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Research Article

Optimizing Drying Processes with Machine Learning: A Data-Driven Classification Approach

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Efficient drying of medicinal and agricultural plants is critical for enhancing food security and maintaining product quality during storage. This study investigates the application of advanced machine learning models—XGBoost, Polynomial SVM (Poly-SVM), and Radial Basis Function SVM (RBF-SVM)—to classify the drying status of five medicinal plants: Moringa, Neem, Lemongrass, Mint, and Hibiscus. The models were trained and tested independently for each plant type using a dataset of 35,000 experimental trials, with environmental parameters such as Solar Radiation, Wind Speed, Altitude, Humidity, and Temperature serving as inputs. Performance was evaluated using key metrics including Accuracy, Precision, Recall, F1-Score, and ROC-AUC.

The results show that XGBoost achieved the highest mean accuracy of 78.0% across all plant types, alongside superior precision (0.80) and ROC-AUC (0.73), making it highly effective in minimizing false positives. Poly-SVM demonstrated the strongest recall (0.98), effectively identifying optimal drying statuses, though with slightly higher false positive rates. RBF-SVM performed competitively with a mean accuracy of 77.8% but showed slightly lower boundary discrimination. These findings confirm that machine learning models can significantly enhance drying efficiency, contributing to food security by minimizing post-harvest losses and extending the shelf-life of agricultural products. Future research will explore real-time monitoring and feature optimization to further improve classification reliability.

Keywords: Agriculture; Machine Learnig; Classification; Solar Drying

1. INTRODUCTION

Solar energy is one of the most promising renewable energy sources. Its widespread availability in sun-rich regions makes it especially relevant for agricultural applications. Among these, solar drying stands out as an effective and environmentally friendly technique for preserving perishable agricultural products. This process reduces the moisture content of products such as fruits, vegetables, and herbs, thereby limiting microbial growth and nutritional loss [1]. Solar drying is an efficient preservation technique that extends the shelf life of food, minimizes waste, retains nutritional value, and enhances storage and transportability [2]. Compared to traditional open-air sun drying, solar dryers offer greater control over drying conditions, reduce contamination risks, and improve drying efficiency [3]. Due to their high-water content, Fruits and vegetables, often suffer structural damage, taste loss, and nutrient degradation during conventional drying. However, with careful analysis and process control, high-quality dried products can be achieved [4].

Modeling, simulation, optimization, process control, and fault diagnosis are critical for advancing drying technology. These tools enable professionals to select optimal methods, optimize industrial-scale systems, maintain product quality, reduce energy use, and enhance efficiency [5], [6]. Rapid advancements in digital technologies and software have facilitated the integration of artificial intelligence (AI) into most existing drying methods, offering numerous advantages [7]. AI enables the optimization and precise control of the drying process, leading to improved product quality—an advantage not achievable through traditional drying techniques [8]. The integration of artificial

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intelligence (AI) further revolutionizes these processes: machine learning (ML), neural networks (ANN), fuzzy logic, and genetic algorithms (GA) enable predictive modeling, real-time control, and parameter optimization. For instance, ANNs predict moisture kinetics in onion and garlic drying [9], [10], while fuzzy logic shortens drying times and improves efficiency in peony flower processing [11], [12]. Hybrid systems like Genetic Neuro-Fuzzy (GNF) combine AI methods for accuracy in complex environments [13].

Emerging technologies like IoT and digital twins enhance AI's capabilities. IoT systems monitor microclimate parameters in real time, as seen in Senise pepper drying, where neural networks predict rot-risk conditions [14], and in IoT-BC dryers for leafy vegetables [15]. Digital twins integrate sensor data with physics-based models to optimize energy and quality in carrot drying [16]. ML models, including LSTM and CNN-LSTM, predict moisture content and optimize conditions for okra and apples [17], [18], [19] [20], [21], [21] [23], [24], [25]. Evolutionary algorithms like particle swarm optimization further refine drying parameters for banana slices [26].

Despite AI's integration into industrial drying, its application to medicinal plants remains underexplored. Existing research focuses on generic crops, neglecting AI-driven classification models for plant-specific drying states and the interplay of environmental variables (temperature, humidity, airflow) with quality parameters [27], [28], [29] [30], [31], [32]. This gap hinders real-time systems capable of preserving bioactive compounds and efficacy. Additionally, the lack of standardized datasets limits robust model development. This study pioneers SVM and XGBoost to classify medicinal plant drying states using environmental and process data. By correlating quality metrics with drying conditions, the models aim to enhance precision, reduce energy waste, and minimize product loss, critical for preserving phytochemicals [33], [34], [35] [36], [37], [38]. The work addresses data scarcity and computational constraints, offering scalable solutions for producers and advancing sustainable practices. It bridges technological innovation with practical feasibility, modernizing pharmaceutical industries while boosting production efficiency and food security.

