P-ISSN 2322 - 0678 & E-ISSN 3048 - 9946
Gujarat Journal of Extension Education Vol. 41 : Issue 2 : June - 2026 https://doi.org/10.56572/gjoee.2026.41.2.0019

PERCEPTION OF FARMERS TOWARDS THE USE OF DRONES IN AGRICULTURE: A MACHINE LEARNING APPROACH

R. K. Garasia[1], R. S. Parmar[2] and J. K. Patel[3]

1 Master Student, Department of Agricultural Extension and Communication, BACA, AAU, Anand - 388110
2 Professor and Head, Department of Agricultural Information Technology, AAU, Anand - 388110
3 Director, Extension Education Institute, AAU, Anand - 388110
Email : rajvigarasia2102@gmail.com

ABSTRACT

Agriculture is increasingly influenced by digital innovations aimed at improving productivity and sustainability. Among these innovations, drone technology has emerged as a promising tool for precision farming. However, the successful adoption of this technology largely depends on farmers' perception and acceptance. The present study aimed to analyse and predict farmers' perception towards the use of drones in agriculture using machine learning techniques. The study was conducted in seven talukas of the Ahmedabad district, with a random sample of 120 farmers. Eleven independent variables were considered, while perception towards drone usage was treated as the dependent variable. Six classification algorithms—Multilayer Perceptron (MLP), Support Vector Machine (SMO), k-Nearest Neighbours (IBk), KStar, J48, and Random Forest (RF)—were implemented using WEKA open-source software. The models were selected based on accuracy, Kappa statistics, MAE, RMSE, precision, recall, F1-score, and MCC. Among the applied models, the J48 algorithm demonstrated the best performance, achieving 79% accuracy, the highest Kappa value (0.33), F1-score (0.76), and MCC (0.34). The findings indicate that tree-based models, particularly J48, were more effective in predicting farmers' perception towards drone adoption. The study highlights the potential of machine learning techniques in agricultural technology adoption research.

Keywords: *drone technology, perception, farmers, Machine learning*

INTRODUCTION

Agriculture is one of the most significant yet vulnerable sectors, as it depends heavily on climate, soil conditions and water availability. Increasing challenges such as climate change, soil degradation, pest outbreaks and food security concerns have created a strong need for advanced and sustainable farming technologies (Vinaya and Gadde, 2025). In this context, agricultural drones have emerged as a promising innovation to improve precision, efficiency and productivity. Drones are remotely operated with sensors and imaging systems. In agriculture, they are used for crop monitoring, pesticide and nutrient spraying, yield estimation and real-time field analysis (Yeragorla et al., 2023). Their potential to reduce input costs and enhance farm management has led to increasing promotion and support from the Government of India. The integration of such technologies is further strengthened by Artificial Intelligence (AI), which enables data-driven decision-making in agriculture. AI serve as a cross-disciplinary tool and it is capable of bringing a model shift in how we see farming today. By using AI solutions, farmers can maximize the production with less inputs simultaneously improving crop quality. AI is becoming the key drivers for providing the digital solution almost in all the fields and business sectors (Omede et al., 2025). Machine learning (ML) is a subset of artificial intelligence, which focuses on the development of classification algorithms which enables computers to study from the secondary datasets. ML enables a machine to automatically study from past data, improve performance from experiences, and forecast things without being clearly programmed. As a multidisciplinary field, ML integrates AI with data mining, mathematics algorithms, computer science and statistics. Machine Learning (ML) techniques use classification algorithms to extract valuable knowledge from large experimental datasets for agricultural operations, enabling data-driven decision-making and improved farm management practices (Vegad et al., 2020). In their 2022 study, Parmar *et al.* (2022) evaluated multiple classification algorithms to analyze soil fertility conditions, including J48, Random Forest, Decision Table, PART, and Naive Bayes. Their comparative analysis showed that Random Forest**,** a tree-based ensemble learning algorithm, achieved the highest performance among the tested models. As adoption of drone technology depends largely on farmers' attitudes and acceptance, understanding their perception becomes essential. Therefore, the present study applies machine learning algorithms such as Multilayer Perceptron, Support Vector Machine, k-Nearest Neighbours, KStar, J48, and Random Forest to analyse and predict farmers' perception towards the use of drones in agriculture.

