skills.

D. Digital Information

Agricultural applications, websites, digital marketplaces, and social networks can provide crop, weather, market, and programme information. Challenges include poor-quality information, language barriers, unreliable connectivity, and conflicting advice.

E. Improving Access to Information

Potential measures include regional-language content, village-level demonstrations, training, better rural connectivity, and opportunities for farmers to share experiences. Combining digital information with local support may make technology easier to understand and evaluate.

VI. FUTURE INTENTIONS AND FORECASTING

A. Reported Future Adoption Intentions

The project material reports that 67% of surveyed farmers were interested in using at least one precision agriculture technology within the next two to three years, 21% were undecided, and 12% were unwilling. These percentages are reported from the project material and must be verified against the original questionnaire, respondent-level data, sampling information, and calculations. Interest or intention should not be interpreted as actual subsequent adoption.

B. Barriers to Future Adoption

Potential barriers identified in the project include high initial costs, lack of training, poor network connectivity, limited awareness, fear of technology failure, and maintenance expenses. The relative importance of these barriers may differ by region, farm size, crop, and technology.

C. Forecasting Process

The proposed process includes data collection, cleaning and encoding, feature selection, model training, testing, and evaluation. An 80:20 training-test split and cross-validation are described in the project material. Forecasts should be based on a clearly defined target population and time horizon. The model should be evaluated on data not used during preprocessing or training, and probability estimates should be presented as uncertain predictions rather than guarantees.

D. Implications for Stakeholders

A validated prediction system may help extension organisations identify information and training needs, support policymakers in planning outreach, and help agritech providers design services at accessible prices. Such use should be guided by transparency, informed consent, privacy safeguards, and monitoring for unfair outcomes.

VII. LIMITATIONS

The conclusions depend on the quality and representativeness of the survey and secondary data. The project material available for preparing this manuscript does not include the complete raw dataset, detailed sampling information, model code, full evaluation tables, or confusion matrices. Consequently, the reported model performance and survey percentages cannot be independently verified from the material provided.

Adoption intention is not equivalent to actual adoption. Farmers may change their decisions because of cost, access, weather, policy, or other circumstances. Forecasts are also limited to the population, location, and time period represented in the data. The final submission should include complete bibliographic details, reproducible methods, verified statistics, and the outputs needed to support its claims.

VIII. CONCLUSION

Precision agriculture technologies can support decisions about crop monitoring, irrigation, and the use of agricultural inputs. Their adoption depends not only on technical availability but also on affordability, awareness, connectivity, training, and local support. Machine learning methods such as Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and XGBoost can be considered for analysing adoption intention when suitable data and a transparent evaluation procedure are available.

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The project material reports that 67% of surveyed farmers expressed interest in future use of at least one precision agriculture technology, that Random Forest achieved approximately 90% accuracy, and that XGBoost obtained the highest F1-score. These figures require verification using the original dataset and model outputs before they can be presented as confirmed research findings. Future work should preserve the respondent-level dataset, document the full modelling pipeline, report all evaluation metrics, and test the models in other locations. Predictions should be used responsibly as decision-support information and not as a replacement for farmers' judgement.

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REFERENCES

[1] R. Gebbers and V. I. Adamchuk, "Precision agriculture and food security," Science, vol. 327, no. 5967, pp. 828–831, 2010.

[2] D. J. Mulla, "Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps," Biosystems Engineering, vol. 114, no. 4, pp. 358–371, 2013.

[3] K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: A review," Sensors, vol. 18, no. 8, Art. no. 2674, 2018.

[4] Y. S. Tey and M. Brindal, "Factors influencing the adoption of precision agricultural technologies: A review," Precision Agriculture, vol. 13, no. 6, pp. 713–730, 2012.

[5] S. Wolfert, L. Ge, C. Verdouw, and M. J. Bogaardt, "Big Data in Smart Farming: A review," Agricultural Systems, vol. 153, pp. 69– 80, 2017.

[6] F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011

[7] E. M. Rogers, Diffusion of Innovations, 5th ed. New York, NY, USA: Free Press, 2003.

[8] S. Fountas, D. Wulfsohn, B. S. Blackmore, H. L. Jacobsen, and S. M. Pedersen, "A model of decision-making and information flows for information-intensive agriculture," Agricultural Systems, vol. 87, no. 2, pp. 192–210, 2005.

[9] A. Chlingaryan, S. Sukkarieh, and B. Whelan, "Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review," Computers and Electronics in Agriculture, vol. 151, pp. 61–69, 2018.

[10] C. Zhang and J. M. Kovacs, "The application of small unmanned aerial systems for precision agriculture: A review," Precision Agriculture, vol. 13, no. 6, pp. 693–712, 2012.

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MANDATORY CHECKS BEFORE JOURNAL SUBMISSION

- Verify the 67%, 21%, and 12% survey figures from the original survey dataset and questionnaire.
- Verify the reported Random Forest accuracy and XGBoost F1-score using the saved code, test data, and evaluation outputs.
- Add the actual dataset size, sampling method, study location, survey dates, and ethical/informed-consent details where applicable.
- Add complete author affiliations and a valid corresponding-author email address.
- Confirm that all six listed authors approve the final manuscript and meet the journal's authorship criteria.
- Check every reference against the original publication and add missing DOI details where available.
- Remove this checklist and author-information page from the submitted manuscript if the journal requires only the formatted paper.

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