The remainder of this paper is structured as follows: Section 2 describes the Methodology, including the Data Description, the theoretical foundations of the Support Vector Machine (SVM) and XGBoost models, and the Data Preprocessing techniques applied. Section 3 presents the Results and Discussion, analyzing the classification performance of the models across the five medicinal plants: Moringa, Neem, Lemongrass, Mint, and Hibiscus. Both numerical metrics and graphical results are evaluated to assess model accuracy, precision, recall, and discriminative power. Section 4 concludes the study with a summary of key findings and recommendations for future research.

2. METHODOLOGY

2.1. Data Description

The dataset, sourced from Kaggle [21], comprises 35,000 solar drying experiments across five medicinal plants (Moringa, Neem, Lemongrass, Mint, and Hibiscus) capturing 20 variables related to environmental conditions, process parameters, and quality outcomes. Key features include solar radiation, temperature, humidity, airflow, tray position, and drying zone, alongside output labels like drying status, quality score, and spoilage risk. Scatter plots (Figures 1) were generated to explore relationships between variables and drying outcomes. These visualizations reveal complex, non-linear interactions and partial class separability, underscoring the need for advanced models like XGBoost and SVMs to capture the underlying patterns effectively.

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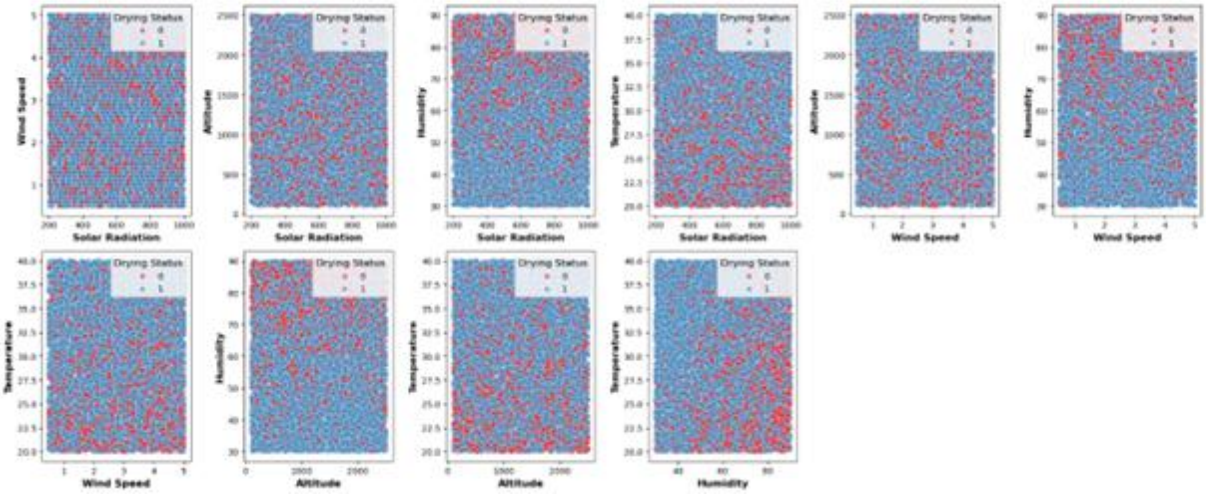

Figure 1. Two-by-Two Scatter Plots of Input Features for Moringa Drying Status Classification.

2.2. Mathematical Models

This section presents the theoretical foundations and mathematical formulations of two powerful supervised learning algorithms—Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost)—as applied to the classification of drying status for medicinal plants under varying environmental and process conditions [39], [40], [41] [42], [43], [44]

2.3. Flowchart of the Drying Status Classification

The structured workflow for implementing and comparing machines learning models—Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost)—in the context of medicinal plants drying status classification is illustrated in Figure 2. the flowchart outlines each stage of the pipeline, from data collection and preprocessing to training, prediction, and evaluation. The dual-path framework enables parallel experimentation and performance analysis between the two approaches, providing insight into their applicability and accuracy under real-world drying conditions.

Figure 2. Flowchart of the Drying Status Classification Using SVM and XGBoost.

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The data pipeline for this study begins with the collection of relevant features affecting the drying process of medicinal plants, including environmental parameters (e.g., temperature, humidity, solar radiation), operational settings (e.g., airflow, tray position, time of day), and categorical variables (e.g., plant type, weather conditions). These features are used to predict the drying status, categorized as Optimal or Moderate. Following data collection, preprocessing is performed to prepare the dataset for machine learning, involving encoding of categorical variables, normalization or standardization of numerical features, handling of missing values, and, where necessary, feature selection. This step is crucial for the performance of models like SVM and XGBoost, which rely on well-scaled and structured input. The dataset is then split into training and testing sets—typically using a stratified 70/30 split—to maintain class distribution and ensure fair evaluation. Model training is conducted using two parallel pipelines: SVM, utilizing either polynomial or RBF kernels with a One-vs-Rest approach, and XGBoost, which builds an optimized ensemble of decision trees. Finally, both models generate predictions on the test data—SVM by selecting the class with the highest decision function score, and XGBoost by applying the softmax function to its output probabilities—thereby evaluating their generalization capability on unseen samples.