OBJECTIVE

To analyse and predict farmers' perception towards the use of drones in agriculture using machine learning techniques

METHODOLOGY

The study was conducted in seven talukas of the Ahmedabad district, namely Maandal, Dashkroi, Viramgaam, Dhandhuka, Bavla, Sanand, and Dholka. An ex-post facto research design was adopted for the investigation. The data were collected from a random sample of 120 farmers. The experimental dataset comprised 11 independent variables, namely age, gender, education, family size, farming experience, annual income, landholding, self-confidence, risk orientation, scientific orientation, and innovativeness. Farmers' perception towards the use of drones in agriculture was considered the dependent variable. The dataset was prepared in an Excel sheet and saved in .CSV format for analysis using open-source WEKA software. Fig.1 presents the conceptual workflow of the machine learning–based perception analysis system. The raw data were first cleaned and organized before analysis. Six machine learning classification algorithms namely Multilayer Perceptron (MLP), Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), KStar, J48, and Random Forest (RF) were applied to the processed dataset. The performance of each algorithm was examined and compared using several statistical measures, including correctly classified instances, incorrectly classified instances, Kappa statistics, MAE, RMSE, RAE, and RRSE. Additionally, classification performance metrics such as TPR, FPR, Precision, Recall, F-Measure, and MCC were considered. Overall model performance was primarily assessed based on precision, recall, and accuracy (Baby, 2021).

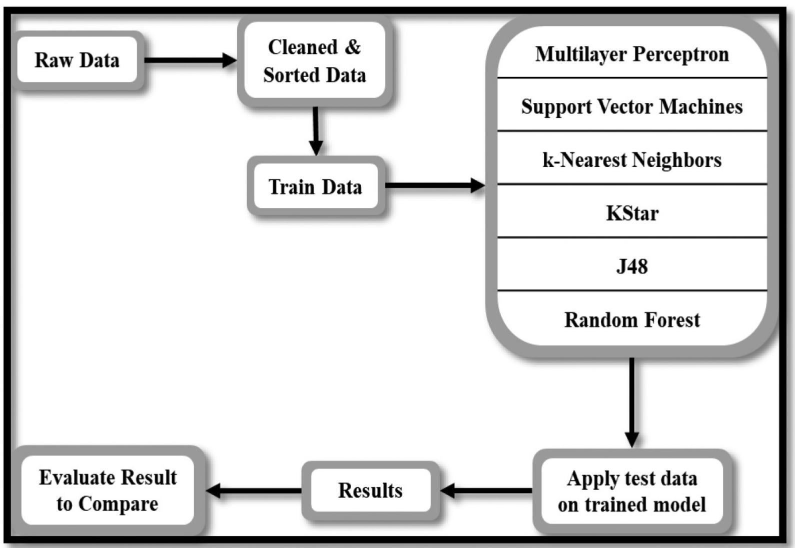

Fig. 1 : Conceptual workflow of the ML based perception analysis system

RESULTS AND DISCUSSION

Table 1 presents the comparative performance of the six fitted classification algorithms based on correctly classified instances, Kappa statistics, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Relative Absolute Error (RAE), and Root Relative Squared Error (RRSE). Among the fitted models, SMO and J48 achieved the highest classification accuracy of 79 per cent. However, model selection should not rely exclusively on accuracy, particularly when class distribution may be imbalanced. Therefore, the Kappa statistic was also considered to assess the agreement between predicted and actual classifications beyond chance. The J48 algorithm demonstrated a comparatively higher Kappa value, indicating a fair level of agreement and better consistency in classification. Lower MAE and RMSE values further suggest that the prediction errors of the J48 model were relatively smaller compared to the other algorithms. Additionally, evaluation metrics such as precision, recall, F1-score, and Matthews Correlation Coefficient (MCC) supported the superior performance of J48 in terms of balanced classification. Although SMO and J48 exhibited similar accuracy levels, the overall evaluation metrics indicate that J48 provides a more stable and interpretable model for predicting farmers' perception towards drone adoption. Therefore, J48 may be considered the most suitable model among the tested algorithms for this study.

Table 1. Comparative performance of the fitted classification algorithms

Classifier Algorithms		Prameters					
		Correctly Classified Instance	**Kappa Statistics**	**MAE**	**RMSE**	**RAE (%)**	**RRSE (%)**
Function Based	Multilayer Perceptron	**(%)**	0.31	0.17	0.37	71.55	107.98
	Support Vector Machine (SMO)	79	0.0	0.27	0.36	116.44	105.79
Lazy Based	k-Nearest Neighbors (IBk)	68	0.18	0.21	0.44	87.98	128.85
	KStar	75	0.28	0.18	0.36	78.45	105.60
Tree Based	**J48**	**79**	**0.33**	**0.19**	**0.33**	**79.93**	**97.37**
	Random Forest	76	0.28	0.19	0.33	82.01	98.63

Figure 2 illustrates the comparative prediction accuracy of fitted classification algorithms. Among the six algorithms examined in this study, Support Vector Machine (SMO) and J48 demonstrated the highest prediction accuracy, each achieving 79 per cent. These were followed by Multilayer Perceptron (MLP) and Random Forest (RF), both attaining 77 per cent accuracy. In contrast, the IBk (k-Nearest Neighbors) classification algorithm recorded the lowest prediction accuracy at 68 per cent. The results indicate that SMO and J48 provide comparatively better predictive performance for modeling farmers' perception towards drone adoption.

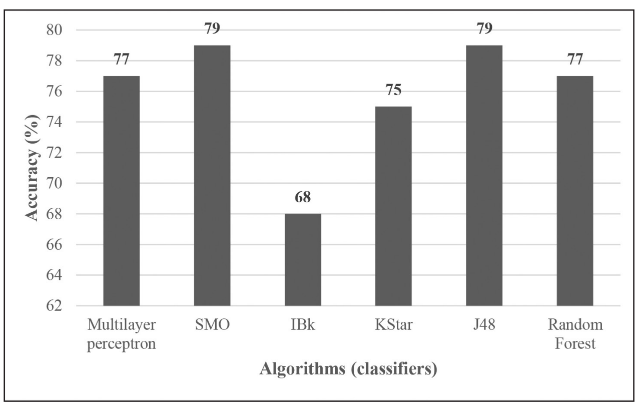

Fig. 2: Comparative prediction accuracy of fitted classification algorithms

Figure 2 illustrates the comparative prediction accuracy of the different fitted classification algorithms. Among the six algorithms examined in this study, Support Vector Machine (SMO) and J48 demonstrated the highest prediction accuracy, each achieving 79 per cent. These were followed by Multilayer Perceptron (MLP) and Random Forest (RF), both attaining 77 per cent accuracy. In contrast, the IBK (k-Nearest Neighbors) classification algorithm recorded the lowest prediction accuracy at 68 per cent. The results indicate that SMO and J48 provide comparatively better predictive performance for modeling farmers' perception towards drone adoption.

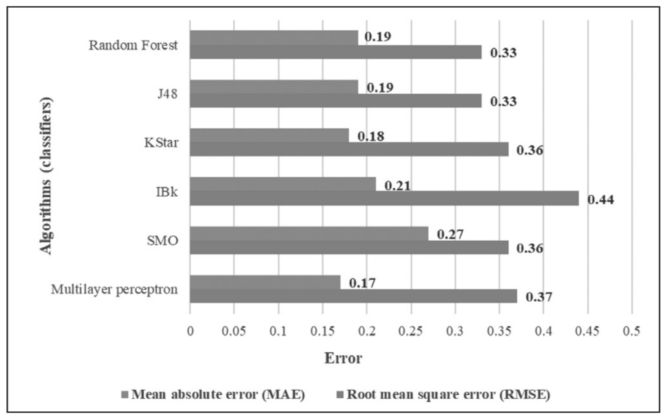

Fig. 3: Comparison of error metrics among various classification algorithms

Figure 3 presents the comparative performance of various classification algorithms examined using error metrics under 10-fold cross-validation. The MLP classifier achieved the lowest MAE (0.17), indicating superior generalization ability and minimal prediction deviation from actual values. The RF and J48 classifiers produced an RMSE of 0.33, reflecting reasonably stable predictive performance with moderate error dispersion. In contrast, the SMO algorithm exhibited a higher MAE (0.27), suggesting comparatively greater average prediction error. The IBk classifier recorded the highest RMSE (0.44), indicating larger variance in prediction errors and relatively weaker predictive reliability. Overall, the comparative analysis demonstrates that the MLP model outperformed the other classifiers in terms of minimizing both average and squared prediction errors under cross-validation.

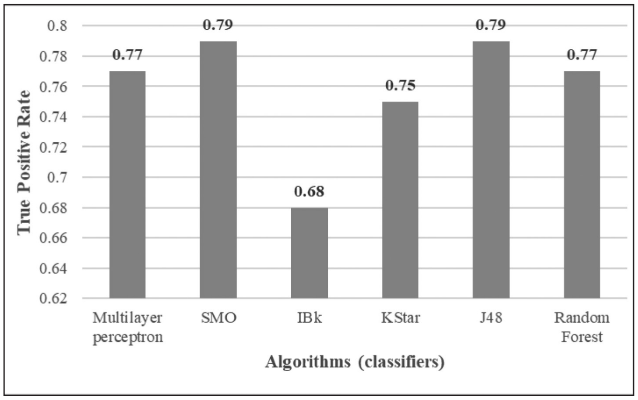

Fig. 4: Comparison of true positive rates among various classification algorithms