2.4. Model Evaluation

To assess the performance of the classifiers, several evaluation metrics are computed. These include the confusion matrix, which shows true vs. predicted labels, as well as a classification report that summarizes precision, recall, and F1-score for each class. Accuracy may also be reported. These metrics provide insight into the strengths and weaknesses of each model—for instance, SVM may excel in linearly separable cases, while XGBoost typically performs well with nonlinear and complex feature interactions.

3. RESULTS AND DISCUSSION

In this section, the results of the drying classification for each medicinal plants (Moringa, Neem, Lemongrass, Mint, and Hibiscus) are presented and analyzed. The evaluation is conducted using three machine learning models. For each medicinal plant, the models were trained and tested independently, ensuring that the evaluation was performed on a per-plant basis. This approach allows for precise analysis of each medicinal plant's drying characteristics and the model's capability to classify its drying status.

All models were trained and assessed using the same input and output datasets, ensuring consistency across experiments. The input features consist of both environmental and process parameters previously described, including solar radiation, wind speed, altitude, humidity, and temperature. The output variable remains the binary classification of Drying Status (0 for incomplete, 1 for optimal).

3.1. Model Performance Analysis for Moringa Drying Classification

The classification performance of XGBoost, Polynomial SVM (Poly-SVM), and RBF-SVM for Moringa drying status was assessed using accuracy, precision, recall, and F1-score. XGBoost achieved the highest accuracy (77.9%), slightly outperforming Poly-SVM and RBF-SVM (77.6% each). It also led in precision (0.797), indicating better specificity. However, both SVM models had superior recall (Poly-SVM: 0.987, RBF-SVM: 0.985), showing greater sensitivity. F1-scores were nearly identical (~0.87) across models, reflecting a balanced trade-off between precision and recall.

Table 1. Performance Metrics for Moringa Drying Classification Using XGBoost, Poly-SVM, and RBF-SVM

Metrics	Accuracy	Precision	Recall	F1	ROC	TP	FP	FN	TN
XGBoost	0.779	0.797	0.958	0.870	0.735	2396	611	105	121
Poly-SVM	0.776	0.781	0.987	0.872	0.700	2469	693	32	39
RBF-SVM	0.776	0.782	0.985	0.872	0.665	2464	68	37	44

3.2. Model Performance Analysis for Lemongrass Drying Classification

The performance evaluation of XGBoost, Poly-SVM, and RBF-SVM for Lemongrass drying classification (Table 2) shows all models performing strongly. XGBoost achieved the highest accuracy (78.3%) and precision (0.801), indicating better balance and reliability in identifying the "Optimal" drying status. While Poly-SVM and RBF-SVM had slightly lower precision (0.784), they demonstrated superior recall (0.990 and 0.989), effectively capturing nearly all optimal cases. F1-scores were comparable across models (~0.87), suggesting balanced performance. However, XGBoost had the highest ROC-AUC (0.737), indicating better class discrimination. Confusion matrix

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analysis revealed XGBoost had fewer false positives but slightly more false negatives, while SVMs favored sensitivity at the cost of increased false positives.

Table 2. Performance Metrics for Lemongrass Drying Classification Using XGBoost, Poly-SVM, and RBF- SVM

Metrics	Accuracy	Precision	Recall	F1	ROC	TP	FP	FN	TN
XGBoost	0.783	0.801	0.957	0.872	0.737	2345	583	106	137
Poly-SVM	0.781	0.784	0.990	0.875	0.723	2427	670	24	50
RBF-SVM	0.781	0.784	0.989	0.875	0.686	2425	667	26	53

3.3. Model Performance Analysis for Mint drying classification

All three models—XGBoost, Poly-SVM, and RBF-SVM—performed similarly in accuracy, with RBF-SVM slightly ahead (77.6%) (Table 3). XGBoost led in precision (0.795), indicating better control over false positives, while Poly-SVM and RBF-SVM showed higher recall (0.987 and 0.980), capturing more "Optimal" instances. F1-scores were close, slightly favoring the SVMs (~0.870) over XGBoost (0.865). In terms of ROC-AUC, XGBoost performed best (0.737), suggesting stronger overall class separation. Confusion matrices showed that XGBoost had fewer false positives but more false negatives, while Poly-SVM was most aggressive in detecting optimal cases, resulting in the fewest false negatives but the most false positives. RBF-SVM offered a balanced compromise between the two.