Figure 4 illustrates the comparison of TPR among the six fitted classification algorithms examined in this study. SMO and J48 achieved the highest TPR of 0.79, indicating superior sensitivity and a stronger ability to correctly identify positive instances. MLP and RF followed closely, each recording a TPR of 0.77, demonstrating competitive and stable classification performance. In contrast, the IBk classifier exhibited the lowest TPR of 0.68, suggesting comparatively weaker detection capability for positive cases. A higher true positive rate generally reflects better recall, which is particularly important when minimizing false negatives is critical. When interpreted alongside other performance measures such as precision and F-measure, the results suggest that SMO and J48 provide a more balanced trade-off between correctly identifying positive instances and limiting misclassification. Overall, the comparative evaluation indicates that these two algorithms deliver more reliable classification performance in the present study.

Figure 5 presents the comparative analysis of False Positive Rates (FPR) for the six classification algorithms evaluated in this study. The results indicate noticeable variation in the ability of the models to correctly identify negative instances. Among all classifiers, the Multilayer Perceptron (MLP) achieved the lowest FPR (0.45), demonstrating superior capability in minimizing false alarms. J48 and KStar followed closely, each recording an FPR of 0.48, suggesting relatively stable and competitive performance in distinguishing negative cases. In contrast, the SMO classifier exhibited the highest FPR (0.79). This indicates that a substantial proportion of negative instances were incorrectly classified as positive, reflecting weaker specificity compared to the other models. The higher false positive rate in SMO may be attributed to the sensitivity of support vector–based classifiers to parameter selection, kernel configuration, or class distribution characteristics within the dataset. Overall, the findings suggest that MLP provides better reliability in applications where minimizing false positives is critical. Conversely, the relatively high FPR of SMO may limit its suitability for scenarios requiring strict control over false alarm rates.

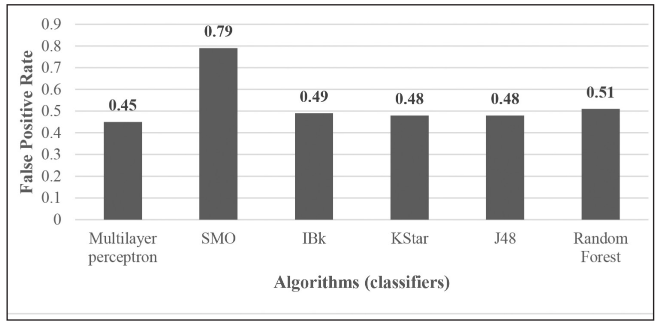

Fig. 5: Comparison of false positive rates among various classification algorithms

Figure 6 shows the comparison of Kappa statistics among the classification algorithms examined in this study. Among the six algorithms, J48 achieved the highest Kappa value (0.33), indicating better agreement between predicted and actual class labels beyond chance. It is followed by the Multilayer Perceptron (MLP), which obtained a Kappa value of 0.31. In contrast, the SMO classifier recorded the lowest Kappa statistic (0.00), suggesting that its classification performance is equivalent to random agreement and demonstrates very weak predictive reliability for the given dataset.

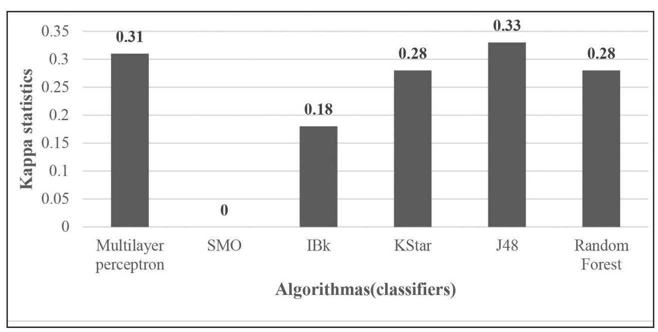

Fig. 6: Comparison of Kappa statistics among classification algorithms

Table 2 presents the results obtained after fitting the six classification algorithms to the experimental dataset. Among the examined models, J48 achieved the highest prediction accuracy (0.79), precision (0.77), and recall (0.79), indicating superior overall classification performance compared to the other algorithms. In contrast, IBk recorded the lowest prediction accuracy (0.68), precision (0.71), and recall (0.68), reflecting comparatively weaker predictive capability on the given dataset. To further assess classification performance, the F1-score and Matthews Correlation Coefficient (MCC) were computed to examine the balance between precision and recall, and the overall quality of the fitted models, respectively. J48 attained the highest F1-score (0.76) and MCC (0.34), demonstrating better balanced classification and stronger correlation between predicted and actual class labels. Conversely, IBk produced the lowest F1-score (0.69) and MCC (0.16), indicating reduced predictive reliability and weaker agreement beyond chance. Overall, the results confirm that J48 outperforms the other fitted classification algorithms across multiple evaluation metrics, establishing it as the most effective model for the experimental dataset.