Table 3. Performance Metrics for Mint Drying Classification Using XGBoost, Poly-SVM, and RBF-SVM

Metrics	Accuracy	Precision	Recall	F1	ROC	TP	FP	FN	TN
XGBoost	0.773	0.795	0.948	0.865	0.737	2288	590	126	154
Poly-SVM	0.775	0.778	0.987	0.870	0.724	2383	679	31	65
RBF-SVM	0.776	0.782	0.980	0.870	0.662	2366	658	48	86

3.4. Model Performance Analysis for Hibiscus Drying Classification

For Hibiscus drying classification (Table 4), all models—XGBoost, Poly-SVM, and RBF-SVM—demonstrated strong performance, with RBF-SVM achieving the highest accuracy (78.3%). XGBoost led in precision (0.805), effectively reducing false positives, while Poly-SVM had the highest recall (0.980), excelling at detecting "Optimal" instances. F1-scores were similar across models (~0.87), reflecting balanced performance. XGBoost showed the highest ROC-AUC (0.728), indicating superior class discrimination. Confusion matrix analysis revealed XGBoost favored precision with fewer false positives (570) but more false negatives (133), whereas Poly-SVM minimized false negatives (50) at the cost of more false positives (651). RBF-SVM provided a middle ground between the two, balancing sensitivity and specificity.

Table 4. Performance Metrics for Hibiscus Drying Classification Using XGBoost, Poly-SVM, and RBF-

Metrics	Accuracy	Precision	Recall	F1	ROC	TP	FP	FN	TN
XGBoost	0.781	0.805	0.946	0.870	0.728	2350	570	133	159
Poly-SVM	0.782	0.789	0.980	0.874	0.715	2433	651	50	78
RBF-SVM	0.783	0.792	0.977	0.875	0.680	2426	639	57	90

Across all plant types, XGBoost consistently achieved the highest ROC-AUC scores (≈0.73–0.74), indicating superior overall discrimination between "Optimal" and "Moderate" drying statuses. While SVM models (Poly-SVM, RBF-SVM) demonstrated higher recall, they incurred more false positives, highlighting a tendency toward over-classification of "Optimal" cases. In contrast, XGBoost maintained a better balance, with fewer false positives and slightly lower recall, confirming its stronger precision and class separation. These trends are clearly reflected in both the ROC curves and the confusion matrices (Figure 3).

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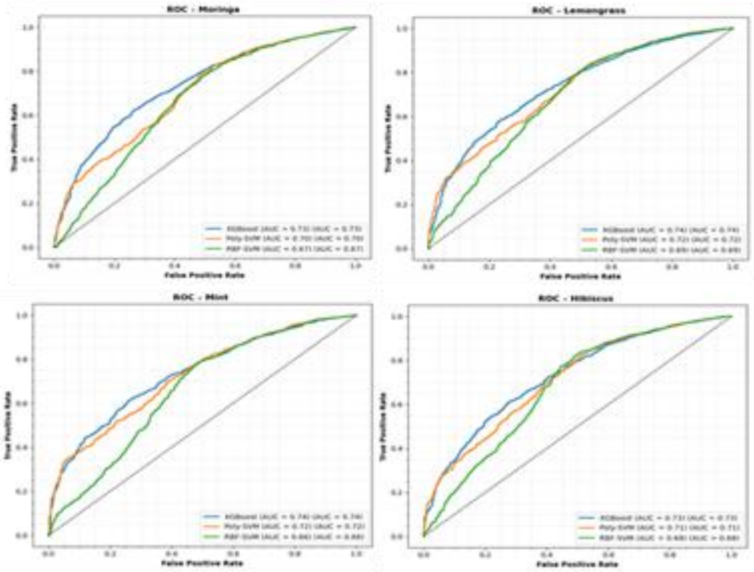

Figure 3. Confusion Matrices and ROC Curves for all Drying Classification Using XGBoost, Poly-SVM, and RBF-SVM

4. CONCLUSION

This study evaluated the performance of XGBoost, Polynomial SVM, and RBF-SVM in classifying drying statuses for five medicinal plants using consistent features and metrics. All models effectively captured non-linear relationships between environmental and process variables. XGBoost consistently achieved the best balance between precision and recall, with high ROC-AUC scores, making it ideal where minimizing false positives is critical. Poly-SVM showed the highest recall, making it preferable for maximizing detection of optimal drying but at the cost of more false positives. RBF-SVM performed competitively but trailed slightly in class separation and precision. Visual analyses using ROC curves and confusion matrices supported these findings. Ultimately, model selection should align with specific goals—favoring XGBoost for precision and Poly-SVM for recall. Future research could enhance performance further through ensemble strategies and feature optimization.

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