Table 2. Comparative analysis of performance metrics for classification algorithms

Parameter	Classifier Algorithms					
	Function Based		Lazy Based		Tree Based	
	Multilayer Perceptron	SMO	IBK	KStar	J48	Random Forest
Accuracy	0.77	0.79	0.68	0.75	**0.79**	0.76
Precision	0.75	0.76	0.71	0.74	**0.77**	0.74
Recall	0.76	0.79	0.68	0.75	**0.79**	0.76
F1 score	0.75	0.70	0.69	0.74	**0.76**	0.75
MCC	0.32	-	0.16	0.26	**0.34**	0.26

CONCLUSION

The present study used six machine learning classification algorithms to predict farmers' perceptions toward the use of drones in agriculture. The results revealed noticeable variation in predictive performance across the models. Among all algorithms, the J48 decision tree demonstrated the best overall performance, achieving 79% accuracy, the highest Kappa statistic (0.33), the highest F1-score (0.76), and the highest Matthews Correlation Coefficient (MCC) of 0.34. J48 also exhibited comparatively lower error rates, indicating superior stability and reliability. Although SMO achieved a similar accuracy (79%), its Kappa statistic was 0.00, suggesting no agreement beyond chance and highlighting weaker predictive consistency. The Multilayer Perceptron and Random Forest models showed satisfactory and consistent performance across most evaluation metrics, whereas IBK recorded the lowest predictive accuracy (68%) with higher error rates. Overall, these findings suggest that tree-based models, particularly J48, are more effective in predicting farmers' perceptions of drone adoption. The application of machine learning techniques in this study provided more accurate classification and deeper predictive insights than traditional statistical approaches, reinforcing their value for agricultural technology adoption research.

RECOMMENDATIONS

- Use machine learning models such as j48 to identify and classify farmers based on their perception toward drone technology. Such predictive classification can help extension agencies and KVKs prioritize awareness campaigns, demonstration and training programmes for farmer groups requiring grater support and for better resource allocation.
- Government agencies and agri-tech firm should encourage rural youth and women to participate in drone-based training and entrepreneurship initiatives. The use of machine learning models can help identify farmers who are more likely to adopt drones and become drone service providers, helping to promote drone technology in rural areas.

ACKNOWLEDGEMENT

I would like to express sincere gratitude to the Department of Agricultural Extension and Communication and also Department of Agricultural Information Technology, AAU, Anand for guidance and support. Gratitude is also extended to all the farmers for their valuable time and insights.

CONFLICT OF INTEREST

This is to declare that there is "No conflict of interest" among researcher.

REFRENCES

Baby, A., Parmar, R. S., Raj, M. P. & Reddy, K. I. (2021). Prediction for rice yield using data mining approach in Ranga Reddy district of Telangana, India. *Journal of Agrometeorology.,* **23**(2): 242-248.

Omede, U. D., Aniobu, N. A. and Ikpe, E. (2025) Challenges hindering the implementation of AI-driven data management systems and strategies for integrating AI into data processing and management in colleges of education in Benue state of Nigeria. *Gujarat Journal of Extension Education,* 40(1): 91–95. https://doi.org/10.56572/gjoee.2025.40.1.0015

Parmar, R.S., Mehra, V.I., Kamani, G.J. (2022). Analyzing Soil fertility using Data Mining Techniques, *Gujarat Journal of Extension Education*, 34(2): 47-50.

Vegad, N., Parmar, R.S., & Chauhan, N. (2020). E-extension employability of scholars pursuing post-graduation in agricultural extension in SAUs: using data mining techniques. *Gujarat Journal of Extension Education*, **31** (1): 11-17.

Vinaya Kumar, H. M. and Gadde, S. (2025). A tool to measure livelihood vulnerability of climate-sensitive farming communities. *Indian Journal of Extension Education,* 61(4), 160–164. https://doi.org/10.48165/IJEE.2025.614RT01

Yeragorla Venkata Harikrishna, J. B. Patel and Vinaya Kumar, H. M. (2023). A study on assessing the attitude of atma and kvk personnel towards e-extension. *Guj. J. Ext. Edu.* 35 (2): 14-17. https://doi.org/10.56572/gjoee.2023.35.2.0004

Received : April 2026 : Accepted : June 2026